



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 3, March 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijrset@gmail.com

www.ijrset.com

CNN-Based Automated Diagnosis of Apple Plant Diseases from Leaf Images

K Perumal¹, B Naveen Kumar Reddy², G Obaiah³, P Nikhitha⁴, S Nafeesa Sulthana⁵

¹Assistant Professor, Department of CSE, AITS, Tirupati, India

^{2, 3, 4, 5}Student, Department of CSE, Annamacharya Institute of Technology and Sciences, Tirupati, India

ABSTRACT: Plant illnesses are an extreme reason for crop misfortunes in the horticulture universally. Discovery of infections in plants is difficult and testing because of the absence of master information. Profound learning-based models give promising ways of recognizing plant infections utilizing leaf pictures. Not with standing, need of bigger preparation sets, computational intricacy, and over fitting, and so forth. are the significant issues with these strategies that still should be tended to. In this work, a convolutional brain organization (CNN) is fostered that comprises of more modest number of layers prompting lower computational weight. Some expansion procedures, for example, shift, shear, scaling, zoom, and piping are applied to produce extra examples expanding the preparation set without really catching more pictures. The CNN model is prepared for apple crop utilizing a freely accessible dataset Plant Village to recognize Scab, Dark decay, and Cedar rust illnesses in apple leaves. The thorough exploratory outcomes uncovered that the proposed model is well t to recognize apple leaf illnesses and accomplishes 98% classification precision. It is additionally clear from the outcomes that it needs lesser measure of capacity also, takes more modest execution time than a few existing profound CNN models. Despite the fact that, there exist a few CNN models for crop sickness discovery with equivalent exactness, yet the proposed model necessities lower capacity furthermore, computational assets. Accordingly, it is exceptionally appropriate for conveying in handheld gadgets.

KEYWORDS: Apple diseases, classification, convolutional neural network, deep learning, disease Detection, image processing, machine learning.

I.INTRODUCTION

Agribusiness is one of the fundamental wellsprings of the means of individuals for a long time. It contributes in the sustenance of about fifty percent of the worldwide populace [1]. Farming enormously affects individuals all around the world, either straightforwardly or in a roundabout way. Farming creation needs to ascend by 50-60% to guarantee the food security before long, particularly for nations having fast development of populace [2]. Cultivation contributes around 30% to the Gross domestic product of the Indian agribusiness industry [3]. Apple is one of the most broadly consumed

1) Dark decay is a parasitic disease brought about by *Diplodia seriata* growth. It grows little sneaks on the upper surface of the leaf during leaf unfurling. Afterward, frog-eye spots with rosy or purplish edges show up on the contaminated leaves. As the sore ages, it becomes chlorotic what's more, higher seriousness prompts defoliation debilitating the tree. Dark decay influences the two leafy foods of the tree.

2) Scab is a serious contamination communicated through *Venturia inaequalis* organism. Illness side effects show up as pale yellow or on the other hand olive-green spots on the upper surface and as smooth or dim injuries on the lower surface of the leaf. As the contamination spreads, it makes leaves twist up or drop. The extreme contamination prompts persistent defoliation and harm to the tree. Scab likewise influences the two foods grown from the ground of the tree.

3) Cedar rust is likewise a parasitic disease brought about by *Recficenter- nosporangium juniperi-virginianae* growth. At first, the rosy or light yellow round sores show up on leaves' upper surface and progressively expand into brilliant orange-yellow spots. Extreme disease brings about pale yellow or orange spots on natural products, and an untimely fall of leaves. natural product internationally and among the four most created natural products after banana, grape, and orange [4]. The creation of apple crop has expanded somewhat recently, however it isn't in extent to the development of the development region.

II.RELATED WORK

Picture handling and ML can possibly help ranchers or then again orchardists in distinguishing plant sicknesses in computationally keen ways rather than manual exams. SVM is able to do isolating non-straight information utilizing hyper planes. In [6], creators utilized SVM to examine tomato crop wellbeing status. The comparable work was finished by Deshapande et. al. [7] to recognize parasitic illness in maize crop. Creators in [8] and [9], additionally utilized surface highlights of sickness sores in perceiving the sicknesses in cucumber utilizing SVM classification method. Vishnoi et al. [11] likewise utilized surface data to recognize illnesses in mung bean and apple crops utilizing SVM. Creators in [12] utilized surface attributes with SVM to check wellbeing status of palm trees.

Khan et al. [7] utilized hereditary calculation to choose upgraded includes and utilized them to order the illnesses in apple leaves and accomplished a relatively better exactness of 97.10%. Zhang et al. [9] additionally utilized ANN to find sicknesses in maize crop utilizing variety, surface, and shape highlights. In [10], creators utilized a brain network with variety and shape properties of irresistible leave to examine sickness in rice crop. Lately, CNN has arisen as a promising strategy for plants specific applications.

Essentially, creators in [33] fostered a profound CNN for plant illness recognition, which was superior to a few pattern classifiers. Some profound CNN models were moreover created by Agarwal et al. [14] to find the efficient arrangement to establish illness location issue. Notwithstanding, these models are computationally costly comprising of larger number of layers and take really preparing time. Coulibaly et al. [7] investigated a fine tuned VGG-16 model to identify mold illnesses in millet crop pictures. Likewise, move learning based CNN model was utilized in [8] to characterize tomato leaf diseases. VGG-16 model with two extra Commencement modules was utilized in [9] to precisely recognize apple leaf sicknesses. The model accomplished exactness of 97.14% however consideration of two Inception units made VGG-16 more computational costly.

As of late, ne-tuned InceptionV3 model was investigated by Tahir et al. [5] to recognize apple leaf infections. They accomplished 97% exactness. In another review, AlexNet model was utilized to anticipate apple scab infection yet the expectation precision was not tracked down better compared to some current strategies [6].

The pre-prepared models have shown great execution in plant illness recognition. In any case, these models are not specially prepared for such reason and thusly, lead to opportunities for accuracy mistake. In light of the writing study, it tends to be laid out that fostering a deep is attractive CNN model specially intended to efficiently distinguish plant illnesses with high precision and less computational weight.

III.IMPLEMENTATION METHOD

Data Pre Processing:

The apple leaf pictures are taken from the Plant Village dataset accessible straight forwardly through the Plant Village project [7]. The dataset contains 3171 RGB pictures of apple plant leaves that are isolated into four classes. The three classes relate to 3 apple illnesses to be specific dark decay, scab, and apple cedar rust. The excess one class addresses sound/uninfected leaf pictures. The masterfully organized apple leaf pictures of size 256*256 for each of the four classifications were caught with a basic foundation at different plant advancement stages in research center condition [8].The sickness classes are named after the apple sicknesses and solid class addresses leaves with practically no sickness. Plant village dataset has been utilized in a huge number of exploration works. It is vital to have various pictures of leaves in the dataset so that model can learn significant varieties during the preparing. A few changes, for example, shift, shearing, scaling, zoom, and flipping are utilized in this work to change the pictures. These changes make minor varieties in pictures that assistance to present assortment in the preparation set. It thus helps to lessen over fitting and assists the model with accomplishing better resistance and capacity to sum up.

Deep Convolutional Neural Network

The profound CNN is a feed-forward ANN based profound learning procedure. Here, the word profound alludes to larger number of layers in a CNN. Generally, a profound CNN is developed by stacking a few structure blocks, for example, convolutional layers with a regular non-direct enactment unit, pooling layers, and completely associated layers. It enjoys showed specific benefits over the cutting edge ML based techniques as it doesn't require any extra endeavors for include designing. It is effectively utilized in a few applications including picture/text classification, NLP, and accuracy horticulture, and so forth [6]. The starting layers of profound CNN extricate various kinds of lower level elements.

IV. PROPOSED METHOD

The proposed profound CNN (Conv-3 DCNN) model formed of 3 convolutional layers and two completely associated layers after the three max-pooling units. ReLU is investigated as a nonlinear actuation capability at every convolution layer and at first thick layer. Softmax capability is utilized at the result layer to group apple plant sicknesses. The softmax capability is liable for multiclass classification and expects to be that each example has a place with precisely one class. A dropout layer is likewise utilized furthermore at the third max pool layer with the impact of over fitting. The dropout unit fundamentally dispenses with a few irregular chose neurons. At first, at the first convolution level 32 filters (3 *3) with substantial cushioning and step1 chosen to tangle over RGB pictures of size 256 * 256. It produces 32 component guides of size 254 *254. In yield highlight map the number of channels is same as the quantity of filters applied. At the first pooling layer, the recently created highlight maps are down sampled by a portion of size 2 *2 and 32 element guides of size 127*127 are created. Similar bits are utilized at particular higher layers. The functioning system of the proposed profound CNN strategy can be perceived with the assistance of layered design.

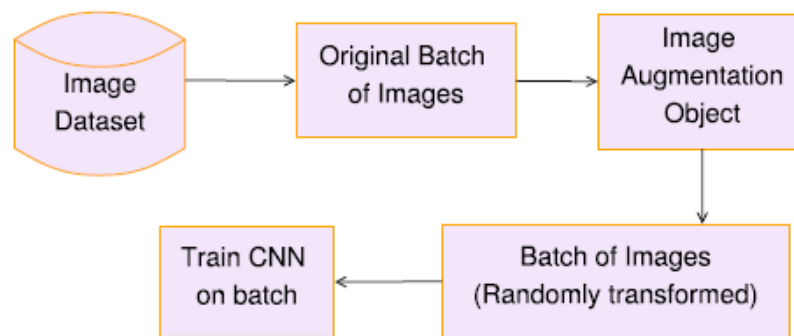


Figure1 . Representation of the process of data augmentation/manipulation.

V. EXPERIMENTS RESULTS

CNN model is prepared and assessed on the dataset depicted in Segment. The dataset is parceled into preparing, approval, and test with a proportion of 70-20-10 utilizing hold-out approval technique. In like manner, the preparation, approval, and test sets are involved 228, 634, and 319 pictures respectively, The profound CNN model is executed in Python utilizing Keras, Scikit-learn, Opencv, and Cushion libraries on the Google Colab virtual stage comprising of Nvidia P100 GPU with 12 GB Slam. The outcomes are pictured with the assistance of Matplotlib library. With a learning pace of 0.0001 and mini batch size of 50, the model is prepared for 1000 ages. The unmitigated cross entropy approach is utilized to appraise the misfortune. where N means no. of classes, for example, $\frac{1}{N} \sum_{m=1}^N -\log p_m$, y addresses a paired pointer that demonstrates right naming of class m furthermore, perception I, and p is the likelihood of anticipating that the perception I has a place with the class m. tuning is performed utilizing irregular inquiry methods to choose the best reasonable hyper parameters. The subtleties of upgraded hyper parameters connected with the grew profound CNN model are accounted for InceptionV3 [13], Xception [14], and Mobile Net [15]. All the pre-prepared models are applied on a similar preparation and test dataset. These models are utilized through the exchange learning move toward which works on the model speculation and permits fast advancement.

Performance Metrics Used For Model Evaluation:

The model presentation is assessed in regard of different measurements which can be gotten from disarray lattice.

- 1) Exactness: Precision is a generally utilized exhibition metric that gives the proportion of right expectation and the complete no. of information tests or the complete forecast made by the classifier. Both in general and individual class precision still up in the air from the disarray framework.
- 2) Accuracy: It gives the small amount of every positive forecast that are really certain.
- 3) Review or Responsiveness: It is the proportion of proportion of accurately anticipated positive examples and all sure tests.
- 4) Specificity/Genuine Negative Rate (TNR): It denest the proportion of accurately anticipated negative examples what not negative examples.
- 5) F1-Score: It gives the consonant mean of the accuracy also, reviews, and alludes to the no. of accurately classified occasions. It goes from 0 to 1.

6) Cohen Kappa: Cohen Kappa is a proportion of between rater unwavering qualities. It’s higher worth defines the model to be more solid. It goes from 0 to 1.

VI.RESULTS AND ANALYSIS

The profound CNN lessens the need of extra element designing processes. The element maps acquired at various convolutional also, pooling layers for an apple leaf contaminated with Cedar Rust The early convolutional layers gain proficiency with the highlights like edges, corners, and straightforward surface and saving the majority of the data in the information picture. Pooling layers down sample the component maps. Yet, more profound layers defines a disconnected type of unique picture and encodes undeniable level data, for example, infection spots and complex surface. Specifically, the component maps at second convolutional layers tells less about the picture and more about the injuries specific to an illness. Sixteen component maps specific to second convolutional dark (conv2Cpool2) besides, the component maps get sparser at additional more profound layers that identify specific data about examples and shapes. These component maps address just the complex data, for example, injury shape and size. The completely associated layers figure out how to interface undeniable level elements to the classes.

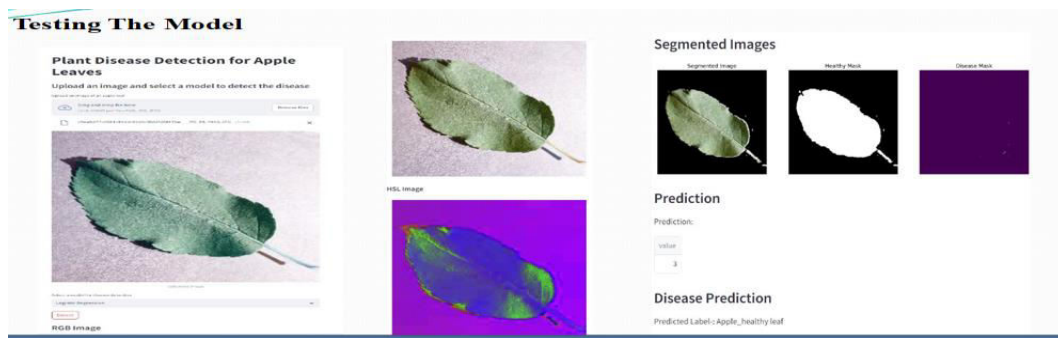


Figure 2: Test the model in apple leaf detection

In this analysis, the proposed CNN model is assessed for its precision. The preparation precision is plotted alongside approval precision against the quantity of images. It tends to be seen that there is just a little distinction in preparing and approval precision bends. It pronounces that the proposed model firts well for the resolved issue. It can likewise be seen from the diagram that model precision at first increments strongly with expanding ages. Later it gets to the next level gradually. At first, when the model begins learning, the approval misfortune is obviously higher than the preparation misfortune. When the model took in the elements of infection classes, the approval misfortune is diminished and the approval precision is expanded. The a large portion of the examples lie along the slanting of the disarray framework demonstrating a decent presentation. Different boundaries including review, accuracy, Kappa, f1-score can be accessed through disarray lattice. The in general exactness of the model at boundaries specified in the On assessing the precision for individual infections, it is seen that the proposed model identifies every sickness with a decent exactness as yielded.

Model	No. of Parameters	Training Time (h)	Testing Time (s)	Size	FLOP	Depth	Accuracy	Precision	Recall	F1-Score	ROC AuC
VGG-19	143,667,240	25	257	549 MB	1.96E+10	19	0.96	0.94	0.92	0.92	0.97
ResNet-152	58,772,356	19	73	230 MB	1.13E+10	152	0.95	0.95	0.91	0.93	0.96
DenseNet-201	20,242,984	17	48	80 MB	4.37E+09	201	0.94	0.95	0.92	0.93	0.94
MobileNetV2	3,538,984	9	54	14 MB	3.14E+8	53	0.97	0.96	0.93	0.94	0.93
ResNet-50	25,636,712	12	20	98 MB	1.10E+10	50	0.90	0.90	0.88	0.88	0.89
VGG-16	138,357,544	15	16	528 MB	1.58E+10	23	0.96	0.94	0.95	0.94	0.94
InceptionV3	23,851,784	12	14	92 MB	2.00E+09	159	0.95	0.95	0.94	0.94	0.97
Xception	22,910,480	13	113	88 MB	1.10E+10	126	0.95	0.93	0.94	0.93	0.96
MobileNet	4,253,864	10	82	16 MB	5.69E+11	88	0.96	0.95	0.94	0.94	0.97
Deep CNN	121,964	8	11	11 MB	1.32E+08	3	0.98	0.98	0.97	0.97	0.99

Table: Comparison of classification accuracy of proposed model with the methods exploited in prior researches in the domain.

VII.CONCLUSION

A profound CNN model was proposed in this work to distinguish illnesses in apple crops with the assistance of leaf pictures. It can help the non-master ranchers in apple plantations and lower the weight on plant pathologists. The model was prepared on 3171 apple leaves for 1000 ages. The exactness of the model was assessed to 98% on Plant Village dataset. The thorough examination shows the proposed model to be better than different pre-prepared CNN models. The strategy was additionally tracked down better compared to a few other existing techniques on the premise of different boundaries including precision and memory necessities. The model accomplishes great exactness for various sicknesses between 97% to almost 100%. The model effectively adjusted the exactness and accuracy. The AUC-ROC bend showed that the proposed model is dependable and steady. The conceivable expansion of this work incorporate assortment of more leaf pictures of apple plants from different topographically various regions with fluctuating picture quality at various plant development stages in various development conditions. The enormous dataset with further developed picture changeability would permit more thorough examinations assisting with working on the model to identify illnesses at various stages for an assortment of apple crops.

REFERENCES

- [1] T. Deshpande, "State of agriculture in India," PRS Legislative Res., no. 113, pp. 1_29, 2017. [Online]. Available: <https://www.prsindia.org/policy/discussion-papers/state-agriculture-India>.
- [2] The State of Food Security and Nutrition in the World 2020. Transforming Food Systems for Affordable Healthy Diets, FAO and UNICEF, FAO and IFAD and UNICEF and WFP and WHO, Rome, Italy, 2020, Accessed: 25-June-2021. [Online]. Available: <http://www.fao.org/documents/card/en/c/ca9692en/>
- [3] Horticulture Statistics Division (Government of India). (2018). Horticultural Statistics at a Glance 2018. [Online]. Available: https://agricoop.nic.in/sites/default/_les/Horticulture%20Statistics%20at%20a%20Glance-2018.pdf
- [4] World Production, Markets, and Trade Report_Fresh Apples, Grapes, and Pears: World Markets and Trade, United States Dept. Agricult. Foreign Agricult. Service, Foreign Agricultural Service/USDA, Washington, DC, USA, Accessed: Jul. 12, 2021. [Online]. Available: <https://www.fas.usda.gov/data/fresh-apples-grapes-and-pears-world-markets-and-trade>
- [5] National Horticulture Board. Report on Apple production in India. Accessed: Dec. 2020. [Online]. Available: http://nhb.gov.in/report_les/apple/APPLE.htm
- [6] V. K. Vishnoi, K. Kumar, and B. Kumar, "Plant disease detection using computational intelligence and image processing," J. Plant Diseases Protection, vol. 128, no. 1, pp. 19_53, Feb. 2021, doi: 10.1007/s41348-020-00368-0.
- [7] S. Kaur, S. Pandey, and S. Goel, "Plants disease identification and classification through leaf images: A survey," Arch. Comput. Methods Eng., vol. 26, no. 2, pp. 507_530, Apr. 2018, doi: 10.1007/s11831-018-9255-6.
- [8] V. K. Vishnoi, K. Kumar, and B. Kumar, "A comprehensive study of feature extraction techniques for plant leaf disease detection," Multimedia Tools Appl., vol. 81, no. 1, pp. 367_419, Jan. 2022, doi: 10.1007/s11042-021-11375-0.
- [9] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2014. [Online]. Available: <https://arxiv.org/abs/1409.1556>, doi: 10.48550/ARXIV.1409.1556.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details