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Plant Leaf Health Detection Enabled CNN Scheme in IoT Network

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Abstract—**Plant diseases are a major threat to the success of new products and agricultural productivity. Modern technology that can aid in the early diagnosis of plant disorders includes synthetic intelligence (AI) techniques, location sensors, data analytics, and inference algorithms. It can be very challenging to identify diseases in plants, but doing so will have a fantastic impact on how much the environment and output are improved. The challenge of the examination is to identify the plant's minor ailments to prevent a severe loss in the production of the plant. We combined IoT-based technology with a device learning scheme in addition to food production. This investigation sought to identify potentially hazardous plants through inflamed leaves utilizing CNN-enabled methodology, which helped to lessen the worst situation for the vast majority of less developed nations. In this study, we examined the amazing invisible varieties of plant leaves that cannot be identified without difficulty with inside the leaves, modelling the IoT community-based absolutely completely Plant health Detection device. In this study article, we looked into and built an IoT-community device with a CNN model that might effectively find invisible micro topics within the vegetation by achieving 95% accuracy with the look at. In order to train the model for the identification of diseases in leaves, we used an IoT-network system and the CNN technique. With a 90-5 accuracy rate, this typical overall performance detection.**

Keywords—Convolutional Neural Network, VGG16, Trained datasets, Testing datasets.

I. INTRODUCTION

The most important sector of our Economy is Agriculture. Various types of disease damage the plant leaves and effects the production of crop there for Leaf disease detection is important. Regular maintenance of plant leaves is the profit in agricultural products. Farmers do not expertise in leaf disease so they producing lack of production. Leaf disease detection is important because profit and loss depend on production. So that here use deep learning techniques to detect apple, grape, corn, potato, and tomato plant leaves diseases. Apple, grape, corn, potato, and tomato plant leaves which are categorized total 24 types of labels apple label namely: Apple scab, Black rot, apple rust, and healthy. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Corn label namely: Corn Cercosporin spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight. Potato label namely: Early blight, healthy, and Late blight. Tomato label namely: bacterial spot, early blight, healthy, late blight, leaf mold, Septoria leaf spot, spider mite, target sport, mosaic virus. Plant leaf disease detection also useful in agriculture institute. Some plant leaf disease detection automatic techniques are beneficial for large work of monitoring in farm of crops disease detection gives the brief introduction of leaf disease detection using convolutional neural network, its applications, objective of the system and motivation. contains literature survey that provide summary of individual paper it provides overview of existing work for leaf disease detection using CNN that has been done using done using feature based approach presents Implementation and its results, tools and technology used to achieve this and dataset. This disease detected using convolutional neural network (CNN), and also this model is compared with VGG16.

II. RELATED WORKS

The layout and improvement of automated reputation and identify structures for flowers is crucial and has several uses the following are the number of problems which might be confronted in the aid of using the prevailing plant identity structures. image acquisition in the first load the image in digital picture process and that consist capturing the image through digital camera and stores it in digital media for additional MATLAB operations. The main aim of image pre-processing is to enhance the image information contained unwanted distortions or to reinforce some image features for any processing. Preprocessing technique uses various techniques like dynamic image size and form, filtering of noise, image conversion, enhancing image and morphological operations.

In image segmentation is used K-means cluster technique for partitioning of pictures into clusters during which a minimum of one part of cluster contain image with major space of unhealthy part. The k means cluster algorithmic rule is applied to classify the objects into K variety of categories per set of features. After clusters are formed texture features are extracted using GLCM (Gray-Level Co-occurrence Matrix). In classification is used for testing the leaf disease. The random forest classifier is used for classification. The early detection of these diseases can assist in their efficient management, thus making huge differences between survival and destruction of crops in farmlands affected by these plant diseases. Deep neural networks have been successfully applied in the field of artificial intelligence. This has inspired increased research into the use of deep learning in the domains of image processing and computer vision. This paper presents a study on the use of deep learning-based approach to identify diseased plants using leaf images by transfer learning. The study uses NAS-Net architecture for the convolution neural networks (CNN). The model is then trained and tested using a publicly available Plant Village project dataset that contains varied images of plant leaves with multiple

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variations in infection status and location in the plants. Using the model, an accuracy rate of 93.82% was achieved.

III. PROPOSED METHOD

Before The dataset consist of 31,119 images of apple, corn, grape, potato and tomato, out of 31,119 images 24000 images are used. all Images are resized into 256 x 256 that images divided into two parts training and testing dataset, the whole range of the train test split using 80-20 (80% of the whole dataset used for the training and 20% for the testing. Then train CNN model. Convolutional neural networks (CNN) can be used for the computational model creation that works on the unstructured image inputs and converts to output labels of corresponding classification. They belong to the category of multi-layer neural networks which can be trained to learn the required features for classification purposes.

A. WORKFLOW MODEL OF CNN

Less pre-processing is required in comparison to traditional approaches and automatic feature extraction is performed for better performance. For the purpose of leaf disease detection, the best results could be seen with the use of a variation of the LeNet architecture. It consists of convolutional, activation, max-pooling and fully connected layer also LeNet is simple CNN model. This architecture used for the classification of the leaf diseases in LeNet model. It consists of an additional block of convolution, activation and pooling layers in comparison to the original LeNet architecture. Each block consists of a convolution, activation and a max pooling layer. Three such blocks followed by fully connected layers and soft-max activation are used in this architecture. Convolution and pooling layers are used for feature extraction whereas the fully connected layers are used for classification. Activation layers are used for introducing non-linearity into the network. Convolution layer applies convolution operation for extraction of features. With the increase in depth, the complexity of the extracted features increases. The size of the filter is fixed to 5×5 whereas number of filters is increased progressively as we move from one block to another. The number of filters is 20 in the first convolution block while it is increased to 50 in the second and 80 in the third. This increase in the number of filters is necessary to compensate for the reduction in the size of the feature maps caused by the use of pooling layers in each of the blocks. After the application of the convolution operation feature maps are zero padded, in order to preserve the size of the image. The max pooling layer is used for reduction in size of the feature maps, speeding up the training process, and making the model less variant to minor changes in input. The kernel size for max pooling is 2×2. Re-LU activation layer is used in each of the blocks for the introduction of non-linearity. Also, Dropout regularization technique has been used with a keep probability of 0.5 to avoid over-fitting the train set. Dropout regularization randomly drops neurons in the network during iteration of training in order to reduce the variance of the model and simplify the network. Finally, the classification block consists of two sets fully connected neural network layers each with 500 and 10 neurons respectively. The second dense layer is followed by a soft max activation function to compute the probability scores for the ten classes.

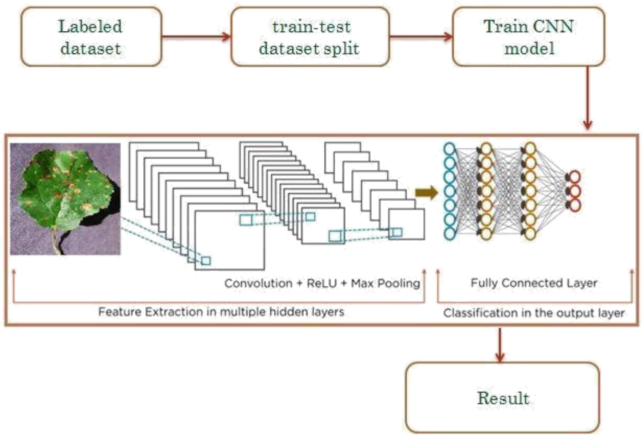

Fig 3.1 Workflow model of convolutional neural network

B. VGG16

The overall accuracy over the whole period of training and testing regular intervals for every epoch will be computed. The overall accuracy score will be used for performance evaluation. Transfer learning is a knowledge-sharing method that reduces the size of the training data, contains 224*224 image fix size. To transfer the learning of a pre-trained model to a new model it has been used in various applications, such as plant classification, software defect prediction, activity recognition and sentiment classification.

- In this, the performance of the proposed Deep CNN model has been compared with popular transfer learning approach VGG16. The input to convolution layer size is 224 x 224 RGB fixed image size. The image is passed to convolutional layers, where the filters used with a very small receptive field which is the smallest size to capture the notion of left, right, up, and down, center.
- Avoid Some of the configurations, it utilizes 1×1 convolution filters, which can be linear transformation followed by non-linearity of the input channels. The convolution stride is fixed that is one pixel the spatial padding of convolution layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1 pixel for convolution layers.

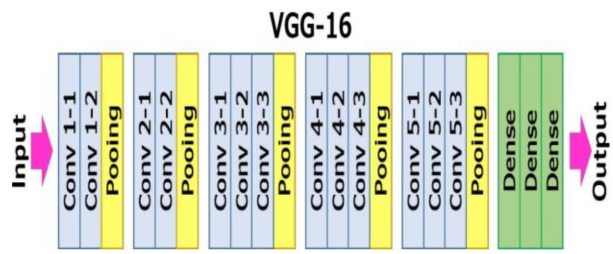

Fig 3.2 VGG16 layered architecture

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IV. RESULT AND DISCUSSION

The Plant leaf illnesses dataset with augmentation data-set, 39 one kind instructions of plant leaf and history photos are available. The data-set containing 61,486 photos. We used six one kind augmentation strategies for growing the data-set length There are many Arduino-well matched and Arduino-derived through including output drivers, regularly to be used in school-degree training to simplify the development of buggies and Others are electrically equal however extrude the shape factor, now and again keeping compatibility with shields, now and again not. Some variations use absolutely one of the kind processors, with various tiers of compatibility and functioning.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dropout_1 (Dropout)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None,    )               752670
=================================================================
Total params: 15,467,358
Trainable params: 752,670
Non-trainable params: 14,714,688
```

```
4800/4800 [==============================] - 5s 943us/step
accuracy: 90.229166%
```

Fig 4.1 Training of datasets in CNN

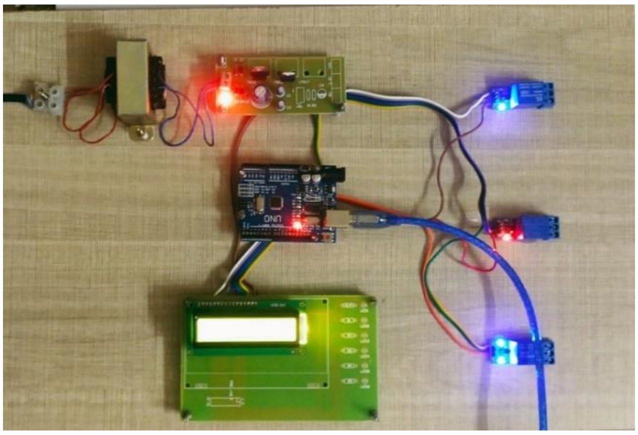

Fig 4.1 Plant leaf detection using Arduino

The comparison table shows the parameter metrics of accuracy epochs where the Proposed is more efficient and consists of CNN testing accuracy score 90.23% than VGG16.

Table 4.1 Comparison table of CNN and VGG16

EPOCHS	CNN Accuracy	VGG16 Accuracy
150	90.557%	51.235%
120	86.263%	50.965%
90	86.581%	47.112%
60	85.201%	46.589%
30	84.780%	45.336%

CONCLUSION

We have identified many works related to current device characteristic primarily based totally approach. It's finished with the aid of using picture processing approach on this we've studied steps like picture Acquisition, picture pre-processing, Image Segmentation, functions extraction, classification. Proposed device to acquire this purpose, we've use CNN and get accuracy is 90.23%. We have additionally use VGG16 version to come across leaf ailment however in our case CNN has higher end result than VGG16. In destiny we are able to upload extra instructions of leaves and ailment type.

REFERENCES

[1] Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala, 2019, "Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition," International Conference on Advances in Big Data, Computing and Data Communication Systems.

[2] Peng Jiang, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang 2019, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolution Neural Networks," IEEE ACCESS.

[3] Geetharamani, Arun Pandian 2019, "Identification of plant leaf diseases using a nine- layer deep convolution neural network," Computers and Electrical Engineering.

[4] Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala 2018, "Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition," Proceedings of TENCON of IEEE Region Conference.

[5] Abirami Devaraj, Karunya Rathan, Sarvepalli Jaahnavi and K Indira 2019, "Identification of Plant Disease using Image Processing Technique," International Conference on Communication and Signal Processing, IEEE.

[6] Velamakanni Sahithya, Brahmadevara Saivihari, Vellanki Krishna Vamsi, Parvathreddy Sandeep Reddy and Karthigha Balamurugan 2019, "GUI based Detection of Unhealthy Leaves using Image processing technique and digital signal processing.

[7] Balakrishna K Mahesh Rao 2019, "Tomato Plant Leaves Disease Classification Using KNN and PNN," International Journal of Computer Vision and Image Processing.

[8] Masum Aliyu Muhammad Abdu, Musa Mohd Mokji, Usman Ullah Sheikh, Kamal Khalil 2019, "Automatic Disease Symptoms Segmentation Optimized for Dissimilarity Feature extraction in Digital Photographs of Plant Leaves," IEEE 15th International Colloquium on Signal Processing & its Applications.

[9] Sneha Patel, U.K Jaliya, Pranay Patel 2020, "A Survey on Plant Leaf Disease Detection," International Journal for Modern Trends in Science and Technology.

[10] Priyanka Soni ,Rekha Chahar 2016, "A Segmentation Improved Robust PNN Model for Disease Identification in Different Leaf Images," 1st IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems.

[11] S. Arivazhagan, R. Newlin Shebiah S. Ananthi, S. Vishnu Varthini 2013, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features".

International Journal of Engineering Research & Technology (IJERT)
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[12] Adedamola Adedoja & Pius Adewale Owolawi & Temitope Mapayi 2018, “Deep Learning Based on NAS Net for Plant Disease Recognition Using Leave Images”.

[13] Prajwala TM, Alla Pranathi, Kandiraju Sai Ashritha, Nagaratna B. Chittaragi, Shashidhar G. Koolagudi 2018, “Tomato Leaf Disease Detection using Convolutional Neural Networks,” Proceedings of 2018 Eleventh International Conference on Contemporary Computing.

[14] J. Han and C. Moraga 2020, “The Influence of the Sigmoid Function Parameters on the Speed of Back propagation Learning,” in Proceedings of the International Workshop on Artificial Neural Networks: From Natural to Artificial Neural Computation, Berlin, Heidelberg.