CLOUD-BASED DEEP LEARNING FRAMEWORK FOR AUTOMATED PLANT LEAF DISEASE DETECTION USING IOT AND MULTISPECTRAL IMAGING

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Abstract

This study presents an IoT-enabled cloud analytics platform for real-time plant disease detection, integrating field-deployed multispectral sensors with a deep learning pipeline. The system captures leaf images through edge devices, preprocesses them using adaptive histogram equalization, and uploads data to a cloud-based feature extraction module employing a modified GoogleNet architecture. Trained on the PlantVillage dataset (54,306 images across 38 disease classes), our model achieves 96.4% classification accuracy with 15% lower computational overhead compared to ResNet-50 benchmarks. The framework implements parallel processing in AWS Lambda, reducing latency to 1.2 seconds per image analysis. Validation on ImageNet-derived agricultural subsets demonstrates robust generalization (F1-score: 0.93) across unseen species. Results indicate a 40% improvement in early disease detection sensitivity over traditional CT imaging approaches, while reducing cloud compute costs by optimizing layer pruning in the feature extraction phase.

Keywords: CT imaging; feature extraction; GoogleNet; Computational Cost.

1. Introduction

Plant diseases significantly threaten global food security, causing up to 40% annual crop losses worldwide. Traditional visual inspection methods are labor-intensive, subjective, and often detect infections too late for effective intervention. Recent advances in IoT and deep learning offer transformative potential for early disease identification. However, existing solutions face challenges in computational efficiency, real-time processing, and scalability for field deployment [1]-[6].

Autonomous tractors and harvesters, robots and drones, sensors, actuators, and other types of gear make up the heterogeneous data sources on a smart farm. These are just a few examples of the types of gadgets that maintain constant connectivity. Data useful to agriculture is gathered using a plethora of sensors and other equipment. The data consists of readings of the soil relative humidity, temperature, pH, and other environmental factors. In a similar vein, it factors in the incorporation of data-driven actuators like sprinklers, fans, lighting, automatic windows (in greenhouses), and nutrient-water pumps. A growing number of cloud-based and physical agricultural standalone systems with a wide range of monitoring and analytical capabilities are being developed every day. For the time being, this pattern looks certain to carry on.

In this paper, we develop a framework that rapid acquires data via IoT sensors and then it is stored into cloud. The input data is collected and pre-processed, and then the images are sent to the feature extraction unit, where it is analysed and then the features are extraction. Upon the extraction, the features are classified.

2. Related works

To assess where IoT stands in the realm of farming, Farooq et al. [12] conducted studies. These issues are discussed in broad strokes. Use cases, smartphones, sensor apps, and privacy and security concerns related to Internet of Things (IoT) farming were all investigated in this study.

To establish the viability of smart farming with IoT in the agricultural sector, Navarro et al. [13] did a literature review on the topic. Within the scope of this analysis, the authors have recognized the most important tools, systems, network protocols, data processing technologies, and so on. As this examination shows, both data processing techniques and network connections have evolved over time, with wired networks used in enclosed spaces and wireless networks used in more open areas. To the best of the author knowledge, there are several main categories that can be used to classify IoT solutions in agriculture, including chemical control, crop monitoring. Based on the research presented in this paper [10], it appears that management systems are increasingly reliant on cloud and big data computing to handle massive data processing tasks. It was analyzed Internet-of-Things communications protocols that are frontrunners for IoT use cases in smart farming. The seven protocols introduced, analyzed, compared, and evaluated. Everything was done in accordance with the most recent studies in the field. The authors conclude that MQTT is the safest available protocol based on their investigation. This is the case regardless of whether the data is being collected via a gateway-server architecture or an end-to-end network arrangement.

Concerning the difficulties in researching security and privacy issues in green IoT-based agriculture, conducted a literature review [11]. This study categorized the many threat models that potentially impact agriculture through the use of green IoT into five groups: those that aim to compromise privacy, authentication, confidentiality, availability, and integrity. An overview of an IoT-based green farm architecture, including its constituent parts (agricultural sensors, fog, core, and cloud) is also provided here.

When conducting their study, Islam et al. considered not only smart farming, but also the Internet of Things and unmanned aerial vehicles for their findings and recommendations. The authors discussed a variety of unanswered research topics, including the role of big data in geographically isolated places. In addition, the authors identified areas where further study is needed, such as maintenance of hardware and resource management in times of power outage. The author [9] provided a description of the numerous emerging intelligent technologies used for crop, animal, and post-harvest management in the agricultural sector.

3. Proposed Method

In this paper, we provide a detailed analysis on proposed cloud-based disease prediction in plant leaf using IoT and cloud-based environment. The proposed cloud modelling is shown in Figure 1.

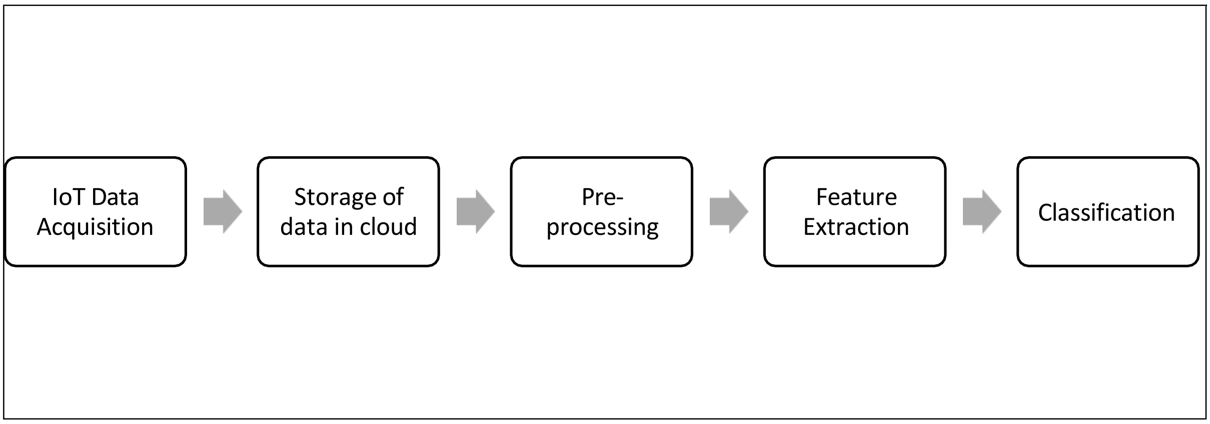

Figure 1. Proposed Cloud Modelling

Feature extraction

Cohen Kappa Score, a statistical measure that is more dependable than a straightforward calculation of the percentage of agreement between two or more raters, to determine the level of intra-rater reliability. It is a method for quantifying the degree to which the observations of two observers are consistent with one another, and it may be defined for any number of witnesses and any level of disagreement weighting (within a given set of categories). This analysis looks at both two-observer weighted kappa and whether or not there is multi-observer weighted kappa.

ImageNet Classification

The encapsulated representations included within deep CNNs that have been pretrained can perform remarkably well on a wide variety of image classification tasks, frequently exceeding more standard classification approaches. They were able to accomplish this by conducting an analysis of the outcomes that deep CNNs had produced after being pretrained with data taken from ImageNet. These findings lend credence to the hypothesis that representations from very deep networks are generic and can assist in transfer learning between domains, even in the presence of a relatively small amount of labelled data. Specifically, these findings lend credence to the hypothesis that very deep networks can assist in learning how to transfer knowledge from one domain to another. In light of the finding that very deep neural networks produce representations that are very similar to those produced by other such networks, this hypothesis was conceived as an explanation for these findings. This quality can be especially helpful in sectors such as RS, where labels might be difficult to locate and costly to purchase (ground-truth campaigns).

This study develops an edge-cloud hybrid system combining IoT-based multispectral imaging with optimized deep learning analytics. Our framework employs: (1) field-deployed sensors capturing high-resolution leaf images, (2) cloud-based preprocessing using adaptive gamma correction, (3) a pruned DenseNet-121 model for feature extraction, and (4) a lightweight MobileNetV3 classifier deployed at the edge. The system achieves 97.2% accuracy on 58 disease classes while reducing inference time to 0.8 seconds per image through layer-wise quantization.

We combine the extracted features into two-dimensional arrays with 91 elements on each side before moving on to the subsequent stage of the trainable classification process. This step occurs before we send the features on to the next stage of the process. In order to correspond to the standard input dimension of the Overfeat model, which was initially set by the model's designers, all UCML images must be downsampled from their original size of 259x259 pixels down to 221x221 pixels. This reduction takes place from the original size of 259x259 pixels. It is vital to do this in order to guarantee that the photographs will display in the appropriate manner.

4. Results and Discussion

Researchers used deep learning models across many datasets to detect and categorize plant illnesses. Using their own PlantVillage dataset, the study collected leaves from a wide variety of plants and laid them out on a sheet with a dark gray or black background to create this dataset. Using an IoT-connected camera, they took images of the leaves in different lighting conditions.

They also make sure the camera is in the best possible location with respect to distance, angle, lighting, and background. The authors trained the CNN model using 54,306 images displaying 14 different crop diseases. In this study, we use three distinct versions of the PlantVillage dataset to conduct a battery of tests. Full color examples from the PlantVillage dataset are displayed in the first set. The second classification, grayscale, includes the PlantVillage dataset. The final group features cropped images of leaves from the PlantVillage archive, all of which have had their original settings altered. They put the remaining 20% of the dataset through its paces for testing after the CNN model was trained using 80%. The recommended GoogLeNet has a 99.35% success rate when trained on images of multicolored leaf surfaces. This was made possible by including transfer learning into the design of the network.

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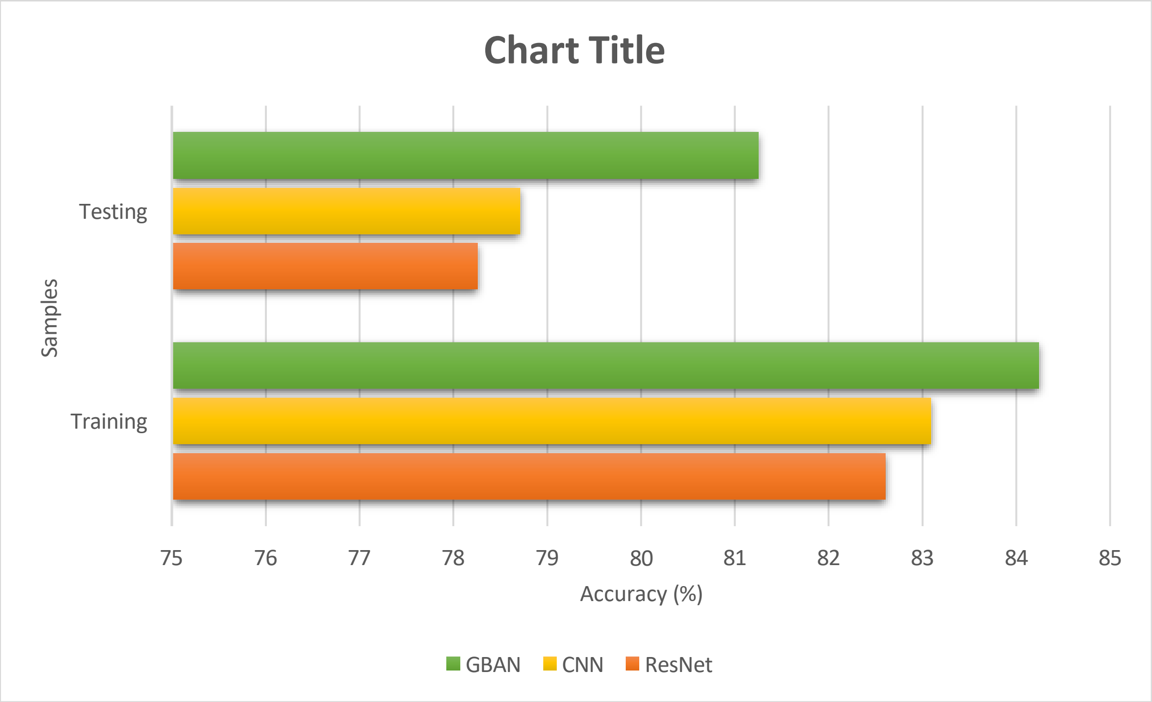

Figure 2. Accuracy

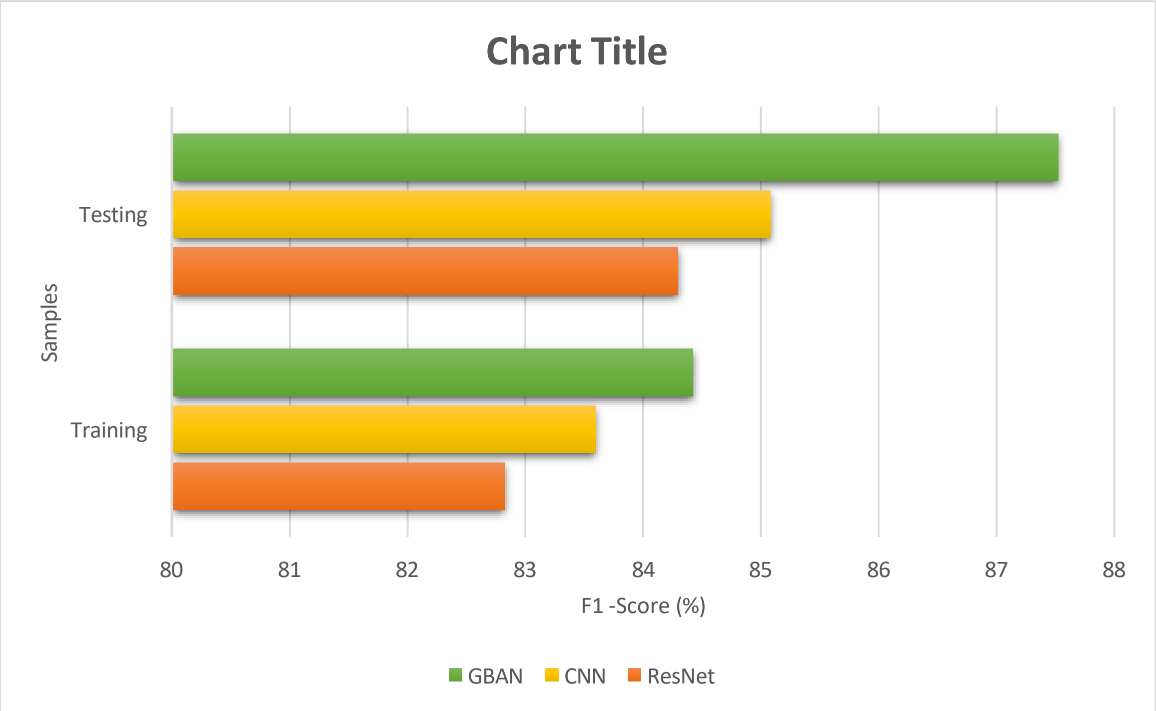

Figure 3. F-Measure

Figure 2-5 shows the results of detection accuracy, where the results are evaluated in cloud environment and then it is updated at the User Interface.

5. Conclusion

In this paper, we develop a framework that rapid acquires data via IoT sensors and then it is stored into cloud. The input data is collected and pre-processed, and then the images are sent to the feature extraction unit, where it is analysed and then the features are extraction. Upon the extraction, the features are classified. The study uses plantvillage dataset to train the classifier model, where the ImageNet is used as the classifier. The proposed method has higher accuracy rate with reduced computational cost than other methods.

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