International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 12, No.1 (Jul-2022)

https://dx.doi.org/10.12785/ijcds/120127

Plant Health Detection Enabled CNN Scheme in IoT Network

Ali Orangzeb Panhwar[1,2], Anwar Ali Sathio[1,3,*], Mujeeb ur Rehman Shaikh[1], Abdullah Lakhan[1], Muhammad Umer [1], Rabia Mushtaque Mithiani [1] and Sanwali Khan[1]

[1]*Lab of A.I and Information Security, DepartmentofComputer Science and Information Technology,Benazir Bhutto Shaheed University Lyari, Karachi , Sindh, Pakistan*
[2]*Faculty of Engineering and Technology, IICT, University of Sindh, Jamshoro, Pakistan*
[3]*Department of Computer Science, Sindh Madressatul Islam Karachi Sindh, Pakistan*

Received 24 Jun. 2021, Revised 25 Jan. 2022, Accepted 25 Feb. 2022, Published 20 Jul. 2022

Abstract: Green Environment is a key for Healthy Environment, to keep environment green every country doing a lot to preserve their Healthy growth in the agriculture. The detection of diseases in plants is very hard job and will have a significant impact of environmental development growth as well as production.The problem of the study is to diagnosis the plant's micro diseases to prevent the big loss of plants' production as well as food production, we used the IoT based technology with machine learning scheme This study aimed to detect unhealthy plants through infected leaves using CNN enabled method helped to mitigate the worst situation for the less developed countries. This research study had modelled the IoT network-based Plant Health Detection System, in which we explored the different invisible patterns of plant leaves which can't be detected easily in the plants. In this research article, we have investigated and developed a IoT-network system with a CNN model successfully that can detect the invisible micro things in the plants by getting 95 percent of accuracy in the study. In this research study, we used IoT-Network system by applying the CNN technique to train the model for detection of diseases in leaves. This model scheme provided the best performance detection with an accuracy of 95 percent, demonstrating the performance of the proposed CNN scheme after implementation.

Keywords: CNN, IoT, Leaves Disease, Detection , Leaves Pattern, Plant Health

1. Introduction and Overview

Today is the world of Artificial Intelligence and the Internet of Things (S-IoT) are going to be widely used in every smart and intelligent system because these fields are one of the strongest fields nowadays. We know that plants are necessary for our real-life environment because they provide us with a natural and healthy environment. The system for detecting plants attracts significant attention in the field of plants, where finding the cure of infected plants plays an important role [1], [2]. The rapid development of new emerging technologies makes fast changes in the environmental of this world. Internet technology has been providing a unique solution for the development of farming, agriculture, and especially in the forestry with intelligent robotic farming systems [3], where IoT based sensors are used via internet to utilize max level of technology. Internet of Things (IoT) can be used in intelligent-based farming to enhance the quality of plants[4]. Artificial Intelligence helps state of the art ecosystem and raid progress without loss in minimum cost. However, Artificial intelligence enables machines to think like humans and act with least human interference [4], [5], [6].

The Plant Health Detection System through leaves health observable and different invisible patterns that can't be seen on the plants by naked eyes can be mitigated using this technology [7], [8], [9], [10]. The major impact of this emerging Technology fuels the environment with healthy natural resources which are very necessary benefits for natural healthy environment, the visual detection of plant's disease is more challenging task than image processing, A.I based disease detection techniques being used will take less effort and cost too . The Plants' diseases can be classified into two classes, either infectious or non-infectious. Plant diseases mainly caused by a pathogenic organism like Fungus, Bacterium, Virus, or Parasites. In plants, there are some common diseases observed like brown and yellow spots, or early & late scorch, fungal, viral, and other bacterial diseases. The first attack of these diseases are leaves then other parts of the plants. We analyzed the leaves' images by using c image processing A.I techniques and extracted the features of diseases , they can also be extracted according to their color, texture, and other characteristics from a quantitative point of view[1,5]. There are many research challenges exists in the literature of art studies. (1) all existing methods of plant health detection focused on static mechanism which are predefined as the designed time.(2) another challenge , all baseline schemes only adopt known classification of plant health detection rather than run time classification.(3) all the existing system of plant

E-mail address: Orangzebpanhwar@gmail.com,anwar.sathio@bbsul.edu.pk

health are homogeneous in terms of devices however, these systems cannot support heterogeneous healthcare sensors in the system.

To solve the above challenges, objective of this study to enhance the technology development using A.I to look after the plants' health, and helps the green environment supporting technology. We developed one real-time IoT-based system that detects the health of plants using A.I and IoT enabled systems and also keep the records of the tested plants for future usage and analysis. The Detection of plants' health using A.I technology and IoT systems to save the plants from the bacteria viral attacks in mean time that almost invisible with naked eyes and slow impact over effected leaves.

In the suggested scheme of study, this tested model has been enabled and efficient for dynamic environment with heterogeneous systems. In this CNN scheme we designed a new customized novel model to detect the leaf disease as well as identified the unhealthy leaves. We trained our intelligent system for plants health estimation, then we applied machine learning algorithm CNN by image processing to detect the leaf diseases. The important purpose of this technology is to save the green environment for better health related environmental system which is very necessary for living standards of the healthy World.

In this study we reviewed the major plant diseases, these has been addressed with their details below :

- Anthracnose: This is a common group of pathogenic species which are found in eastern part, anthracnose is mainly caused by fungi in the genus Colletotrichum, infected plants develop dark, water-soaked lesions on stems, leaves or fruit.
- Brown Root: This is fungal disease that affect the blossoms in spring, it grows back into the small branches to cause cankers that can kill stems, due to severeness of disease, the large numbers of flower-bearing stems are killed [1].
- Club Root: This disease is caused by the soil-borne fungus Plasmodiophora brassicae that infects susceptible plants through root hairs. These types of plants face difficulty in absorbing water and nutrients. Only affects their roots brassica crops (cabbage, broccoli, cauliflower, etc.).
- Leaf Curl: This is a Fungal disease that affect peaches and nectarines, this is a common disease and found in backyard orchards. The symptoms of this disease can be seen in spring as reddish areas being developed on effected leaves [11], these areas become thick and puckered causing leaves to curl and distort, in case of severeness, it reduces the fruits production ultimately.
- Leaf Spot: In this disease the infected plants develop spot like dark or black water-soaked on the foliage, sometimes with a yellow halo, usually consistent in size. When it's wet, the dots grow and clump together, the spots dry, and have a speckled appearance.
- Mosaic Virus: This disease affects horticultural and vegetable crops like roses, beans, tobacco, tomatoes, potatoes, cucumbers, and peppers etc. And this is a viral disease, found in all over United States [11]. Plant viruses are being difficult to identify since their symptoms are like those of numerous nutritional shortages. Stripes/streaks/spots on leaves in yellow, white, or green Leaves that are wrinkled, curled, or tiny [11].

2. LITERATURE REVIEW

The ability to detect plant disease at an early stage has yet to be investigated, while the key issue is to reduce pesticide use in the agricultural sector while increasing the quality and quantity of output [12].The studies show the relevant machine learning methods applied for diagnosis the plant's health and found that these methods are being very effective to detect the micro-organs using image processing as well as live camera monitoring in the Agri-fields[1], [2], [3], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36]. There is lot of problems to switching from one disease control program to another is extremely challenging for farmers [13]. Generally, the early diagnosis plays important role in plant treatment and estimation, as only the protection measures can be introduced after detection in early stages [14]. Manual control of the plant diseases is very difficult, getting healthy plants taking Pesticides on viral diseases such as virus, fungus, and bacteria cause quality, so proper plant care is needed for the protection [37]. In early detection of symptoms diseases means it detects where they appear on the leaves of plants[9].

Detection and identification of diseases in plant is mistreatment digital imaging approach is extremely effective in providing early-stage signs and symptoms of characteristic diseases. Many researchers have developed agricultural related applications such as leaf disease detection, fruit disease detection [38] Traditional methods are accurate but there is a need to detect the disease automatically without human resources the patterns of the plant leaf and diagnose the disease [39]. Detecting damaged parts of leaves through software that helps the farmer to get more yields too, mitigate the diseases, getting sample data and process them using algorithms that yield the best result [40]. The conventional approaches are very complex, and error pruned whereas different spots, patterns on plant leaves are useful in disease Detection [41]. The use of digital image processing is more reliable for plant's disease detection where detection of leaf diseases has involved a lot of efforts, plant disease awareness and further processing time [42]. The leaves' health detection using advanced computer technology, such as image processing, helps to identify diseases at early stage and provides information for monitoring of plant's Health [15].

There are many diseases which effects crops by pathogens, fungus, bacteria, viruses, and this leads to decrease the production [15], [16], [17]. The monitoring and diagnosing the plant's disease has some limitation with human visibility in early time, computer vision techniques are well adapted to get the such goals like detection and identify the first symptom of disease [18], [19], [20]. The suggested system to diagnose the disease detection by images of plant leaves illness would be used an image processing and clustering approaches to achieve the goal [21], [22]. The Internet of Things (IoT) is a system indirectly applied to improve agricultural quality productions using intelligent-based farming systems, since the automatic detection is more useful and beneficial than manual error pruned process [23]. Precision Agriculture (PA) is required to increase the productivity of specific crops production, although manual diagnosis of crop plant disease is difficult and time-consuming, AI based system can minimize the cost in whole, another research says that automatic detection can be a highly useful tool for identifying agricultural diseases [24]. When plants get infected by diseases, pathogens can spread from one plant to another plant and may infect all parts of plant, afterwards this may cause badly impacted to all Agri-fields and environments [25]. Plant's leaves are important for fast grow of plant and could increasing production, of agriculture and the detect of these plant's diseases may support fast technology techniques, need to be adopted [26]. The performance of the classifier is evaluated in order to categorize and recognize the best approaches with variety of plant groupings and pathogen attacks [27].

The researchers have used CNN technique to detect the diseases in plants by using machine learning techniques [28]. In [43] we observed that CNN as compare to different schemes such as "Neural Network: Faster Region-based Convolution Neural Network (Faster R-CNN), Region-based Fully CNN(R-CNN) and Single shot Multibook Detector (SSD)" other advanced methods result more better accuracy more than 94 percent, its good comparative score.

3. Proposed Methodology

A. IoT based processing

In this model we used IoT based hardware alongwith Arduino interface, that support to ESP-32 micro controller for capture the images storing at cloud environment for testing purpose. After this data storage on cloud, we processed data for preprocessing before getting data into CNN model.

B. CNN Layers

These layers are major building blocks used in CNN, a simple technique which provides a filter to an input image that results in an activation. The result of applied filters is being highly specific features that can be detected anywhere to input images. A CNN is a basically a sequence of layers and each layer transform one volume of activations into another by means of a differentiable function. In our research , building of CNN architecture, we used three main types of layers: Convolutional Layer, Pooling Layer, and fully connected Layer. These layers stacked to form a complete CNN architecture.

Figure 1. Figure 1 CNN Process Model.

C. Input Layer

This is a first layer that reduced the size of images and process them by the dimension 256x256 sizes with 2D match. RELU Layer is the model applies on nonlinear properties of the model. It will not beaffected on other fields of linear layers in the model. Max Pooling Layer This layer deduced the size of special layer of model in which the method finds irregular classification of data without linear and nonlinear form and remove abnormality of data from data set. Flatten Layer In this layer transforms all the pixel value converts into matrix of 1Dimension of the features into a vector. Dense Layer In this layer we connect 512 neurons to all layers to detect image classification for unhealthyplant leaves. The CNN applies a filter to an input layer to create a feature map that mainly summarizes the presence of detected features in the input data. The innovative feature of convolutional neural network is that it learns filters during training process in the context of a specific prediction problem. Sigmoid Layer The sigmoid function activated and having an output size of 1 checking the image health either 0 or 1 in our model to analyze the output probability of image either healthy status(good or bad). The sigmoid resulted excellent output for the layer that mostly takes in a set of numbers and returns a probability distribution value in the range of 1 and 0 [29], [30].

Plants	Disease	Healthy Images	Unhealthy Images
Apple	Apple Scrab	2,000	1,000
	Black Rot		1,000
Grapes	Black Rot	2,000	1,000
	Black Measles		1,000
Tomato	Early Blight	2,000	700
	Late Blight		700
	Leaf Mold		600
Corn	Common Rust	2,000	700
	Leaf Blight		700
	Leaf Spot		600
Potato	Early Blight	2,000	1,000
	Late Blight		1,000
Total 5 Plant's leaves	12 Diseases	10,000	10,000

Figure 2. Figure 1 CNN Process Model.

D. *Synchronization Process of IoT (Internet of Things) with CNN*

There is an important role of IoT in agricultural field and in IoT-based PHDS, a system is developed to monitor the crop field and plants using sensors (light, humidity, temperature, soil moisture, etc.). And main the reason behind the use of IoT systems is to connect the intelligent-based systems with the internet to make it more smarter technologies. The process in IoT is very technical in a procedural way, first we control it and capture the images of our plants and plant's leaves through the IoT based application system, then processing the given data for getting results.

E. *Dataset*

The plant leaves dataset was retrieved from the Kaggle [31] provided data set for related to plant's leaves, plant's disease, and different fruits for the project. The we used open-source data set about 87K RGB images of both healthy and unhealthy leaves , classified into 38 different classes where total given data set divided into 80/20 ratio of training and validation set. In the proposed model we used only 20,000 images of different leaves of fruits and that was divided into training set of 14000 images and testing set of 6000 images. Description of data set which is used [32] described in the table 1 applied in the proposed model scheme.

In this paper we have presented an extensible CPU power measurement framework that supports our own research but is also generally applicable to the computer engineering community in general for accurate computational power consumption measurements. Our results illustrate the need for a precise direct energy measurement capability since it is very hard to predict the operating parameters (e.g., frequency, thread count, TurboBoost, and network interface) that will achieve the lowest energy consumption.

In our future work we are planning the design for a more scalable direct measurement method by moving the data acquisition system directly into the node chassis. This system could potentially capture real-time energy measurements from cluster systems with large node/CPU counts. In addition, we are investigating how to calculate the actual power consumption of individual CPU cores within the restriction of measuring the power consumption of the aggregate CPU. Finally, we are exploring how to automatically profile a particular CPU or system for the power optimization feature set it exposes to operating system or program level control so that the total space of control combinations can be systematically examined.

4. Proposed Methodology

In image processing technique, we need conversion of the RGB image to grayscale, applied the edge detection to identify and compared images. The analysis of that data being processed and transmitted to a web application. First the images were acquired using Arduino camera and processed it, once the hardware setup finished, then it collected the image data. When data be purified in pre-processing, before applying image processing technique such as CNN, or SVM etc. In this research, we tested the CNN on leaves data set to diagnoses the diseases. Furthermore, the baseline approaches related to our work and proposed methods already discussed in literature review with details.

A. *Convolutional Neural Network (CNN)*

The CNN may be volved by ordinary neural network. This technique has been composed of neurons with weights and biases. The CNN can do activation with non-linearity processes on an input image, assigning importance (learnable weights and biases) to various aspects and objects in the image, and has an ability to differentiate one from another. In CNN, the pre-processing of the data is required while the filters in primitive methods are hand-engineered. The CNN can learn these filters and characteristics with indent, the body text with indent, this is an analogous to the compatibility of the human brain pattern of neurons. In a restricted region of the visual field, known as the receptive field, individual neurons respond to stimuli only and collection of such fields overlaps that to cover the entire visual area. We have applied Sobel operator to detect horizontal and vertical edges and rescale with subsequent image data, in this context we used Laplacian and Gaussian filters for edge detection along with lowpass and high pass gaussian fillers. We also used gaussian distribution function to control the noise from the images.

B. *Pre-processing of data*

In the process of denoising and resize, the input image can be in any size from 0–255-pixel size, so we preprocessed the resize in 256x256 all images of data set for fast working and calculation. Denoising remove the noised data due to light intensity and remove blurriness from the image. The next step of the model is feature extraction in which, we extracted the necessary parts from the image and remove un-necessary parts to improve the calculation and make the image clearness for testing to an algorithm. After image pre-processing, we trained our CNN model [32], [33], [34], [35], then live testing side, we use the camera module to capture the image through our robotic car, that camera was

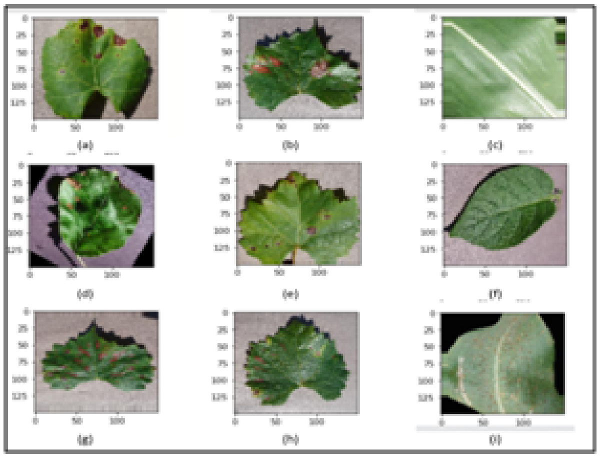

Figure 3. Figure 1 CNN Process Model.

```
model = Sequential()

model.add(Conv2D(16, (3,3), input_shape= (256,256,3), activation = 'relu'))
model.add(MaxPooling2D(pool_size = (2,2)))

model.add(Conv2D(32, (3,3), activation = 'relu'))
model.add(MaxPooling2D(pool_size = (2,2)))

model.add(Conv2D(64, (3,3), activation = 'relu'))
model.add(MaxPooling2D(pool_size = (2,2)))

model.add(Flatten())

model.add(Dense(units = 512, activation = 'relu'))
model.add(Dense(units = 1, activation = 'sigmoid'))
```

Figure 4. Figure 1 CNN Process Model.

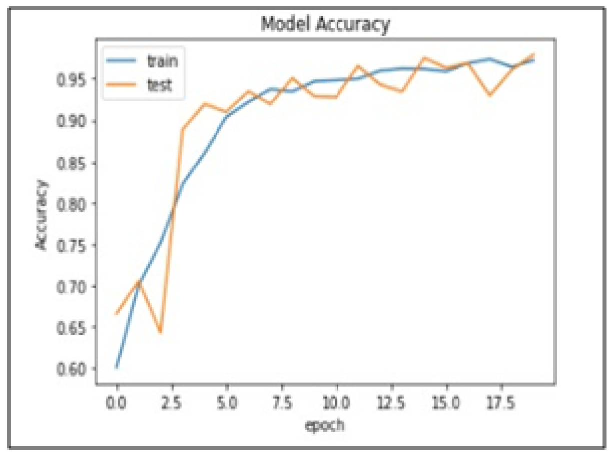

Figure 5. Figure 1 CNN Process Model.

fixed on the robotic car to capture the images of plant leaves, upload the image to the server for testing purpose. After remove the noise from the images processed into our trained model of CNN then image directly move towards evaluation phase to know its accuracy and predict the result. This architectural model shows in figure 1 the whole process of the project that how these systems run and how process the images.

5. RESULTS AND DISCUSSIONS

In the current version of manuscript, the result discussion showed that, all the results in the numeric format and values are shown in terms of numeric statistics form. Therefore, all the results are the straightforward and shown their results of proposed method by the study.

The novel aspects of the study are that to devise the lightweight Internet of Things (IoT) based interface to collect the data and identified by the proposed machine learning method. The method is more adaptive than existing dynamic machine learning model where runtime changes in data and environment can easily handle by the method in terms of new plant disease can predict in the model with the training and testing model.

The type of the problems, relating to detection of diseases, researchers have used CNN "Sequential model [36], [44], [11], [45] successfully, that's why we developed the same model by using "KERAS" to stack all the layers for the population of sequential data. We set first input layer, which has certain unique and significant properties. We created the first layer by executing the add () function and passing the type in the Conv2D layer [36]. The filter size of this layer has an output dimension size like the output filter numbers in the convolution [43], [46], [47], [48]. The width and height of the 2D convolution window was determined by the kernel size [49], [50], [51]. The input shape is the point remembering we resized our project images into 256 by 256 pixels. We passed that along with the channel of pixes [256,256,3] and another point in the first layer is the "activation = relu," which is selected an activation function for non-linear data for CNN model. The Max pooling applied as 2D layer which lower the spatial size of input features and reduced the number of parameters, overfitting, and computations in CNN model simultaneously[36]. And other layer was flattened job to learn and extract spatial information from the layer conv2D, that was sent to dense layer after getting once it flattened done.

In this research we have applied Adam's optimization replacement algorithm for training our model. The Adam optimizer combines the best properties of the A daGrad and RMSProp , and can handle sparse gradients on the noisy problems, it's not a fixed , a part of a process called hyperparameter tuning. We have passed three parameters to our model to compile the () command and the learning rate was lr=0.001: Loss "binary cross-entropy". We specified the loss function, so that our optimizer may be minimized. In this connection we had worked with two-class problems, reason for using binary cross-entropy in the model.

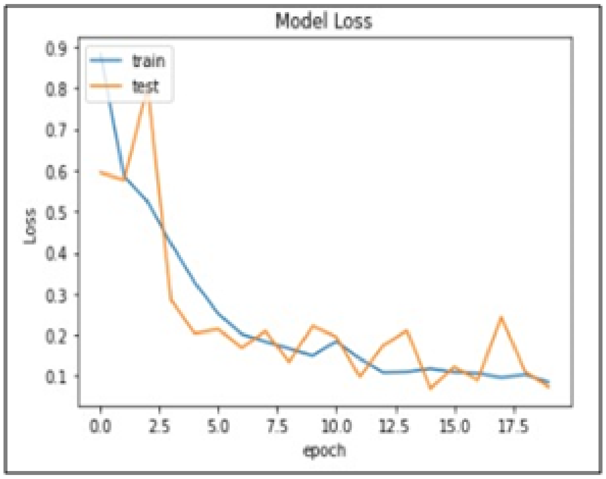

Figure 6. Figure 1 CNN Process Model.

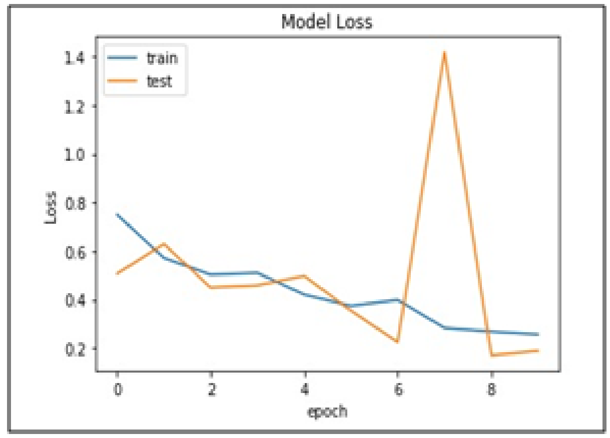

Figure 7. Figure 1 CNN Process Model.

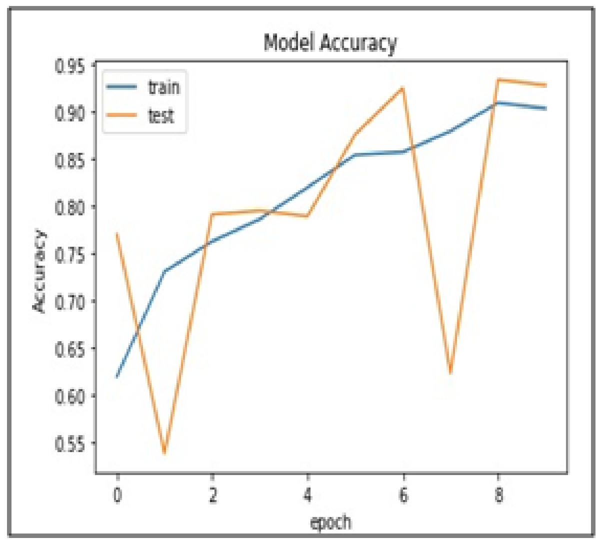

Figure 8. Figure 1 CNN Process Model.

A. Training of Dataset with CNN model

The model was trained with 20 epochs, gives the accuracy and loss that how much it gets learned. At the first Epoch 1/20, the loss result was earned as “ 1.4954” output and the accuracy rate were “0.5735”. And at the final validation, the loss was “ 0.5952” and the accuracy rate were gotten as “0.6659”. In the next Epoch selected “5/20” , the loss output was “0.3434” and accuracy rate were “0.8529”. After final validation, the loss output earned as “ 0.2033” and accuracy rate were gotten as “ 0.9196” comparatively. Finally, in the last Epoch taken as “11/20” , we got loss output as “0.1498” and accuracy rate were gotten as “ 0.9450” and at the final validation, we got the loss output as “0.5952” and accuracy ratio were resulted as “ 0.6659”.

B. The Analysis of CNN Model and Performance Evaluation

The study in this research analyzed through standards of evaluation any project success ratio and quality of the model, the entire procedure to measure the project result based achieved goals. The following criterion we evaluated to analyze the CNN methods :

C. Accuracy During Training phase of the CNN scheme

In the Figure 4, we got the accuracy level on 11/20 epoch at best resulting as“ 0.6659” on final validation during the training session of the CNN scheme, this accuracy can be seen on blue lines as images used for training showed in blue lines and orange lines are images for testing data images.

D. Confusion Matrix Summary

Confusion matrix is one of the useful methods of AI to give the output of the results, which allow us to do precision, recall, accuracy and f1 of our project. It’s a kind of table that usually used to describe the performance of our classified model, based on test data in which values are being known. This matrix for the binary classification, exactly shows the four different outputs in a table form which are, true positive, false positive, true negative and false negative. We used this analysis method to check the accuracy of our model and efficiency of our CNN model, how much is accurate result output for testing our model. The first line of bunch given to this model was healthy and unhealthy images. The Y_pred,it’s an actual bunch of images which has capability to be predicted. When these images were tested on this model for training to verify the model accuracy, how much model can check, predict, and validate those images accurately. We used confusion matrix to get to know how many true or false values we got from this model. The output of the confusion matrix composed of maximum 3000 images of healthy and unhealthy leaves which correctly supported by this CNN scheme and as we can see the average accuracy of both healthy and unhealthy images.

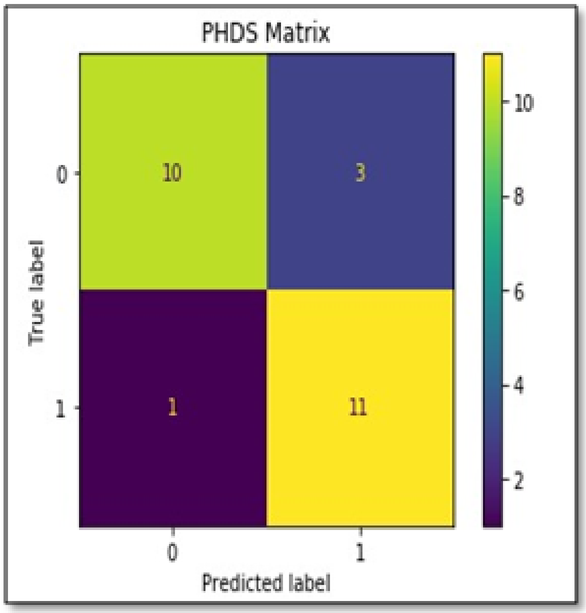

Figure 9. Figure 1 CNN Process Model.

E. Accuracy of the model through confusion matrix analysis

We studied the accuracy of the CNN scheme using confusion matrix, in the Figure 6 , in the graph blue lines showing the accuracy of training images whereas orange lines showing the testing of those images. We can clearly see the high and low elevation of the graph, as accuracy is increasing time by time. Loss report of confusion matrix in CNN scheme :

The loss of the confusion matrix showed in the Figure 7 , graph shows the loss of the training images that was high in the beginning of the training after while was getting down by decreasing the loss in the training. Precision: this matrix based on the equation 1 to evaluate the detection and the accuracy of model, we computed the number of positive class, this helps us in the project's model performance.

$$Precision = Tp/Tp + Fp \tag{1}$$

Recall : this matrix based on the equation 2 to evaluate the computing of number of positive class for prediction getting all the positive trained samples from the dataset.

$$Recall = Tp/Tp + Fn \tag{2}$$

F1 Score status: The Score of F1 is achieved in a single score that balanced the analysis of precision and recall in a single number.

$$F1 = 2.Pr/P + r \tag{3}$$

F. Project Implementation

The implementation is the most important phase of the project, where plans and visions turn into reality. Figure 4 showed the logical conclusion of the project implementations successfully and turned all aspects into display action so that we can summarized the prediction for this project. The captured leaves data results also showing on the web page with the result of 95.42 percent showed in figure 9.

Figure 10. Figure 1 CNN Process Model.

G. Advantages and disadvantages

This model is a dynamic and adopt the run time changes of states of different plants based on parameters. Therefore , this proposed method obtained the dynamic results in terms of accuracy, precision and execution of data as compared to all baseline approaches. In the result discussion the proposed scheme showed that the results achieved in the optimal way according to the given objectives furthermore the given data is more classified before processing in the method. In this way we can achieve more dynamic and optimal results in terms of given parameters.

In this model, we need to consider the resource complexity to process the multilevel data set of plant diseases. Whereas resource complexity has directly impact on execution performance in terms of polynomial time, furthermore the time complexity of each heuristic of the proposed scheme to be determined in the next proposal of the study.

6. CONCLUSION & FUTURE WORK

We have studied an IoT network-based system to detect the disease using CNN scheme. In the study we used machine learning method-CNNs in IoT based environment to dynamically identify the plant diseases and explain the guidelines and procedures to optimize the potential implementation in real-world solution. This is a novel approach used with IoT based network , other published solutions based on CNN methods are not currently applicable for field with high level accuracy. This novel approach may lead to the potential of deep learning techniques for plant diseases' detection. Our findings are the development of new sustainable agricultural tool that contribute to a more agri-food production in the less developed countries. This system explored leaf detection system had used standard data set Kaggle of 20,000 images. The accuracy and loss curve were generated by using various combinations of hidden layers CNN scheme and had presented a complete framework for the detection of leaves from the images using IoT network system. The proposed system is composed of main steps like Image Processing and Feature Extraction by using CNN model for the training that come out results of detection with 97 percent accuracy where in literature [37] showed the accuracy at 90 percent in random. The research main purpose was to propose the IoT-based Plant health detection System using automatic system, which was observing the different invisible patterns that could not be seen by human eyes in unhealthy plants. We proposed an intelligent model that can detect the invisible micro patterns in the leaves of plants getting result outcome through cloud-based data system and detect the leaves health status by accuracy with 95.42 percent showed in the Figure 9. This project is very useful for agriculture fields, farmers, planning & development departments as well as environmental agencies. In future, this model may be extended to advanced Deep Learning techniques for further investigation and analysis to improve the the accuracy. We use this application real life agriculture sector, green environmental development. In the future work we will the consider the multilevel data set of plant disease detection and calculate the time complexity of the proposed scheme.

Acknowledgment

References

[1] A. A. Bharate and M. Shirdhonkar, "A review on plant disease detection using image processing," in *2017 International Conference on Intelligent Sustainable Systems (ICISS)*. IEEE, 2017,https://doi.org/10.1016/j.jfoodeng.2014.07.001, pp. 103–109.

[2] B. Zhang, W. Huang, L. Gong, J. Li, C. Zhao, C. Liu, and D. Huang, "Computer vision detection of defective apples using automatic lightness correction and weighted rvm classifier," *Journal of Food Engineering*, vol. 146, pp. 143–151, 2015, https://doi.org/10.3390/s16081222.

[3] S. P. Savant and P. Khanagoudar, "Autonomous fruit recognition system based on deep convolutional neural network," 2020.

[4] J. Boulent, S. Foucher, J. Théau, and P.-L. St-Charles, "Convolutional neural networks for the automatic identification of plant diseases," *Frontiers in plant science*, vol. 10, p. 941, 2019.

[5] P. Bansal, R. Kumar, and S. Kumar, "Disease detection in apple leaves using deep convolutional neural network," *Agriculture*, vol. 11, no. 7, p. 617, 2021.

[6] A. Granwehr and V. Hofer, "Analysis on digital image processing for plant health monitoring," *Journal of Computing and Natural Science*, vol. 1, p. 1, 2021.

[7] A. Lakhan, F. H. Khoso, A. A. Arain, and K. Kanwar, "Serverless based functions aware framework for healthcare application," *Int. J*, vol. 9, no. 4, 2021.

[8] A. Lakhan, M. A. Dootio, F. Alqahtani, I. R Alzahrani, F. Baothman, S. Y. Shah, S. A. Shah, N. Anjum, Q. H. Abbasi, M. S. Khokhar *et al.*, "Hybrid workload enabled and secure healthcare monitoring sensing framework in distributed fog-cloud network," *Electronics*, vol. 10, no. 16, p. 1974, 2021.

[9] A. A. Mutlag, M. K. A. Ghani, M. A. Mohammed, A. Lakhan, O. Mohd, K. H. Abdulkareem, and B. Garcia-Zapirain, "Multi-agent systems in fog–cloud computing for critical healthcare task management model (chtm) used for ecg monitoring," *Sensors*, vol. 21, no. 20, p. 6923, 2021.

[10] A. Lakhan, M. A. Mohammed, S. Kozlov, and J. J. Rodrigues, "Mobile-fog-cloud assisted deep reinforcement learning and blockchain-enable iomt system for healthcare workflows," *Transactions on Emerging Telecommunications Technologies*, p. e4363, 2021.

[11] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review," *Plant Methods*, vol. 17, no. 1, pp. 1–18, 2021.

[12] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," *Computational intelligence and neuroscience*, vol. 2016, 2016.

[13] M. S. Memon, A. Lakhan, M. A. Mohammed, M. Qabulio, F. Al-Turjman, K. H. Abdulkareem *et al.*, "Machine learning-data mining integrated approach for premature ventricular contraction prediction," *Neural Computing and Applications*, pp. 1–17, 2021.

[14] B. Keresztes, F. Abdelghafour, D. Randriamanga, J.-P. da Costa, and C. Germain, "Real-time fruit detection using deep neural networks," in *14th International Conference on Precision Agriculture*, 2018.

[15] A. Lakhan, M. A. Mohammed, S. Kozlov, and J. J. Rodrigues, "Mobile-fog-cloud assisted deep reinforcement learning and blockchain-enable iomt system for healthcare workflows," *Transactions on Emerging Telecommunications Technologies*, p. e4363, 2021.

[16] M. Haris and A. Glowacz, "Road object detection: A comparative study of deep learning-based algorithms," *Electronics*, vol. 10, no. 16, p. 1932, 2021.

[17] J. Aguilera, D. I. H. Farías, R. M. Ortega-Mendoza, and M. Montes-y Gómez, "Depression and anorexia detection in social media as a one-class classification problem," *Applied Intelligence*, pp. 1–16, 2021.

[18] S. Jha, C. Seo, E. Yang, and G. P. Joshi, "Real time object detection and trackingsystem for video surveillance system," *Multimedia Tools and Applications*, vol. 80, no. 3, pp. 3981–3996, 2021.

[19] A. A. Kuznetsova, "Statistical precision-recall curves for object detection algorithms performance measurement," *Cyber-Physical Systems Modelling and Intelligent Control; Springer: Berlin/Heidelberg, Germany*, pp. 335–348, 2021.

[20] D. Thuan, "Evolution of yolo algorithm and yolov5: the state-of-the-art object detection algorithm," 2021.

[21] B. Xiao and S.-C. Kang, "Development of an image data set of construction machines for deep learning object detection," *Journal of Computing in Civil Engineering*, vol. 35, no. 2, p. 05020005, 2021.

[22] A. Chriki, H. Touati, H. Snoussi, and F. Kamoun, "Deep learning and handcrafted features for one-class anomaly detection in uav video," *Multimedia Tools and Applications*, vol. 80, no. 2, pp. 2599–2620, 2021.

[23] F. Tambon, G. Laberge, L. An, A. Nikanjam, P. S. N. Mindom, Y. Pequignot, F. Khomh, G. Antoniol, E. Merlo, and F. Laviolette, "How to certify machine learning based safety-critical systems? a systematic literature review," *arXiv preprint arXiv:2107.12045*, 2021.

[24] M. H. Calp, "Use of deep learning approaches in cancer diagnosis," in *Deep Learning for Cancer Diagnosis*. Springer, 2021, pp. 249–267.

[25] S. Palazzo, F. Murabito, C. Pino, F. Rundo, D. Giordano, M. Shah, and C. Spampinato, "Exploiting structured high-level knowledge for domain-specific visual classification," *Pattern Recognition*, vol. 112, p. 107806, 2021.

[26] A. Bhargava and A. Bansal, "Fruits and vegetables quality evaluation using computer vision: A review," *Journal of King Saud University-Computer and Information Sciences*, vol. 33, no. 3, pp. 243–257, 2021.

[27] D. Saha and M. Annamalai, "Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review," *Current Research in Food Science*, 2021.

[28] M. Yang, P. Kumar, J. Bhola, and M. Shabaz, "Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit," *International Journal of System Assurance Engineering and Management*, pp. 1–9, 2021.

[29] C. Akçelik, A. Okatan, and A. Çetinkaya, "Face and emotion recognition using deep learning based on computer vision methods," *algorithms*, vol. 11, p. 12, 2021.

[30] A. Chandio, M. Leghari, A. Orangzeb Panhwar, S. Zaman Nizamani, and M. Leghari, "Deep learning-based isolated handwritten sindhi character recognition," *Indian Journal of Science and Technology*, vol. 13, no. 25, pp. 2565–2574, 2020.

[31] Y. Zhang, P. Phillips, S. Wang, G. Ji, J. Yang, and J. Wu, "Fruit classification by biogeography-based optimization and feedforward neural network," *Expert Systems*, vol. 33, no. 3, pp. 239–253, 2016.

[32] S. Wang, Y. Zhang, G. Ji, J. Yang, J. Wu, and L. Wei, "Fruit classification by wavelet-entropy and feedforward neural network trained by fitness-scaled chaotic abc and biogeography-based optimization," *Entropy*, vol. 17, no. 8, pp. 5711–5728, 2015.

[33] S. Naik and B. Patel, "Machine vision based fruit classification and grading-a review," *International Journal of Computer Applications*, vol. 170, no. 9, pp. 22–34, 2017.

[34] S. Cubero, N. Aleixos, E. Moltó, J. Gómez-Sanchis, and J. Blasco, "Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables," *Food and bioprocess technology*, vol. 4, no. 4, pp. 487–504, 2011.

[35] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," *Computers and Electronics in Agriculture*, vol. 173, p. 105393, 2020.

[36] M. A. Roa-Garzón, E. F. Gambaro, M. Florek-Jasinska, F. Endres, F. Ruess, R. Schaller, C. Emmerich, K. Muenster, and M. Suppa, "Vision-based solutions for robotic manipulation and navigation applied to object picking and distribution," *KI-Künstliche Intelligenz*, vol. 33, no. 2, pp. 171–180, 2019.

[37] S. Hiura, S. Koseki, and K. Koyama, "Prediction of population behavior of listeria monocytogenes in food using machine learning and a microbial growth and survival database," *Scientific reports*, vol. 11, no. 1, pp. 1–11, 2021.

[38] S. Nosratabadi, S. Ardabili, Z. Lakner, C. Mako, and A. Mosavi, "Prediction of food production using machine learning algorithms of multilayer perceptron and anfis," *Agriculture*, vol. 11, no. 5, p. 408, 2021.

[39] H. Guo, K. Jeong, J. Lim, J. Jo, Y. M. Kim, J.-p. Park, J. H. Kim, and K. H. Cho, "Prediction of effluent concentration in a wastewater treatment plant using machine learning models," *Journal of Environmental Sciences*, vol. 32, pp. 90–101, 2015.

[40] M. S. Memon, A. Lakhan, M. A. Mohammed, M. Qabulio, F. Al-Turjman, K. H. Abdulkareem *et al.*, "Machine learning-data mining integrated approach for premature ventricular contraction prediction," *Neural Computing and Applications*, pp. 1–17, 2021.

[41] A. Lakhan, Q.-U.-A. Mastoi, M. Elhoseny, M. S. Memon, and M. A. Mohammed, "Deep neural network-based application partitioning and scheduling for hospitals and medical enterprises using iot assisted mobile fog cloud," *Enterprise Information Systems*, pp. 1–23, 2021.

[42] A. Lakhan and R. Singh, "Implementation of etl tool for data warehousing for non-hodgkin lymphoma (nhl) cancer in public sector, pakistan," *Int. J*, vol. 9, no. 7, 2021.

[43] I. Hussain, Q. He, and Z. Chen, "Automatic fruit recognition based on dcnn for commercial source trace system," *International Journal on Computational Science & Applications (IJCSA)*, vol. 8, no. 2/3, pp. 1–14, 2018.

[44] V. Maksimovic, M. Petrovic, D. Savic, B. Jaksic, and P. Spalevic, "New approach of estimating edge detection threshold and application of adaptive detector depending on image complexity," *Optik*, vol. 238, p. 166476, 2021.

[45] H. Mureşan and M. Oltean, "Fruit recognition from images using deep learning," *arXiv preprint arXiv:1712.00580*, 2017.

[46] J. Gill, A. Girdhar, and T. Singh, "A review of enhancement and segmentation techniques for digital images," *International Journal of Image and Graphics*, vol. 19, no. 03, p. 1950013, 2019.

[47] H. Altaheri, M. Alsulaiman, and G. Muhammad, "Date fruit classification for robotic harvesting in a natural environment using deep learning," *IEEE Access*, vol. 7, pp. 117 115–117 133, 2019.

[48] A. Nasirahmadi and S.-H. M. Ashtiani, "Bag-of-feature model for sweet and bitter almond classification," *Biosystems engineering*, vol. 156, pp. 51–60, 2017.

[49] H. Kang and C. Chen, "Fruit detection, segmentation and 3d visualisation of environments in apple orchards," *Computers and Electronics in Agriculture*, vol. 171, p. 105302, 2020.

[50] F. Femling, A. Olsson, and F. Alonso-Fernandez, "Fruit and vegetable identification using machine learning for retail applications,"

in *2018 14th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*. IEEE, 2018, pp. 9–15.

[51] S. Sakib, Z. Ashrafi, M. Siddique, and A. Bakr, “Implementation of fruits recognition classifier using convolutional neural network algorithm for observation of accuracies for various hidden layers,” *arXiv preprint arXiv:1904.00783*, 2019.

Ali Orangzeb Panhwar, Lecturer at Faculty of CS&IT, BBSU Lyari Karachi Sindh, Pakistan, working since 2015 and also Ph.D Research Scholar at University of Sindh Jamshoro, Pakistan since 2020.

Anwar Ali Sathio, Sr. Lecturer at the Faculty of CS&IT, BBSU Lyari, Karachi Sindh, Pakistan, working since 2014 and also registered as Ph.D Research Scholar at SMIU Karachi,Sindh, Pakistan since 2018.

,

Mujeeb ur Rehman Shaikh, Lecturer at Faculty of CS&IT, BBSU Karachi Sindh, Pakistan, working since 2014.

,

Abdullah Raza Lakhan has the following research interests: Distributed Computing, Artificial Intelligence and Algorithms, Sensors & Ad-hoc Networks, Blockchain Internet of Things (IoT) Data Security Optimisation Algorithms Smart Cities Applications Intelligent Systems. He is working as an Assistant Professor in BBSUL Pakistan.

,

Muhammad Umer, Researcher at Faculty of CS&IT, BBSU, Lyari Karachi Sindh, Pakistan.

,

Rabia Mushataq Mithiani, Researcher at Faculty of CS&IT, BBSU Lyari Karachi Sindh, Pakistan.

,

Sawli Khan, Researcher at Faculty of CS&IT, BBSU Lyari Karachi Sindh, Pakistan.