RESEARCH ON RECOGNITION OF CROP DISEASE AND INSECT PESTS BASED ON DEEP LEARNING IN HARSH ENVIRONMENT

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ABSTRACT

One of the most significant elements that pose a significant risk to agricultural productivity is the presence of agricultural diseases and insect pests. Finding and naming pests as soon as they appear is one of the most efficient ways to cut down on the financial damage they do. In this study, a convolutional neural network was utilized to automatically detect illnesses that might affect crops. This data set was obtained from the public data set that was provided for the AI Challenger Competition in 2018. It contains 27 photos of diseases affecting 10 different crops. Training is carried out with the help of the Inception-ResNet-v2 model in this article. The direct edge in the cross-layer and the multi-layer convolution in the residual network unit of the model. Following the completion of the combined convolution process, it is triggered by the connection into the ReLu function. The findings of the experiments indicate that this model has an overall recognition accuracy of 86.1%, which substantiates the claim that it is successful. Following the completion of this model's training, we developed and deployed the WeChat applet of agricultural disease and insect pest identification. After that, we began the real testing process. The findings demonstrate that the system is capable of correctly identifying crop illnesses and providing the appropriate recommendations.

Keywords: Recognition of pests and diseases, Deep learning, Convolutional Neural Network, Harsh environment

1. INTRODUCTION

China, a powerhouse that accounts for more than 20% of the total population of the globe, has been struggling with the challenge of having inadequate resources of arable land. According to the findings of a study conducted by the Ministry of Agriculture, the amount of land in China that is used for agriculture makes up a percentage that is even lower than 10% of the country's total land area.

According to the findings of several statistical studies, mountainous regions make up around two-thirds of China's total land area, whereas plains regions make up just one-third of the country's total land area. Mountainous regions are home to about one third of the country's total agricultural population as well as fertile land. As a consequence of this circumstance, the production circumstances in China's agricultural industry, forestry industry, and animal husbandry industry are quite bad. According to the data collected by the Food and Agriculture Organization of the United Nations, the amount of cultivated land area per person in China is less than half of the level that is considered to be typical for the globe, and it is continuing its downward trend year after year. As soon as natural catastrophes begin to cause a decline in agricultural production, it will have a significant impact on the output of agricultural goods as well as agricultural development. Understanding how to grow agriculture in a sustainable manner, particularly in the current complicated context, is thus of the utmost importance for China.

Despite the fact that scientific research and technological innovation are always advancing, agriculture productivity continues to advance. However, the crop production has not significantly increased owing to a variety of natural and unnatural variables that have been taken into account. The issue of agricultural diseases and insect pests accounts for the biggest share of the numerous contributing elements. The area of crops in China that are impacted by pests and diseases each year is estimated to be as high as 280 million km2, and the loss in direct production is at least 25 billion kg [1]. This issue has been more prevalent over the last several years and poses a significant risk to the growth of the planting sector. It is now more critical than ever to diagnose crop diseases in a timely manner and take preventative measures. At the current day, agricultural workers often consult books and networks, make contact with neighborhood specialists, and utilize a variety of different techniques in order to prevent and control crop illnesses. However, due to a wide variety of factors, mistakes in judgment and other difficulties often arise, which leads to a significant decline in agricultural productivity.

At the moment, researchers focusing on agricultural diseases are mostly moving in two different ways. The first way is the classic physical method, which identifies various illnesses mostly by spectral detection. This method has been around for a very long time. Different kinds of illnesses and insect pests produce different kinds of damage to leaves, which in turn leads to different kinds of spectral absorption and reflection from healthy crops and those that have been damaged by diseases. The second option is to recognize pictures via the use of computer vision technologies. That is to say, the features of disease pictures are extracted via the use of technology connected to computers, and the recognition is accomplished through the use of the distinct characteristics that sick plants and healthy plants share.

The recent years have seen a fast growth of artificial intelligence (AI), which has resulted in life being more convenient, and AI has become a well-known technology in recent years. Take, for instance, the game of Go, where AlphaGo prevailed against the reigning world champion. Deep learning is an application of artificial intelligence technology that is used in a variety of disciplines, including Apple's Siri and Amazon's Alexa, which serve as voice assistants for their respective companies. Image recognition, which serves as the primary focus of research in the fields of computer vision and artificial intelligence, has seen significant advancements in recent years. In the context of agricultural applications, the purpose of image recognition is to recognize and categorize various kinds of photographs, as well as to do analyses of the various types of crops, diseases, and severity levels. After that, we will be able to devise appropriate countermeasures to deal with the myriad of issues that arise throughout agricultural production in a timely and effective way. with the purpose of further ensuring and improving the production of crops and contributing to the greater growth of agriculture.

With the fast progress of deep learning [2, notably in image recognition [3], voice analysis, natural language processing, and other domains, it demonstrates the one-of-a-kindness and efficacy of deep learning. [Citation needed] Deep learning is a more effective technique for diagnosing plant illnesses than the more conventional approaches that have been used in the past. This pertains to the sector of agricultural production. The model that uses deep learning can monitor, diagnose, and stop the development of crops at the appropriate moment. Image identification of crop illnesses and insect pests might lessen farmers' reliance on plant protection technicians in agricultural production, allowing them more time to find and implement appropriate solutions to any issues that arise. The pace of manually detecting anything is far slower than the speed of identifying something using an intelligent network, which is lot quicker than identifying something artificially. In addition, the precision of the recognition is always improving thanks to the ongoing development. Not only can the establishment of a reliable agricultural network and the combination of the Internet and the agricultural industry help solve problems related to crop yield that are caused by diseases and insect pests, but they can also help foster the growth of agricultural informatization [4].

However, because of the mountain environment's rough topography, the surrounding interference factors are stronger. This is a challenge for radio astronomers. As a result, acquiring a picture is a more challenging task than dealing with the overall surroundings. Additionally, the camera and network transmission that are essential for picture identification and processing will have some degree of influence on the situation. Mountainous regions provide a greater challenge for the implementation of intelligent recognition because of this reason. The purpose of this article is to conduct research on the identification model of agricultural diseases and insect pests, as well as construct a platform for the Internet of Things that can function in the challenging environment of mountainous regions. This model's ultimate goal is to result in an improvement agricultural informatization, reducing the damage caused by diseases and pests to crops, and increasing crop yields are all important goals.

2. LITERATURE SURVEY

Research is ongoing in several areas, including those concerned with the detection and control of agricultural diseases and insect pests. The advancement of technology has led to the creation of a variety of sensor networks and autonomous monitoring systems that have been suggested. In [5,] there is a technique that is presented for the identification of a particular illness in grapes. The pest or illness known as downy mildew may be identified by the real-time system using the meteorological data. The central server operates a forecasting service for both disease and meteorological conditions. Image sensors are one other kind of solution that may be used in conjunction with monitoring traps that are utilized for the purpose of capturing pests [6]. The authors of [6] conceived and constructed a system that has a low power consumption and is powered by a battery. The system is based on wireless image sensors. The setting and remote adjustment of the frequency of recording and sending trap pictures of sensors is something that can be done by the trapping application. In addition, acoustic sensors play a role in the monitoring system. The authors of [7] provide a method that may be used to identify red palm weevil (abbreviated RPW) using them. The noise that is made by the pest may be automatically caught with the assistance of an acoustic device sensor. When the sound level of the pests reaches a certain threshold, the system will send a notification to the customer informing them that an infestation is taking place in the designated region. It was helpful for farmers to save time and energy by allowing them to monitor every portion of their field on their own, which also increased the efficiency of their work. When the predetermined threshold value is exceeded, each of the acoustic sensors will report the amount of noise that they are experiencing [7]. These sensors will all be linked to the base stations. In addition, there have been applications of machine learning in the agriculture sector, such as research on plant diseases and pests and other related topics. The challenge of accurately diagnosing plant diseases has been tackled using a variety of different machine learning strategies that have seen widespread use. In [8], a Neural Network-based approach is suggested for evaluating potato health using leaf image datasets. In addition, the experimental study described in [9] was carried out, the primary objective of which was to develop an imaging-based diagnosis system for plant diseases. In order to differentiate between wheat stripe rust and wheat leaf rust, as well as grape downy mildew and powdery mildew, four distinct kinds of neural networks were trained based on color, shape, and texture variables collected from a disease picture dataset. [9] The findings demonstrated that a neural network that is based on image processing may boost the accuracy of identifying plant diseases. Image processing technologies might also be used to identify the scab disease that affects potatoes [10]. This is an added benefit. To begin, photographs taken at a variety of potato farms were gathered together in [10]. Following the completion of image enhancement, picture segmentation was carried out in order to obtain the target area. In the end, a histogram-based method of analyzing the target area was used so that the phase of the illness could be determined [10].

3.PROPOSED SYSTEM

The central server operates a forecasting service for both disease and meteorological conditions. Image sensors are one other kind of solution that may be used in conjunction with monitoring traps that are utilized for the purpose of capturing pests [6]. The authors of [6] conceived and constructed a system that has a low power consumption and is powered by a battery. The system is based on wireless image sensors. The setting and remote adjustment of the frequency of recording and sending trap pictures of sensors is something that can be done by the trapping application. In addition, acoustic sensors play a role in the monitoring system. The authors of [7] provide a method that may be used to identify red palm weevil (abbreviated RPW) using them. The noise that is made by the pest may be automatically caught with the assistance of an acoustic device sensor. When the sound level of the pests reaches a certain threshold, the system will send a notification to the customer informing them that an infestation is taking place in the designated region. It was helpful for farmers to save time and energy by allowing them to monitor every portion of their field on their own, which also increased the efficiency of their work. When the predetermined threshold value is exceeded, each of the acoustic sensors will report the amount of noise that they are experiencing [7]. These sensors will all be linked to the base stations. In addition, there have been applications of machine learning in the agriculture sector, such as research on plant diseases and pests and other related topics. The challenge of accurately diagnosing plant diseases has been tackled using a variety of different machine learning strategies that have seen widespread use. A technique for evaluating the health of potato plants using leaf image datasets is presented in [8]. This approach is based on a neural network. In addition, the experimental study described in [9] was carried out, the purpose of which was to develop a method for the identification of plant diseases using photographs.

4. RESULTS

In this paper author is applying deep learning convolution neural network (CNN) to predict crop disease and its pests to reduce economical loss in crop business. To build disease recognition model author is applying RESNET CNN model which consists of 3 parts

1) Feature Extraction: CNN compose of multiple layers and first layer define for feature extraction and this features will be extracted from given input image dataset or any other multidimensional dataset.

2) Feature Selection: Using this layer features will be selected by applying a layer called pooling or max polling.

3) Activation module: using this module RELU will be applied on input features to remove out unimportant features and hold only relevant important features

4) Flatten: This layer will be define to convert multidimensional input features into single dimensional input array

5) Dense: This layer can be used to connect one layer to other layer to receive input features from previous layer to new layer to further filter input features in next layer to get most important features from dataset to have best prediction result.

To implement this project we have used crop disease recognition dataset and this dataset saved inside 'CropDiseaseDataset' folder and below screen shots showing various type of crop disease images.

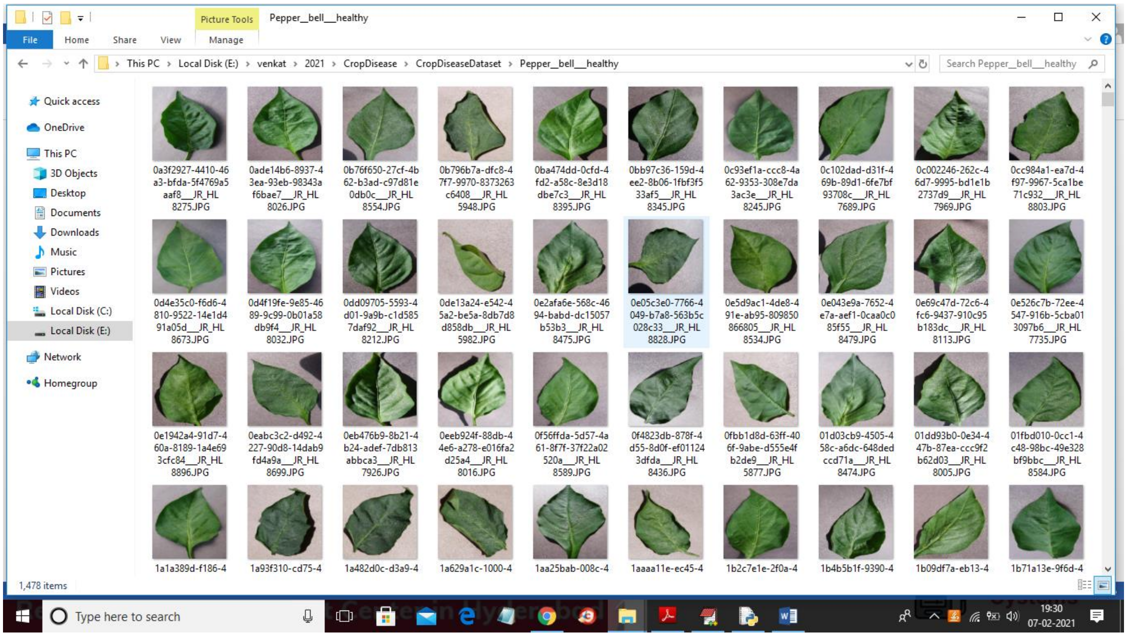

Fig.1: Images

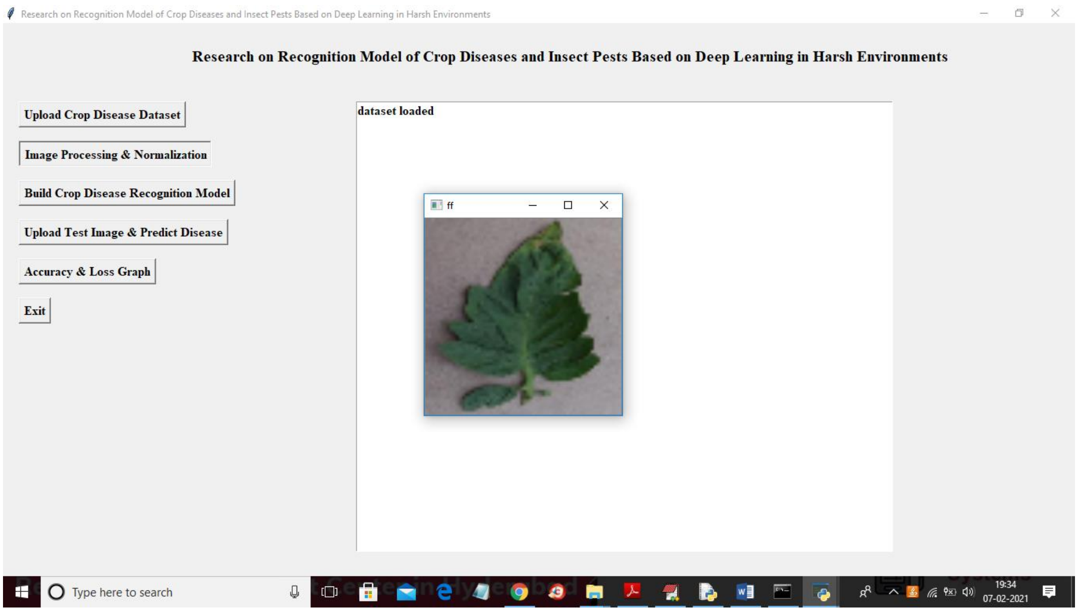

Fig.2: Normalization of images

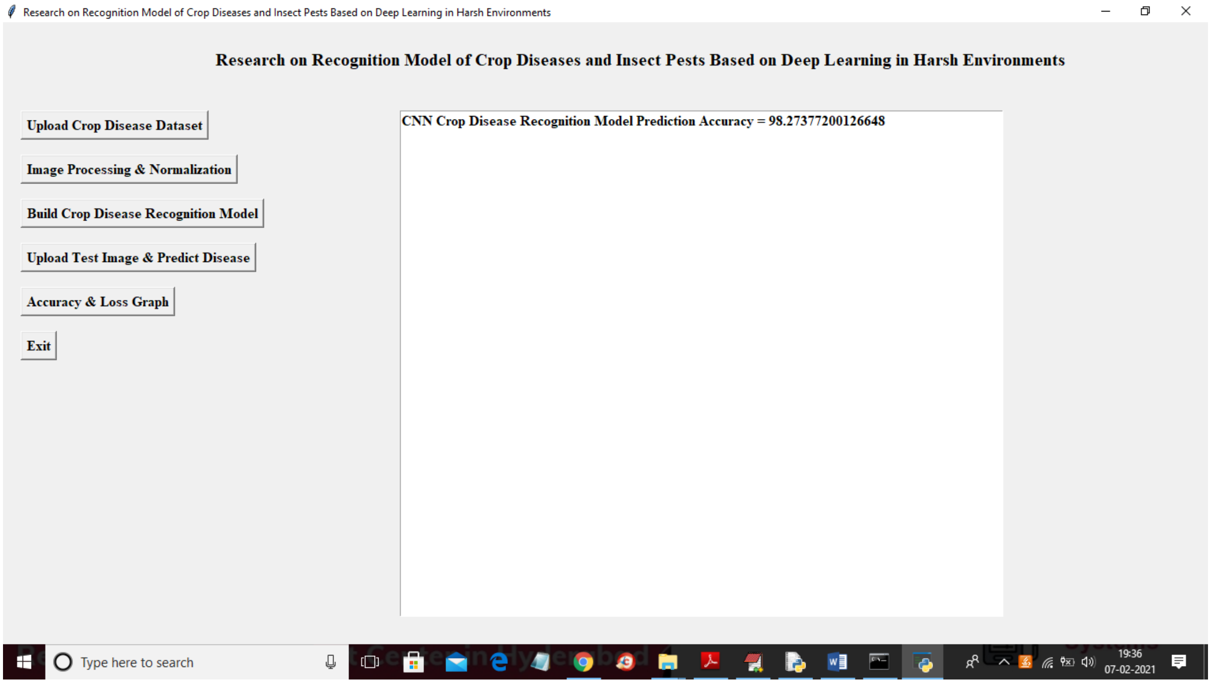

Fig.3: CNN model generated and its prediction accuracy is 98%

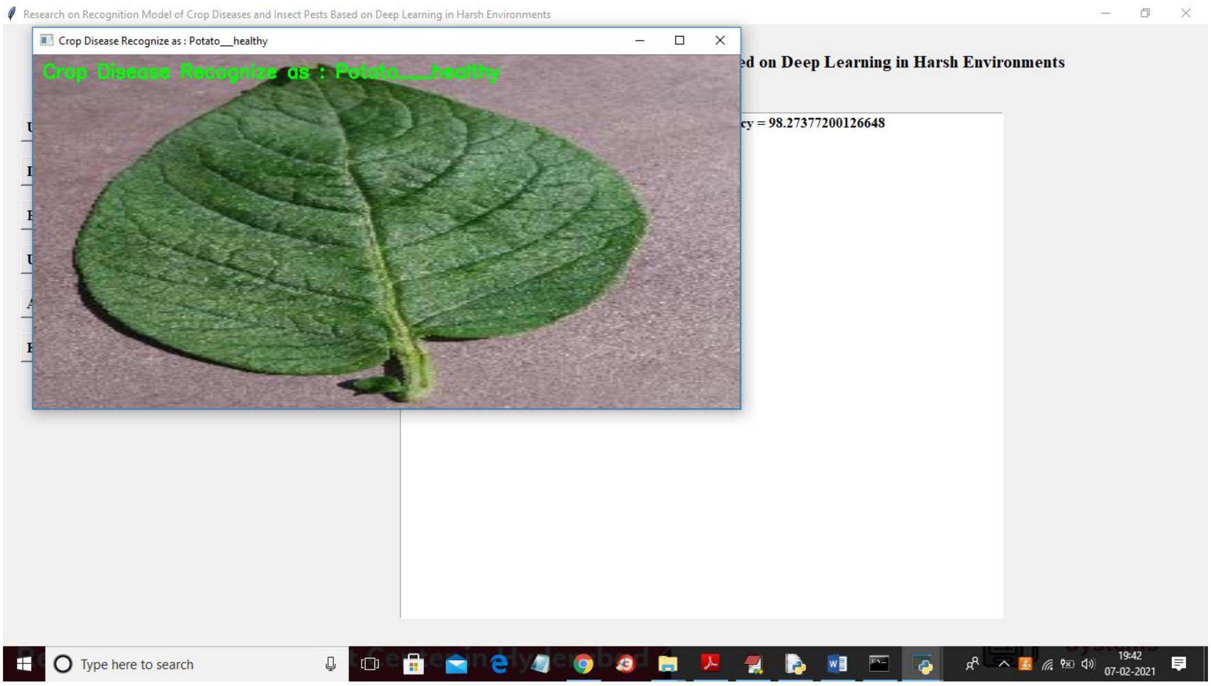

Fig.4: potato leaf predicted as healthy

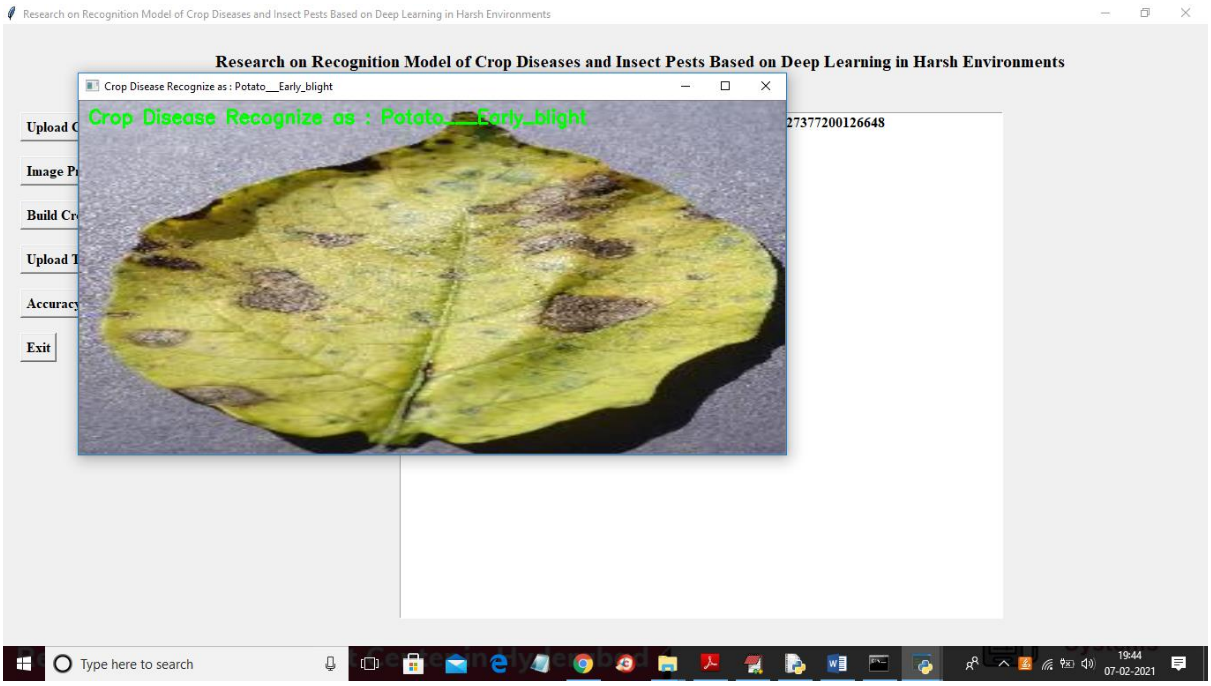

Fig.5: Potato EARLY BLIGHT disease is detected or recognize

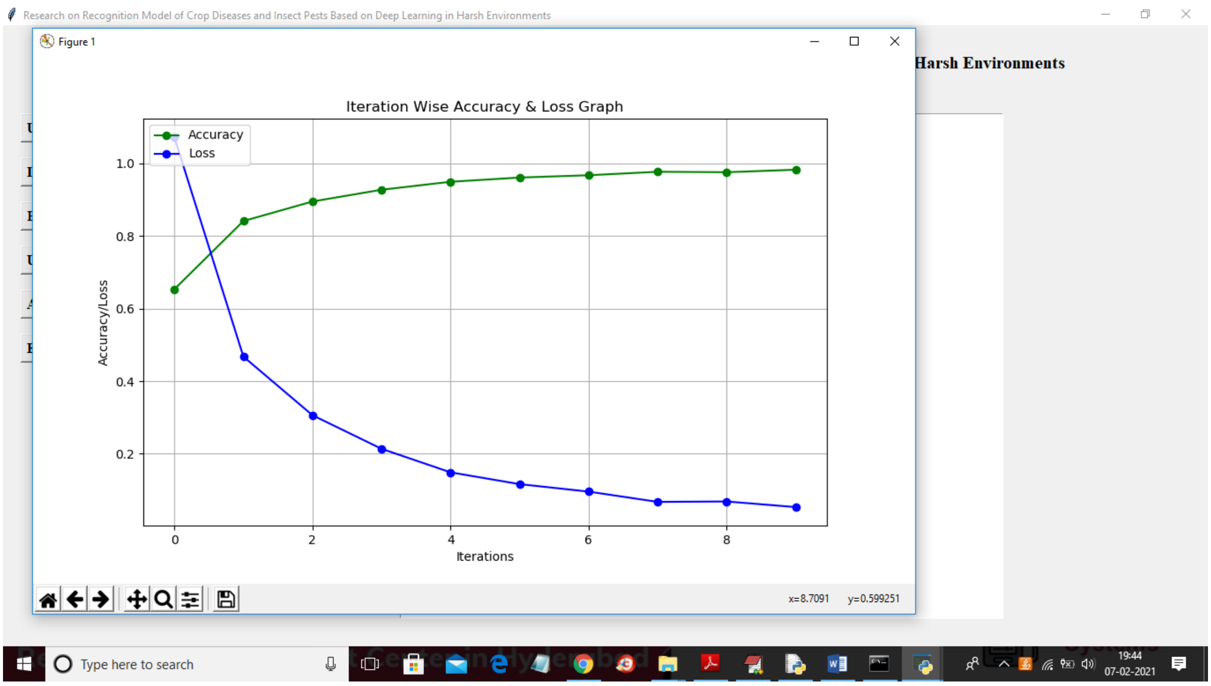

Fig.6: Accuracy graph

5. CONCLUSIONS

In this particular piece of research, 27 distinct diseases were observed among 10 different types of crops. Deep learning theory and convolution neural network technology are used in the construction of the Inception-ResNet-v2 model. Experiments have shown that the model is capable of accurately identifying the data set, with an overall identification accuracy of up to 86.1%. According to the findings, the recognition accuracy of this hybrid network model is much greater than that of the conventional model, and it is also capable of being efficiently used to the identification and detection of insect pests and plant diseases. In the work that will be done in the future, there are two areas that should be improved: 1) Extended data set. Rice and wheat, along with the illnesses that affect them, were not included in this study, as were just 27 of the diseases that may affect 10 different crop species. Other species of crops and diseases, such as those that affect rice and wheat, were not investigated. Therefore, the next phase in the study process is to collect additional photos of different crop types and diseases. 2) Make sure the model is optimized. As a result of the experiment described in this study, we are able to show that the Inception-resnet-v2 variety of mixed network has successfully taken advantage of the related benefit. This model has reached a satisfactory level of recognition accuracy and should be subjected to more research and development. At the same time, we need to develop a network model that is capable of crop picture classification with a better degree of precision.

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