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Novel Edge Device System for Plant Disease Detection with Deep Learning Approach

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Abstract: Plant diseases result in significant economic losses and pose an annual threat to food security in agriculture. The key to minimizing these losses lies in the accurate and prompt identification and diagnosis of plant diseases. Despite the prevalent use of deep neural networks for plant disease identification, challenges such as low accuracy and a high number of parameters persist. There are multiple challenges while using trained deep learning model on edge devices. This paper proposed novel plant disease detection system with MobileNetV2 algorithms and developed novel edge device system with Sipeed Maixduino development board. The system has been trained with 10000 images of 10 different types of tomato plant diseased and healthy leafs. The system has been evaluated and tested with edge device for 10 different types of leaf diseases in tomato plant. The experimental results shows 94% of accurate results during validation of system performance.

Keywords: *Internet of Things, Deep Learning, Machine Learning, Robotic system, Edge Device*

1. Introduction

Detecting plant leaf diseases is a significant challenge, as timely diagnosis proves challenging in many global regions due to a lack of automated crop disease identification methods [1]. Failing to promptly recognize and address plant diseases can result in increased food insecurity, affecting a country's overall income. Identifying plant diseases [32][33] is crucial for effective disease prevention and for managing farm production [2].Accurately detecting crop diseases in their early stages is crucial for ensuring crop quality and yield, enabling timely and effective treatment decisions [3]. However, successful disease detection demands specialized knowledge and extensive experience in plant pathology [35]. Hence, the development of an automated system for disease detection in crops is essential to establish an early disease detection system in agriculture [4].

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This paper provide brief review on various machine learning methods to detect leaf disease and also highlights on use of different edge devices [36][37]. The system has been proposed and implemented with Sipeed Maixduino to detect tomato plant diseases by uploading trained machine learning model in it [39][40][41].

2. Related Work

Numerous researchers developed different application specific system for agriculture. The various research articles has been studied. This section provides key highlights of earlier developed system, brief summary and comparative analysis of reviewed literature.

The development and application of plant disease detection technologies play a crucial role in early identification of infected plants, contributing to cost-effective expansion of plant disease identification systems across various plant types. The author introduces a noteworthy contribution in the form of a stacked ensemble technique, combining ML and DL methodologies [1]. The proposed stacked ensemble learning approach undergoes a thorough evaluation by comparing it with different models employing both techniques, using metrics such as precision, recall, and F-score. The results demonstrate that the proposed technique achieves an impressive accuracy rate of approximately 99%, surpassing traditional ML and DL approaches [42].

The development of an automated system for disease detection in crops is essential to establish an early disease detection system in agriculture [2]. The model employs a Convolutional Neural Network method consisting of five number of pre-trained models. To increase its adaptability, the category 'unknown' has been introduced to generalize the model for a wide range of applications. In validation tests, the disease detection model exhibited high accuracy (97.09%) in classifying crops and disease types. Another author introduces a mathematical model designed for the deep learning-based detection and recognition of plant diseases [4][43], emphasizing improvements in accuracy, generality, and training efficiency. The process commences with employing the RPN to identify and locate leafs in intricate environments. Subsequently, images undergo segmentation based on the RPN algorithm results, capturing symptom features using the Chan–Vese (CV) algorithm

[5]. The model undergoes specific testing for diseases like black rot, bacterial plaque, and rust, showcasing a method accuracy of 83.57%, surpassing conventional methods. The proposed algorithm holds significant relevance in the realms of intelligent agriculture, ecological protection, and overall agricultural production [45][46].

The researcher's addresses the challenge of attaining high accuracy in DL models designed [6] for agricultural applications on edge devices, while acknowledging inherent resource constraints. The paper specifically delves into an agricultural application, employing models for the identification and categorization of plant diseases through image-based crop monitoring [7]. The MobileNetV3-small model effectively categorizes leaves with a test accuracy of approximately 99.50%. Another paper introduces a novel model, CACPNET [8], designed specifically for disease identification in common plant species by combining channel attention and channel pruning. It seamlessly integrates into a ResNet-18 model, incorporating both global pooling to significantly enhance the extraction of features from plant leaf diseases [9]. Following optimal feature extraction conditions, unimportant channels are eliminated using the L1-norm channel weight and local compression ratio, reducing the model's parameters and complexity [47]. CACPNET achieves an impressive accuracy of 99.7% on the PlantVillage public dataset and 97.7% on a local peanut leaf disease dataset. Compared to the base ResNet-18 model, CACPNET demonstrates a 30.35% decrease in floating-point operations (FLOPs), a 57.97% reduction in parameters, a 57.85% decrease in model size, and an 8.3% reduction in GPU RAM requirements.

The main aim of the proposed initiative is to develop an Embedded System that employs Convolutional Neural Network (CNN) technology for the precise identification of plant diseases, specifically targeting those affecting agricultural crop plants [10]. The system's objective is to accurately detect plant diseases [48] in agricultural fields and promptly communicate this information to users. The outcomes are conveniently accessible through a mobile app, presenting on the mobile screen. The system incorporates various environmental parameters, including temperature, humidity, and soil moisture, and is powered by a Raspberry Pi as the processor, utilizing sensors for continuous environmental monitoring [11]. In order to automatically detect plant diseases in agriculture, the Internet-of-Agro-Things (IoAT) idea is introduced [12]. The authors examine crop photos taken by a health monitoring system using an extensively trained CNN model [13]. For constant sensing and intelligent automation, a solar sensor node equipped with a soil moisture sensor is utilized. The technology obtains a 99.24% accuracy rate in plant disease detection after three months of deployment.

Stripe rust is a severe fungal disease that damages wheat, the main crop of Pakistan, and results in 5.5 million tonnes of waste every year. A method to identify and categorize wheat rust disease into four groups—healthy, resistant, moderate, and susceptible—has been presented in an effort to reduce this loss [14]. The background is eliminated and the leaf with the rust illness is extracted using a pre-trained U2 Net model as shown in figure 1 as system architecture process flow. The stripe rust extents are then classified using two deep learning classification models [15], a model called

Xception and ResNet-50, with the latter performing best with an accuracy of 96%. The smart edge computing device is also part of the system to monitor rust assaults.

The changing environmental circumstances cause a significant increase in stress in plants. In research, a novel approach to automatically identify plant stress utilizing deep learning and computer vision for edge computing platforms is proposed [16]. In order to detect the sickness early, the innovative model identifies the disease [17] and, if the disease is discovered, sends an alarm to the cloud. 93% test accuracy and 90% validation accuracy were exhibited by the new CNN model that was suggested. When tested on the Raspberry Pi 4, the tCrop Lite version had a 94% test accuracy and an estimate time of 0.001 seconds.

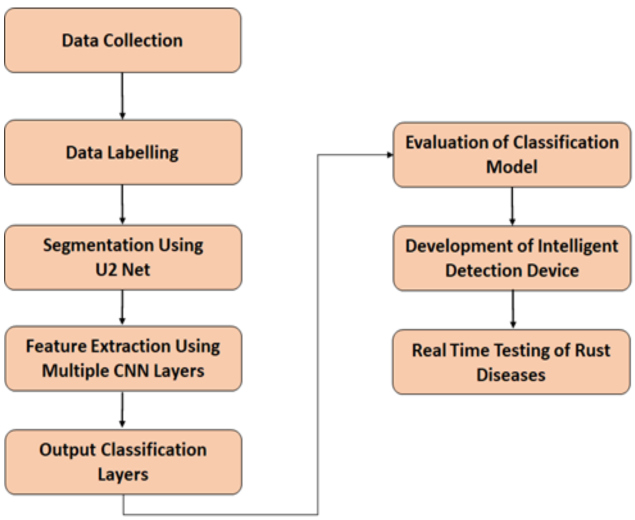

Fig. 1. System Architecture Process Flow

The automation and orchestration of numerous complicated systems is made possible by the Internet of Things [49 that entails the linking of numerous sophisticated sensors and auxiliary devices. Smart devices are used in agriculture to gather and send data from a variety of sensors that keep an eye on complex environmental factors that are essential to promoting healthy plant growth. These variables include, but are not restricted to, water pH, temperature, humidity, and soil moisture. Manual disease monitoring is time-consuming and necessitates specific knowledge of plant pathology. CNN models that use DL techniques have been created to detect and diagnose plant diseases as a solution to these problems [18]. This program accurately classifies [19] the health condition of plants by using photos of diseased plant leaves. The collection comprises of plants that are unaffected by Thrips insects, Bacterial Blight, and Anthracnose Bacteria. With the use of cutting-edge technologies, farmers will be able to properly manage their crops and boost productivity thanks to the proposed IoT framework, which can greatly improve crop monitoring.

Agricultural drone use has spread to a variety of tasks in the field, such as mapping, seeding, growth monitoring, and fertilizer application. This allows the photos to be processed and leaf attributes to be analyzed, which can aid in the detection of disease. The appropriate machine learning (ML) methods [50][51] are applied following feature extraction using image processing techniques [20]. Drones can also be utilized in a variety of applications to minimize labor costs and human effort [21]. Another study suggests using a machine learning model [22] based on several leaf photos to identify plant diseases in four different plant species: tomato, apple, maize, and potato. The type of disease afflicting the leaf is classified using a CNN model that was trained using the Plant Village dataset [23]. Utilizing Vitis AI, the learned model is applied to AMD Xilinx's Kria KV260 FPGA to diagnose the illness. The achieved disease categorization accuracy is approximately 98.04%.

Yield loss of more than 50% owing to pests and diseases is reported, with smallholder farmers accounting for more than 80% of agricultural production and their livelihood depending on a healthy crop yield. With 5 billion smartphones predicted to be in use by 2020, smartphones are frequently utilized by crop growers worldwide [52]. This presents an opportunity to transform smartphones into useful tools for various groups cultivating food [24]. Utilizing cutting-edge technology such as cloud computing and deep learning. Constant observation can stop the disease from spreading. However, it will take a lot of time and work to manually monitor diseases. Therefore, having an automated system is an excellent idea. The research provides a lightweight artificial intelligence technique-based rice leaf disease detection system [25]. The author used a Raspberry Pi to implement the edge computing concept [53]. The author used a Raspberry Pi to process all of our data and took into account three rice plant diseases [54]. On edge device, author got 97.50% accuracy utilizing designed image classification model. The comparison of Different State of Art Algorithms used in Plant Disease Detection System has been given in Table 1.

Table 1 Comparison of Different State of Art Algorithms for Plant Disease Detection System

Parameters	***State of Art Algorithms***			
	ResNet-18 [26]	***DenseNet-201 [27]***	***Inception-v3 [28]***	***MobileNetV2 [29]***
No. of Network Layer	18	201	48	53
Features/ Advantage	There are just two pooling layers employed in the entire network: one at the start and one at the finish.	Strengthen feature propagation, Vanishing-gradient problem, encourage feature reuse	Able to load a pretrained network version that was trained using the ImageNet database's more than a million photos.	Inverted residual structure
Importance	A fundamental component of many computer vision tasks	Employed in high-level neural networks to increase the decreased accuracy brought on by the vanishing gradient	For assisting in image analysis and object detection	Designed for mobile and embedded vision applications.

3. Proposed Methodology

The novel plant disease detection system has been proposed to detect the diseases in tomato plant.

3.1. System Work Flow

The dataset of 10000 images of different 10 categories of tomato plant diseased leaf including 1000 healthy leaf has been obtained from Kaggle platform. The obtained dataset has been resize to 224*224 and then pre-processed with image augmentation techniques. The dataset images to be uploaded to MicroPython Development Environment (MaixPy) for model training and validation using Tensorflow 2.0 with Keras utility [30]. The system used MobileNetV2 algorithm for training. To utilize trained model on edge devices, the Tensorflow model need to be converted to Tensorflow Lite Model. To use it on Sipeed Maixduino with K210 inside, the Tensorflow Lite model to be converted to K-Model [31]. The KPU uses this K-model to detect plant diseases in camera captured real time leaf images. The system workflow is shown in Figure 2.

An Arduino-compatible prototyping board is called Sipeed MaixDuino. Camera, TF card place, interface buttons, TFT display, and MaixDuino extension interface are all integrated into MaixDuino [30]. With MaixDuino, users can quickly create an access control system that recognizes faces. They can also reserve an interface for development and debugging, which doubles as a functional and potent development board for AI learning.

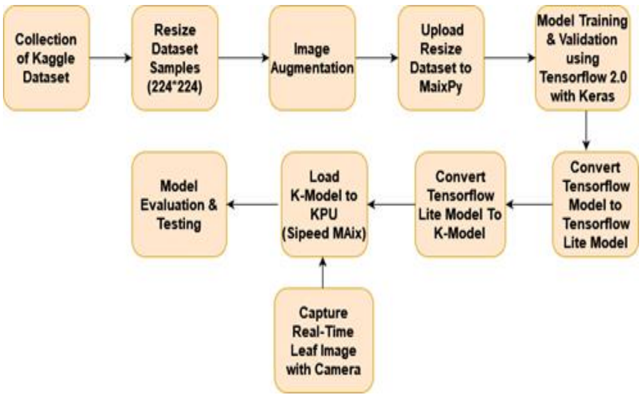

Fig. 2. Proposed System Work Flow Diagram

The powerful M1AI module serves as the foundation of the Maixduino development board, which also includes an 8MB on-chip SRAM and an integrated 64-bit dual-core processor chip. The module has a total computing capability of up to 1TOPS, which includes an FPU and a FFT Accelerator. It performs exceptionally well in AI machine vision and aural applications [31]. This feature makes machine vision and auditory algorithms easier to apply in a range of application settings. The module also includes preprocessing for speech data output and voice direction scanning. An ESP32 module, which combines WiFi and Bluetooth capabilities and allows for easy Internet connectivity through basic operations, adds even more functionality to the development board.

3.2. MobileNetV2 Algorithm

One specialized deep learning design known as MobileNetV2 was created specifically for mobile and edge devices that face resource constraints [29]. It is well known for being efficient as far as of both model size and computing demands, having evolved from the original MobileNet. MobileNetV2 is widely used in a variety of applications, such as object recognition and image classification. It is especially useful in situations where computing resources are limited. MobileNetV2 serves as the core structure for CNN in the field of plant disease detection. The procedure entails gathering a dataset of pictures of both healthy and sick plant leaves, then classifying the images according to the appropriate ailment. The output layer must be adjusted to correspond with the precise number of disease classes in order to fine-tune the algorithm for plant disease identification. The dataset is split into training and validation sets as part of the training process. The model gains relevant properties linked to plant diseases by varying its weights. The model's capacity to successfully generalize to new, untested data is ensured by further validation. After being trained, the model performs inference on fresh images and, when shown an image of a plant leaf, makes predictions about the probability of certain diseases. The trained MobileNetV2-based model is perfectly suited for on-device plant disease detection in terms of practical deployment, particularly on devices limited by elements such as smartphones, IoT gadgets, or edge computing devices. Because of its lightweight architecture, which makes real-time inference easier, it's a great tool for field applications like plant disease detection.

3.3. Edge Device for Disease Detection

The project's main goal is to create an edge device that can identify plant illnesses. It will do this by combining three necessary parts: the Maix LCD, a binocular camera, and the Sipeed Maixduino as shown in figure 3. The Sipeed Maixduino, which functions as the central processing unit, provides computing power and runs algorithms for identifying plant diseases. The binocular camera's integration improves the device's image-capturing powers by using stereo vision to capture in-depth plant leaf scans. The Maix LCD is incorporated into the design to provide users with visual feedback, enabling them to communicate with the device and view the plant disease detection results in real-time.

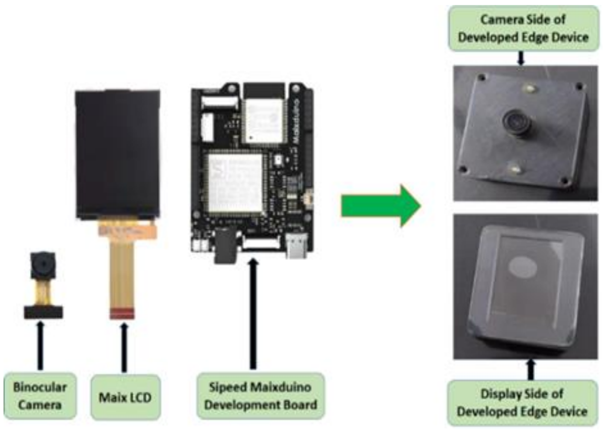

Fig. 3 Developed Edge Device

This feature improves overall usability by contributing to an enhanced user interface. This edge device's main goal is to make it easier to identify plant diseases in real time and on the spot. By utilizing the Sipeed Maixduino's computational power and the binocular camera's imaging capabilities, the device takes pictures of plant leaves and analyzes them for disease indicators. The outcomes are then quickly shown on the Maix LCD, giving consumers immediate feedback. This breakthrough is important because it may be applied to precision agriculture, which will enable farmers and other agricultural professionals to quickly detect and treat plant problems on the farm. The gadget's sophisticated imaging and processing capabilities, along with its small size and portability, make it an invaluable tool for proactive and effective disease management in agriculture.

4. Experimental Results & Discussion

The complex experimentation has been carried with different environmental conditions to obtain better results which has been discussed below.

4.1. Hyper Parameters & Computing Resources

The developed edge device uses following Hyper-parameter and computing resources as shown in Table 2.

Table 2 Hyper-parameters and Computing Resources

Parameters	***Description***
Crop Selection	Tomato Plant
Experimental Scenario	Green House
Image Data Set	Kaggle
Machine Learning Algorithm	MobileNetV2
Data Set Samples	1000 Per Disease
Training Platform	Tensorflow 2.0 with Keras Model
Development Board	Sipeed Maixduino module WiFi version (1st RISC-V 64 AI Module, K210 inside)
Programming Environment	MicroPython Development Environment (MaixPy)

4.2. Edge Device Evaluation and Testing

The developed device has been evaluated and tested with complex experimentation as shown in figure 4. The experiment uses multiple images all 10 categories of tomato plant disease leaf including healthy images also to check the potential of edge device with Sipeed MAixduino. The device also tested with more than 100 images which was not used for training the model.

4.3. System Validation

The device validation has been done for all 10 types of dataset samples used throughout the experiment. The performance of developed edge device has been validated by obtaining accurate results for more than 94% samples. The figure 5 shows the detection of various disease in tomato plant like Early Blight, Bacterial Spot and Healthy leaf.

Fig. 4. Edge Device Evaluation and Testing

5. Conclusion and Future Scope

Machine learning techniques plays an important role in agriculture sector especially in detection plant conditions. The novel plant disease detection system with MobileNetV2 algorithms has been proposed and developed edge device with Sipeed Maixduino development board. The system has been evaluated and tested with edge device for 10 different types of leaf diseases in tomato plant. The experimental results shows 94% of accurate results during validation of system performance. In future, the designed deep learning model can be used on different edge devices like Raspberry Pi etc. and performance should be compared. To operate system with large dataset, the cloud based storage system could be used in future to avoid hardware failure occurred due to limited on-chip memory.

Conflicts of interest

There is no conflicts of interest.

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