A GUI based Plant Leaf Disease Prediction using Deep Learning Approach

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ABSTRACT
Indian economy is highly dependent on agricultural productivity. In field of agriculture detection of leaf disease plays a important role. Therefore, early identification and diagnosis of plant diseases at every stage of plant life cycle is a very critical approach to protect and increase the crop yield. In this project using a deep-learning model, we present a classification system based on real-time images for early identification of plant infection.The proposed classification was applied on each stage of the plant separately to obtain the largest data set and manifestation of each disease stage. The plant stages named in relation to disease stage as healthy (uninfected), early infection, and diseased (late infection). Classification was designed using the residual neural network (RCNN). After applying the automatic RCNN model to automatically diagnose test photographs, plant pathologists approved the findings.

Keywords
Visualizations, RCNN, AI, forecasting

1. INTRODUCTION
Agriculture is essential to human survival. In densely populated rising countries like India, increasing crop, fruit, and vegetable productivity is even more important. Produce productivity and quality must both remain high for better public health. However, issues like virus transmission that could have been halted with early diagnosis impede both productivity and food quality. Since many of these infections are spreadable, agricultural output is completely lost. Human-assisted disease diagnosis is inadequate and unable to handle the high demand due to the dispersed nature of agricultural areas, the poor educational attainment of farmers, their ignorance, and their lack of access to plant pathologists. In order to solve the drawbacks of human-aided disease diagnosis, it is crucial to automate crop disease diagnosis with technology and deliver low-cost, accurate machine assisted diagnostics that are easily accessible to farmers. Robotics and computer vision systems have made strides toward solving a number of problems in the agriculture industry. The potential of image processing to help precision agriculture methods, weed and pesticide technology, monitoring plant development, and management of plant nutrition has been examined. Despite the possibility that many plant diseases Diagnosis is still in its infancy. along with the soil and climate, lesions, etc. The commercial level of investment in fusing agriculture and technology is still low in comparison to investments made in more lucrative sectors like human health and education. lower overall. Promising research initiatives have not been successful because of barriers like access and connections for farmers to plant pathologists, high deployment costs, and scalability ofsolutions. Thanks to recent developments in the fields of mobile technology, cloud computing, and artificial intelligence (AI), a scalable, affordable solution for agricultural illnesses that can be widely used is now feasible. Mobile devices with internet access are now typical in developing countries like India. People can post photos with geolocation using widely available, inexpensive mobile phones with cameras and GPS. They can interface with more advanced Cloud-based backend services that can carry out compute-intensive tasks, maintain a centralized database, and carry out data analytics across widely accessible mobile networks. The ability of AI-based image analysis to effectively recognize and categories images has surpassed that of the human eye in recent years, which is another technological advance. The neural networks (NN) used by the underlying AI algorithms comprise layers of neurons and a connection layout that is modelled after the visual cortex. To achieve high accuracy of image classification on new, unseen images, these networks are "trained" on a huge set of previously identified, "labelled," images. Deep Convolutional Neural Networks (CNNs) since 2012, when "AlexNet" took first place in the ImageNet competition, have continuously been the finest architecture for computer vision and image processing [3]. The breakthrough in CNN capabilities has been made possible by advancements in NN algorithms, massive image data sets, and processing power. Furthermore, improving accuracy, open-AI has advanced, gotten more widely available, and become more thanks to source platforms like TensorFlow. Examples of earlier art that are pertinent to investigation include efforts to gather healthy and sick crop pictures [5], image analysis using feature extraction [6], RGB images [7],spectral patterns [8], and fluorescence imaging spectroscopy [9].In the past, plant disease detection with neural networks involved searching for textural features. The concept leverages the growth of mobile, cloud, and AI to deliver an end-to-end crop diagnosis system that mimics the knowledge ("intelligence") of plant pathologists and makes it accessible to farmers. It also provides a collaborative way to continue growing the illness database and requesting expert assistance asneeded in order to improve NN classification accuracy and track epidemics.

2. LITERATURE SURVEY
2.1 A survey of image processing techniques for agriculture
AUTHORS: Lalit P. Saxena and Leisa J. Armstrong
ABSTRACT: There are several ways that computer technologycan be used to improve agricultural output. One technique thatis beginning to be acknowledged as a useful tool is image processing. This article offers a succinct summary of how scientists and farmers might improve agricultural practices by using image processing techniques. Image processing has aidedin the development of precision farming methods, weed and pesticide technologies, plant development monitoring, and nutrition management. This study highlights the future potential for image processing in several agricultural businessscenarios.

2.2 Imagenet classification with deep convolutional neural networks

AUTHORS: A. Krizhevsky, I. Sutskever and G. E. Hinton,

ABSTRACT: We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution photos submitted for the ImageNet LSVRC-2010 contest into the 1000 different categories. In comparison to the previous state-of-the-art, in this paper top-1 and top-5 error rates on the test data were 37.5 percent and 17.0 percent, respectively. The neural network has five convolutional layers, followed by three fully connected layers, three max-pooling layers, and a final 1000-way SoftMax layer. There are 650,000 neurons and 60 million characteristics in it. To accelerate training, we used non-saturating neurons and an extremely efficient GPU convolution algorithm. We greatly reduced overrides in the fully connected layers by using the "dropout" regularization technique, a recently created regularization method. We provided a version as well.

2.3 Integrating soms and a bayesian classifier for segmenting diseased plants in uncontrolled environments

AUTHORS: D. L. Hernández-Rabadán, F. Ramos-Quintana and J. Guerrero Juk

ABSTRACT: This work proposes a strategy for segmenting diseased plants that develop in uncontrolled conditions, such greenhouses, where the absence of lighting control and the presence of background pose substantial obstacles. The technique combines supervised learning with nonsupervised learning, using a Bayesian classifier and a self-organizing map (SOM). During the training phase, two SOMs are used: one that separates images into color groups, which are then split into two groups using K-means and labeled as vegetation and non-vegetation by employing rules, and a second SOM that corrects classification errors generated by the first SOM. The Bayesian classifier's conditional probabilities are computed using two color histograms made from the two-color classes. During segmentation, an input image is image is segmented during testing

3. IMPLEMENTATION STUDY

In India, pathogens and pests alone result in a loss of field crops of 35%, costing farmers money. Uncontrolled usage of pesticides is dangerous for your health because many of them are toxic and biomagnified. These detrimental effects can be avoided with early disease detection, crop surveillance, and targeted treatments. Typically, agricultural specialists examine for illnesses' external symptoms before diagnosing them. Meanwhile, farmers have little access to experts.

3.1 Proposed Methodology

The main purpose of proposed system is to detect the diseases of plant leaves by using feature extraction methods where features such as shape, color, and texture are taken into consideration. Convolutional neural network (RCNN), a machine learning technique is used in classifying the plant leaves into healthy or diseased and if it is a diseased plant leaf, RCNN will give the name of that particular disease. Suggesting remedies for particular disease is made which will help in growing healthy plants and improve the productivity. First the images of various leaves are acquired using high resolution camera so as to get the better results & efficiency. Then image processing techniques are applied to these images to extract useful features which will be required for further analysis. The basic steps of the system are summarized as

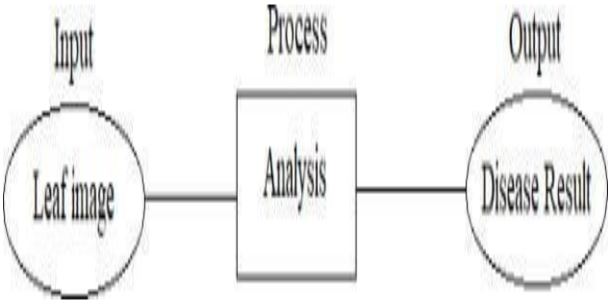

Fig 1: System Architecture

3.2 Methodology and Algorithms

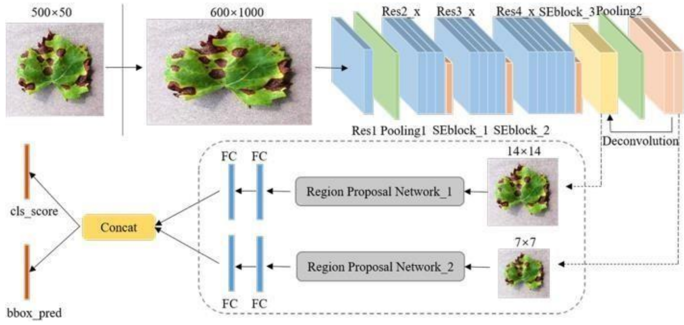

Fig 2: Proposed Model RCNN Algorithm with Region proposal network with pooling layers

3.2.1 *Masked Convolution Layer-- The Kernel*

- In the example below, the green area resembles 5x5x1 input image. The component that conducts the convolution operation in the first half of a convolutional layer is known as the kernel/filter, or K. Yellow is used to illustrate it. K is a 3x3x1 matrix with the following values: 1,0,1,0,1,0,1,0,1,0,1,0,1,0,1.
- Because the Stride Length is 1, the Kernel shifts 9 times whenever it multiplies the matrix K by the image portion P.

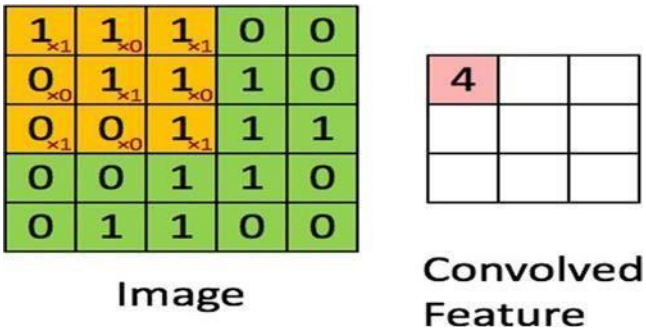

Fig 3: Convoluting a 5x5x1 image with a 3x3x1 kernel to get a 3x3x1 convolved feature

- The filter moves to the right with a certain Stride Value until it parses the entire width. Once the entire image has been traversed, it utilises the same Stride Value to jump back down to the image's beginning (on the left).

3.2.2 *POOLING LAYER*

- The Convolved Feature's spatial size is decreased by the Pooling layer, and dominating features that are rotational and positional invariant are also eliminated. As a result, the model may be trained more quickly.

Maximum and average pooling are the two categories into which pooling can be classified.

- Max Pooling returns the highest value from the image's kernel-covered area.

The average of all the values from the Kernel's portion of the image is returned by average pooling, on the other hand.

```
PSEUDOCODE
for (l = 0;l<L ;l ++){
    for (m = 0;m<M ;m ++){
     for (n = 0;n<N ;n ++){
        sum = bias[l];
        for (k = 0;k<K ;k ++){
             for (s1 = 0;s1 <S1;s1 ++){
                  for (s2 = 0;s2 <S2;s2 ++){
           sum+=weight[k][l][s1][s2] × input [k][m + s1][n + s2];
        }}}
      output [l][m][n] = activation_func(sum);
}}}
```

Fig 4: - pseudo code for masked RCNN model

4. Results and Evolution Metrics

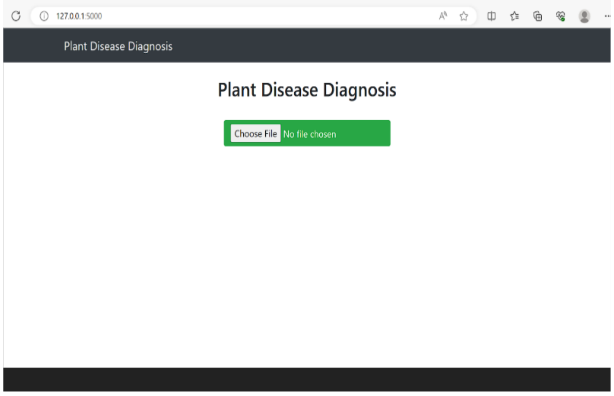

Fig 5: - Main home page

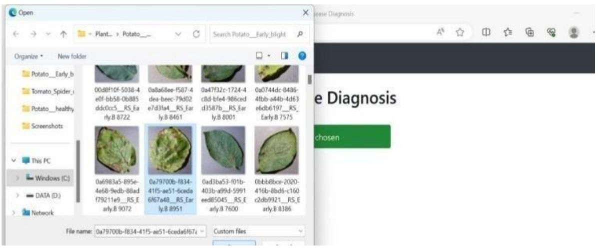

Fig 6: - user input the image to test for plant leaf disease

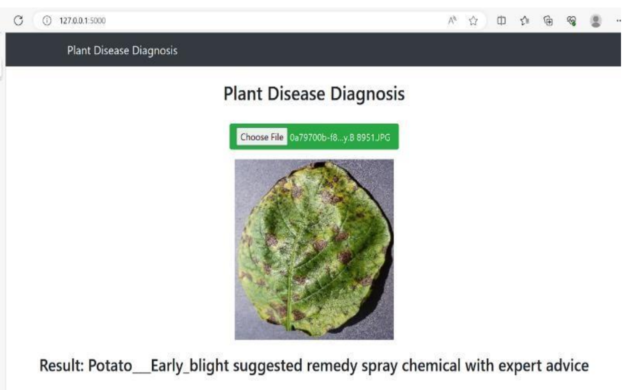

Fig 7: Detected plant leaf disease with suggestion

Table 1: There is no set limit on how many filters can be used on CNN. The problem's complexity determines the maximum number of filters that can be used. The RCNN configuration

	Number Filters	Number of Channels	Number filters
RCNN	64	3	3*3
	128	4	3*3
	256	6	3*3
	512	3	3*3

Table 2: Displays the comparison of RCNN and CNN performance. The two models operate well together. Because RCNN optimizes the residual and addresses the vanishing gradient problem, it outperforms CNN in plant disease prediction applications

S.NO	CNN	RCNN
Accuracy	94.77	98.99
LOSS	0.0857	0.0357
Sensitivity	1.0000	0.9741
Specificity	0.9921	0.9561

5. CONCLUSION

Two of the largest issues in the agricultural sector for farmers are the accurate, prompt, and early detection of crop illnesses and awareness of disease outbreaks, which would be helpful in making judgments about the activities to be taken for disease control. This paper offers a fully automated, inexpensive, and user-friendly end-to-end solution to these issues. This proposal improves known prior art by using deep Convolutional Neural Networks (CNNs) for disease classification, a social collaborative platform for steadily increasing accuracy, geocoded images for disease density maps, and an expert interface for analytics.

6. FUTURE SCOPE

It will be especially helpful for farmers to identify problems periodically, as more individuals are becoming unaware of all plant diseases. The platform's capabilities can be further enhanced by adding real-time prediction integration and providing more thorough forecasts. More sophisticated models are able to anticipate various outcomes for numerous other plants, hence enhancing plant health. As technology develops further, there may be applications in the future that can both forecast and treat diseases.

7. REFERENCES

[1] L. Saxena and L. Armstrong, "A survey of image processing techniques for agriculture," in Proceedings of Asian Federation for Information Technology in Agriculture, 2014, pp. 401-413.

[2] E. L. Stewart and B. A. McDonald, "Measuring quantitative virulence in the wheat pathogen Zymoseptoria tritici using high-throughput automated image analysis," in Phytopathology 104 9, 2014, pp. 985–992.

[3] A. Krizhevsky, I. Sutskever and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, 2012.

[4] TensorFlow.[Online].Available: https://www.tensorflow.org/

[5] D. P. Hughes and and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing," in CoRR abs/1511.08060, 2015. S. Raza, G. Prince, J. P. Clarkson and N. M. Rajpoot, "Automatic detection of diseased tomato plants using thermaland stereo visible light images," in PLoS ONE, 2015.

[6] D. L. Hernández-Rabadán, F. Ramos-Quintana and J. Guerrero Juk, "Integrating soms and a bayesian classifier for segmenting diseased plants in uncontrolled environments," 2014, in the Scientific World Journal, 2014.

[7] S. Sankaran, A. Mishra, J. M. Maja and R. Ehsani, "Visible- near infrared spectroscopy for detection of huanglongbing in citrus orchards," in Computers and Electronics in. Agriculture 77, 2011, pp. 127–134.

[8] C. B. Wetterich, R. Kumar, S. Sankaran, J. B. Junior, R. Ehsani and L. G. Marcassa, "A comparative study on application of computer vision and fluorescence imaging spectroscopy for detection of huanglongbing citrus disease in the USA and Brazil," in Journal of Spectroscopy, 2013.

[9] C. Szegedy,"Rethinking the inception architecture for computer vision," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2818-2826.