

Data Analysis for *Centella Asiatica* Leaf Disease Prediction in Agriculture Using Machine Learning

Received: 16 February 2023, **Revised:** 22 March 2023, **Accepted:** 26 April 2023

P. Deivendran

Associate Professor, Department of Information Technology, Velammal Institute of Technology, Chennai, India
Email: deivendran1973p@gmail.com

C. Shanmuganathan

Department of Computer Science and Engineering, Faculty of Engineering and Technology, SRM Institute of Science and Tehnology, Ramapuram, Chennai, India.
Email: drcsnathan@gmail.com

V.Vinoth Kumar

Assistant Professor, Department of Information Technology, Velammal Institute of Technology, Chennai, India
Email: vinothsharma.vijay@gmail.com

S. Selvakanmani

Associate Professor, Department of Information Technology, R.M.K. Engineering College, Chennai, India.
Email: sskanmani6@yahoo.com

Corresponding Author: P. Deivendran

Keywords

Centella Asiatica, Diseases, herb, Optimization, Classification, pharmacology, database.

Abstract

Plant diseases reduce agricultural output, which affects the economy. As a result, prediction models for plant disease detection and evaluation must be created. If caught early enough, the most prevalent disease, fungus infection, can be treated by adopting the proper precautions. A rise in interest in plant studies has been observed recently on a global scale. *Centella asiatica* is an important medicinal herb that is widely utilized in the east and is becoming more well known in the west triterpenoid saponins, and Tamilnadu which make up the majority of *centella sciatica*'s. Chemical makeup, are regarded to be chiefly responsible for its wide ranging therapeutic effects. Exzema, psoriasis, amenorrhea, illnesses of the female genitourinary system, leprosy, lupus, varicose ulcers, and other skin condition are among the other conditions are among the other conditions for which the herb is recommended. It is also used to alleviate anxiety and improve Due to its extensive positive neuroprotective activity,, *centella asiatica* has been referred to as a brain tonic. The plant is also examined for its toxicity and potential medication interactions. Anticonvulsant medications were discovered to interact with *asiatica* and toxicological research also advised against using them over an extended length of time. Additionally, there are several commercial goods out there that have been utilized mostly for dietary supplements, antioxidants, skin nourishment, and memory enhancement. More research must be conducted on the cultivation and clinical aspects.

1. Introduction

A greater effort has been in recent years to locate foods and drinks with lots of nutrients and health enhancing qualities. Herbs, which have historically been consumed and are widely accepted, have draw interest from consumers because of their traditional usage in folk medicine. It is well recognized that plants offer medicine, food, clothing, and sheltered. *Centella asiatica*, often known as gotu kola. The Apiaceae family of flowering plants includes the perennial

herbaceous plant known as pennywort. It has been used in traditional medicine in numerous nations, and it is native to india and other regions of Asia, including china, srilanka, Nepal and Madagascar. According to reports, *centella asiatica* is used as an analgesic and anti inflammatory to treat small wounds, psoriasis, chronic venous insufficiency, varicose veins, and more. The kind, nature, and concentration of secondary metabolites present determines how medicinally beneficial plants are, including their ability to be anti diuretic, anti microbial, anti diuretic, and antioxidant qualities.

Journal of Coastal Life Medicine

According to reports, photochemical such alkaloids, saponins, flavonoids, tannins, sterols, and phenolic compounds are some of the most significant bioactive molecules. These photochemical are metabolites formed from plants that naturally occur in the leaves, stems, and roots of medicinal plants. These compounds are utilized by the plants as a defense mechanism to ward against numerous diseases. Secondary metabolites known as photochemical have a number of significant pharmacological functions. Traditional medicine has used centella asiatica to treat a variety of illnesses. Leaf disease forecasting is based on a variety of environmental and meteorological factors that affect a pathogen's ability to survive. When a disease comes into contact with a vulnerable host, it can infect and seriously harm agricultural output. Plant disease show the way to a decrease in the amount and quality of agricultural production. Fungi, which can be found in plant leaves, is one of the most prevalent disease. Over 80-90% of plant illnesses are caused by fungi, which are the most varied group of plant pathogens. The nearly 32000 species of parasitic fungi that cause disease degrade the quality of leaves, fruits, stems, vegetables, and their products. Diseases in crops and plants. Direct approaches are the limited use and cannot be used for on field detection, despite delivering reliable data. For on field illness detection, indirect approaches are used directly. With the help of the soil's state and a number of other environmental elements, the proposed model here attempts to develop a real time, reliable predictive model for plant disease identification. Contrarily a number of other conventional models suggest using pesticides on farms because they believe these variables to be homogeneous. It has been noted that plant diseases have a varied distribution in the field since their presence is dependent on particular environmental variables. The use of data analysis for agricultural applications has been investigated in this paper. The focus of this study is on a number of data mining techniques that are constantly being developed in the field of plant science and are quickly emerging as significant technologies. Additionally, illness detection should be affordable, dependable, sensitive, and economical. Here, sensors have been utilized to predict plant illnesses based on various environmental.

The formation of the paper is as follow, the information regarding the sensors employed in this work is highlighted in Section II. In Section III, the four most prevalent fungi illnesses are described together with their symptoms, severity levels, and modes of

transmission. The approach, dataset description, pre-processing processes, exploratory data analysis, and architecture model are all described in Section IV. In Section V, the experimental plan and evaluation metrics are discussed. Additionally, sector VI discusses the outcome, and Section VII wraps up the manuscript.

2. Related Works

The development of solutions utilizing in networks for quicker computing aimed at embedded systems, real-time disease diagnosis, etc., are some current research topics in centella asiatica leaf disease classification at el H.Orchi[1]. The use of intelligent systems that incorporate these remedies might significantly reduce yield of production loss, eliminate tiresome manual monitoring activities at el m.Ebrahim[2], and reduce the need for human effort. Early different image based hand crafted feature extraction techniques were used in tomato leaf disease classification methods at el T.Hayit[3]. These techniques were input into machine learning based on the classifiers. These studies were typically restricted to specific contexts and generally concentrated on a small number of diseases with extensive feature engineering. Using k-means clustering, the region of interest has been recovered in several studies. The technique to segment the sick region support vector machine, decision trees, and other classifiers were employed to predict the class labels from the retrieved characteristics at el deivendran.p[5]. Machine learning approach reply on meticulous preprocessing procedures such physical RoI for cropping, colour space transformation at el v.singh[7], resizing, backdrop elimination, and picture mitering for winning characteristic of extraction because leaf images are so sensitive to their environment at el j.xiong[6]. The standard machine learning algorithms were only able to categorize a small number of diseases from small dataset as a result of the preprocessing increased complexity at el a.poureza[8], as a result, they were unable to generalization to bigger datasets.

The plant centella asiatica, sometimes known as at el t.t.santos[9], has many health advantages. It is used to treat neuromuscular problems, spinal cord injuries, and to improve general memory and brain function. Additionally, gotu kola is used in skin treatments for a variety of skin issues. The approving effects on wound healing were found in a 2022 study on the effects of gotu kola on burn and incision wounds in rats at el p.ganesh[10]. Incision and burn wounds were applied to two groups of rats first. Then, they were divided into

Journal of Coastal Life Medicine

the following subgroups within the chosen group, untreated at el deivendran.p[11], control, and extract. According to the findings of somboonwong et al. 2021 centella asiatica promotes wound healing in both incision and burn wounds at el f.meyar[12]. Similar results were reached by a more recent study in 2020 that used rat models. The trial examined the impact of asiatica extract on burnt-wound rat models at el d.morris[13]. The rats' burn wounds were treated with gelatin nanofibers containing asiatica extract in the study et al. P.singh[14]. Comparatively to rats given only gauze and commercial wound dressings, these rats exhibited a very good recovery rate. This study demonstrated that asiatica extracts enhance collagen production, fibroblast proliferation, and have antimicrobial properties et al L.M.Tassis[15].

According to the closest study of asiatica leaves included a sizable amount of ash, crude fibre, and carbohydrates. The findings imply that the main nutrient present in leaves is glucose. The report by A.cruz al[16] on various varieties of centella asiatica growing in Madagascar with carbohydrate content varying from 45.37-54.8% and ash content ranging from 12.5-16.3% agrees with high concentration of carbohydrate and ash found in our study at el deivendran[17]. According to the carbohydrate content of leaf stalk is 39.5% while that of various traditional Indian leafy vegetables ranges from 24.3 to 68.2% at el M.Tan[18]. The body uses carbohydrates as a source of energy to power cellular metabolism and as a raw material for a variety of businesses. In a given their high fibre content, centella asiatica leaves can support a healthy digestive system by flushing out any toxins and preventing the body from absorbing too much cholesterol. Additionally, it gives the diet more bulk and discourages the overconsumption of starchy foods at el rathishbabu[19], when compared to the reports of there were differences in the present study's fibre, ash, protein, and moisture contents. The leaves of centella asiatica had high levels of peroxide, iodine, and saponification, according to their physicochemical characteristics. As reported by deivendran et al.[20], rehman et al.[20], and rahman et al.[21] the saponification value in this study was greater than the values for Ipomoea involucre leaf is approximately 197.32mg KOH/g and Conarium indicum nut oil is approximately at el j.chaen[21] 178.39 mg KOH/g, but equivalent to coconut oil is approximately 248.52g LPJ/g. Oils with this amount of saponification value will be beneficial in the sectors that produce soap at el

j.muthuselvan[22]. A helpful standard for purity and identity is an oil's iodine value, which gauges its unsaturation. The iodine value of centella asiatica oil is less than 100g, which is considered to be at el u.atila[23]. Lowered peroxide the refractive index of oils is a crucial optical metric that examines how light travels through different materials and can be used to identify oil at el L.goyaln[24]. The main saturated greasy acids in centella asiatica oil were lauric and palmitic acids, whereas linoleic and linolenic acids were the main unsaturated fatty acids. As reported for the leaf stalk of at el rathishbabu[25], palmitic acid was the most prevalent saturated fatty acid identified in centella asiatica leaves. However, the value published for jatropha tanjorensis was lower than that of the current study at el deivendran[26]. Gotu kola and silver sulfadiazine were contrasted in a short clinical trial with research participants who had burn wounds at el s.sood[27]. The dosage form of gotu kola used in this trial was centiderm, an ointment. According to the findings of this clinical investigation, centiderm might help persons with burn wounds at el v.kulkrejan[28]. However, inside this study, the burn wounds had to be on the limbs and represent less than 10% of the total body surface area. Additionally, the burn injuries had to be no older than 48 hours. The use of herbal lotions, such as gotu kola, did not appear to stop or slow the development of radiodermatitis in another small research. Radiation was administered to research participants as part of their breast cancer treatment in this clinical trial. A skin sensitivity is radiodermatitis. According to certain reports, palmitic acid raises cholesterol levels at el srinivasan[29]. On the other hand, davis,[23] showed that if linolenic acid consumption is large than 4.8% of calories, palmitic acid has no hypercholesterolemic effect. The second most common saturated fatty acid, lauric acid, is beneficial in reducing tooth decay at el deivendran [30]. Omega-6 linoleic acid is used to lessen the risk of heart disease, raise HDL levels, and lower the risk of cancer in humans at el a.A.Hussain[31]. It is also used to lower total cholesterol, LDL levels, and HDL levels.

Proteins found in muscle fibres and other bodily components are made up of amino acids at el M.Suchirman[32]. They carry nutrients, guard against disease, and carry out other tasks. Its lack can cause a variety of health problems, including weakened immunity, digestive disorders, depression, reduced infant growth, and many more cells are available. Ten necessary amino acids, including histidine and arginine,

Journal of Coastal Life Medicine

were found in the amino acid profile of centella asiatica leaves, along with eight non-essential amino acids. Histidine, lysine, isoleucine, and phenylalanine were discovered to be the top essential amino acids, whereas glutamate and aspartate were found to be the greatest supplementary amino acids, and amino acid that is not necessary in glutamate is important for signaling and metabolism in the body. Glutamyl residues undergo post-translational carboxylation, which boosts their affinity for calcium and is crucial for hemostasis [22]. Aspartate has been discovered to have a crucial role in the manufacture of immunoglobulin and antibodies, as well as the operation of RNA and DNA additionally, it aids in the treatment of sadness and weariness as well as the promotion of a healthy metabolism in the body [27]. The leaves of centella asiatica may be used as a nutritional supplement to help with concerns relating to nutrition and health. As a significant number of the earlier works were primarily self-curated small datasets, their performances were not comparable. The plantvillage collection, which contains 48,350 photos of 15 different crop species and 30 illnesses, was incorporated, greatly reducing this problem [15]. Ten centella asiatica leaf illnesses, and one healthy class are contained in a subset of this dataset that has been used in the majority of recent deep learning based studies on centella leaf disease classification.

Centella Asiatica Leaf Disease Classification Architecture

The below diagram shown in Fig 1.1 prediction classification techniques that has been utilized by taken as input image will be converted into data preprocessing logic for each leaf image of diseases also focused on different types of segmentation leaves from classification techniques. For the real-time disease localization early stage leaf disease detection, visualizing the learnt features of various CNN model layers, combining leaf segmentation with classification etc., The main goals of these pieces were to break free from the limitations of poor lighting and the

homogeneity of intricate backdrops. Recent transfer learning based techniques to classification have improved classification accuracy with huge datasets while reducing the dependence on hand-crafted feature detectors. These systems had remarkable accuracy, up to 98.79%. However, these models were big and frequently expensive to compute. The accuracy of classification algorithms based on transfer learning has increased with huge datasets, while reducing the dependence on hand-crafted features.

The initially connected network may be broken up into numerous components during a node removal assault operation, each of which is internally connected but isolated from the others. The procedure involves assembling all the distance parts and treating them as a whole system, with the largest part being the most important. The connection robustness of networks can be predicted using the corresponding predictor once they have first been categorized into a number of categories. In addition to addressing these networks in some broad forms, users are able to construct a specific CNN predictor for each of the frequently used network types. Whereas CNN serves as the classifier, one CNN serves as a general predictor that lacks specific network type knowledge, and all remaining CNNs serve as network type predictors, respectively.

Three input neurons, five hidden computation neurons, and three output neurons make up a fully connected feed-forward neural network after constructing the training and testing matrices. It turns out that 43 weights and biases are needed for a 4-5-3 completely associated neural network. After examining the training data, the classification computer selects the 43 best weights and biases and it can reduce the overall classification error. To determine the ideal weights and biases, the algorithm employs cross entropy error and particle swarm optimization. The classification algorithm then adds the ideal biases and weights to the neural network and assesses the model's predictive power.

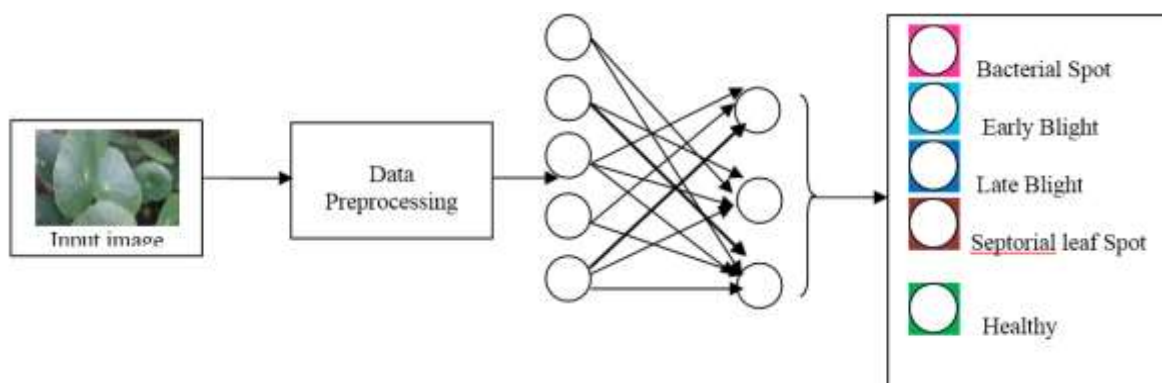


Figure 1.1 Leaf Disease Prediction Classification Architecture

Through the use of multiple hyperparameter, leaf illness categorization has examined the effectiveness of several pretrained model. They concluded from their findings that, due to their higher presentation compare to other model, googlenet,Alexnet , Resnet, DenseNet should be used to build centella asiatica leaf disease detection systems. Some of these studies have also looked into the performance effects of various hyperparameter selections, such as optimizers, consignment sizes, the quantity of leaf, and ne-tuning the replica from various lowest point. These models are superior to

3. Proposed Methods

The below Table 1.1 show the healthy leafs and the Images of the centella asiatica disease are taken with mobile phones, with the centella asiatica leaves set against a 250314nsistent background. The initial collection is made up of 2500 photos, however this number is further decreased because of cluttered backdrops, lighting variations, and poor camera quality. The 1250 centella asiatica photos in the final dataset are labeled with the assistance is divided into 5 category (i) Bacterial Spot (ii) Early Blight (iii) Late Blight (iv) Septorial lea spot (v) Healthy. There are 620 healthy photos, 240 Bacterial spot , 220 early binding and 150 late binding images are included.

Table 1.1 Sample data set

Bacterial Spot	Early Blight	Late Blight	Septorial Spot	Healthy
240	220	150	45	620
Dataset	2100	2100	2100	2100

The amount of data gathered is insufficient to effectively train a deep learning model. By using publicly available dataset, the dataset is improved to help the model perform better datasets employed in the detection of centella asiatica yellow rust. The yellow rust dataset is currently accessible and comprises five infection categories, including bacteril spot, early blight, late blight septorial spot moderately susceptible, and susceptible. There are a total of 13000 photos, with 2300 images for each form of infection kinds, including healthy, resistant, mild, and vulnerable. The distribution of images by class in the two datasets, used to categorize the kind of centella asiatica rust illness is shown in the following figure.

Our suggested architecture receives photos of centella asiatica uses the input of the leaves it create the class leaves, Adaptive histogram equalization is used to enhance the input image during a preprocessing stage. A transfer learning block is then entered with the improved images. Where we use a trained deep CNN model to efficiently extract features. Once the softmax probability for each class has been obtained, we can use them to predict the final label. This is done by feeding shallow highly connected classifier network features that were obtained by the pretrained model. The proposed approach's general pipeline is shown in Fig 1.1 leaf disease prediction classification.

Leaf Classification Techniques

A. Dataset and Images



(i) Bacterial Spot Yellow Leaf



(ii) Early Blight



(iii) Late Blight



(iv) Septorial Spot



(iv) Health

Figure 1.2 Sample images from disease diagnosis

Journal of Coastal Life Medicine

The dataset consists of 12500 photos of healthy and diseased leaves from 10 different crops that have been identified by plant pathology specialist. One healthy class and 8 illness classes contain 9850 photos of

centella asiatica leaves. This collection includes samples of leaves that have been afflicted to various degrees by a wide range of illnesses. In Fig 1.2 displays an example image from each class.

Table 1.2 Sample Leaf Dataset

Class Label	Sample Leaf Count
Bacterial Spot Yellow Leaf	1780
Early Blight	950
Late Blight	1350
Septorial Spot	1650
Health	1250

In classes table 1.2 make it clear that there is an imbalance in the dataset, since different classes have noticeably varied numbers of samples. The disease caused by the yellow leaf curl virus has the most samples, 1780, whereas the disease caused by the mosaic virus has the fewest sample of early blight 950 sample has been collected. The model's ability to generalize is limited since it cannot adequately examine the images of classes with fewer data, moreover because these small sized class do not significantly affect overall accuracy, the overall accuracy may still be good even if the model ignores them. This can be handled using a variety of under sampling and oversampling strategies.

B. Data Preprocessing

Due to the inadequate lighting of the photos included in the dataset, often, illness foci have intensity levels that are similar to those of the immediate surroundings. Additionally, in real world applications, end user

captured photos might not always be well lighted, which could prevent the model from receiving enough information to correctly identify the disease and hence alter the classification outcome. Contrast enhancement methods like histogram equalization can be utilized to enhance the details and resolve the illumination problem. Methods based on histograms frequently work consistently over the full image. However, there's probability that the leaf selection's intensity distribution will be different from the background. As a result the entire image cannot be altered in the same way. To handle the uneven distribution of light sources in order to solve the illumination issues. The RGB colour space of the leaf image was changed to the hunter lab colour scheme. The leaf images intensity channel was split into PQ regions, where P stands for the quantity of background region on the X-axis and Q for the amount on the Y-axis. According to our empirical findings, a assessment of 8 for p and Q produced the finest outcomes.



Enhanced Image

Journal of Coastal Life Medicine



Width Shift



Height Shift



Horizontal Flip



Rotation



Shearing

Journal of Coastal Life Medicine

C. Classification

The centella asiatica yellow rust disease is carried out. The utilized GPU is a 4GB memory on a 2.20GHz intel®, Xeno® CPU. ResNet-50 and Xception are two pre-trained deep learning models that are used on the dataset that is described below. ResNet-50 Model, first deep learning architectures are getting deeper and more sophisticated in order to handle increasingly challenging tasks, which has improved classification and recognition task performance and increased their robustness. The network saturates as a result of vanishing gradients, making it far more challenging to train the model as we continue to add more layers. The ResNet model with residual blocks resolves these issues. This type of categorization of illness kind, the models top is changed to two dense layers with a combined depth of 950. Utilizing th ReLU as an activation.

$$Y = \max(0, x) \rightarrow (1)$$

Which calculated using Eq.(1) following the dense layers comes a failure sheet with a failure ratio of 0.5, reducing the amount of connections that enter the classification layer. Because fewer connections to the classification layer are user overall, computation is more efficient. The classification layer, which has four nodes carrying the softmax function, comes after the dropout layers. The model was created using the Adam optimizer, which seeks to combine the characteristics of AdaGrad and RMSProp and uses categorical cross entropy as one of its primary metrics.

$$CF = \sum_{i=0}^C (T \log((f)si)) \rightarrow (2)$$

D. Performance Evaluation

A pre-trained Xception model with weights optimized on the ImageNet dataset is used to classify the kind of centella asiatica rust infection. The model's input layer is configured as a three-channel image with a 250x250

pixel size. As illustrated in Fig 1.2, the top of the model is where the convolutional layer's output image is flattened before two dense layers with 950 nodes each are added and the ReLU function is triggered. The model is improved by adding a loafer deposit with a dropout ratio of 0.6 following these layers.

$$\sigma(zi) = ez \sum_{j=1}^k a^{n-k} \rightarrow (3)$$

The softmax function, which is calculated using Eqn.(3), activates the final classification layer, which includes four nodes. Here, the numerator divides the product of the squares of each node in the classification divided by the node's score, which corresponds to one of the five classes.. Each layer which provides a probability based on a class of an input image falling under that class. The layer's cumulative probabilities are all equal in the softmax function. Because it uses various convolution kernels to extract specific information from the input images, layer is a crucial component of the CNN. Convolutional layers with several extractions, and the collection of feature maps that correspond to the input image's edges and colour. Equation(4) denies the feature map function.

$$FM_i = f(FM_{k-1} W_i + b_i) \rightarrow (4)$$

The feature map is denoted by FM, the weight by W, the offset vector by b, and the ReLU activation is defined by f(). function as defined in Equation 5 as follows.

$$ReLU(z) = \max(0, z) \rightarrow (5)$$

Here, z is the input and for each pooling layer can be reduces the minimum possibility of overfitting by means of spatial dimension and convolution networks.

Table 1.3 Sample Dataset Division into Classification

Dataset	Healthy	Resistant	Reasonable	Inclined
Training Dataset	1560	1537	1522	1568
Training collected	450	256	146	325
Validation Spilt	153	170	46	150
Testing Split	400	400	400	400

The acquired dataset's from table 1.3 shows the high resolution is lower than the publicly accessible

collection, which was take with high resolution cameras. In a regulated setting and furthermore, the size of the

Journal of Coastal Life Medicine

dataset we can obtained is far smaller than the one that is made available to the general public. The bulk of the photos in the publicly accessible dataset were used to train the models, which makes them more reliable on this dataset but slightly less effective on the gathered dataset. In the figures 1.3 and 1.4 of the confusion matrices show that mainly healthy and susceptible images are accurately identified in comparison to resistant and moderate images. Since healthy images

and resistant images have similar leaf colours and since resistant images include minute rust disease patterns, the resistant images are frequently misclassified as healthy. Similar to how there is as light distinction between moderate and vulnerable images, this mistaken grouping into three categories is primarily due to this mistaken grouping into these categories is primarily due to this.

4. Result and Discussion

Training Dataset	1	0.013	0.0087	0.09	-0.099
Training Collected Data	0.012	1	0.91	0.27	0.24
Validation Spilt Data	0.0073	0.87	1	0.26	0.25
Testing Spilt Data	0.07	0.23	0.26	1	0.17
Testing Spilt Combined Data	0.782	0.27	0.29	0.19	1
Classes	Dataset	Healthy	Resistant	Reasonable	Inclined

Figure 1.3 Existing performance Analysis

The size, amount of parameter, and calculation time of every model are displayed in Fig 1.3 and Fig 1.4, the model's memory conservation depends on a number of variables, including the architecture. The size of the model reflects the size of the network and the inputs to it. Larger models need more number of dataset.. Smaller variants are specifically more suited for used with IoT microprocessor. In a similar vein, the reducing the model's and the parameters is another potent sign of memory optimization because it lightens the models workload. There is a tradeoff between the size of the

model and the number of parameters that must be picked as a result.. When compared to the existing approach, our new Xception and \resNet-50 models achieve the maximum performance is 93% accuracy. As a result of the skip connections, which enable contextual information from the previous layers to be transmitted into the next layer, the results demonstrate that the ResNet-50 model marginally exceeds the Xception model in terms of accuracy is 96% in proposed model compared to other models.

Training Dataset	1	0.016	0.0084	0.08	-0.095
Training Collected Data	0.015	1	0.93	0.27	0.29
Validation Spilt Data	0.0078	0.89	1	0.25	0.26
Testing Spilt Data	0.07	0.23	0.26	1	0.19
Testing Spilt Combined Data	0.789	0.28	0.26	0.15	1
Classes	Dataset	Healthy	Resistant	Reasonable	Inclined

Figure 1.4 Proposed Performance Analysis

5. Conclusion

The most severe disease that can cause a sudden reduction in the quality and productivity of centella asiatica is thought to be centella rust. To minimize this loss, it is essential to accurately and quickly identify rust disease and the severity of it. This calls for a technological solution rather than the conventional manual inspection. In order to achieve this, we put out a technique to identify the five severity categories of centella asiatica dust disease of healthy, resistant, reasonable and inclined. To identify plant diseases an efficient plant leaf disease detection technique that works in real time is required. The centella asiatica plant leaf disease detection method is suggested in this regard. Where the complex background countryside is where the centella plant leaf dataset was gathered. It is difficult to segment and identify diseases in real time photographs because the photos are affected by a variety of other elements, including the background, the setting, the lighting, and the angle at which the image was taken. The U2 net architecture is used in the suggested method to eliminate the complicated backdrop, producing results without degrading the original image's quality.

References

- [1] H. Orchi, M. Sadik, and M. Khaldoun, "On using artificial intelligence and the Internet of Things for crop disease detection: A contemporary survey, vol. 275, pp. 5060, Dec. 2012.
- [2] M. Ebrahimi, M. Khoshtaghaza, S. Minaei, and B. Jamshidi, "Visionbased pest detection based on SVM classification method," *Comput. Electron. Agricult.*, vol. 137, pp. 52-58, May 2022.
- [3] T. Hayit, H. Erbay, F. Varçın, F. Hayit, and N. Akci, "Determination of the severity level of yellow rust disease in wheat by using convolutional neural networks," *J. Plant Pathol.*, vol. 103, no. 3, pp. 923-934, 2021.
- [4] S. S. Chouhan, U. P. Singh, and S. Jain, "Applications of computer vision in plant pathology: A survey," *Arch. Comput. Methods Eng.*, vol. 27, no. 2, pp. 611632, Apr. 2022.
- [5] Deivendran. P, 2022, "Emotion Recognition for Challenged People Facial Appearance in Social using Neural Network," *International Journal of Engineering Trends and Technology* Volume 70 Issue 6, 272-278, June 2022 ISSN: 2231 – 5381 / <https://doi.org/10.14445/22315381/IJETT-V70I6P228> © 2022 Seventh Sense Research Group®.
- [6] J. Xiong, D. Yu, S. Liu, L. Shu, X. Wang, and Z. Liu, "A review of plant phenotypic image recognition technology based on deep learning," *Electronics*, vol. 10, no. 1, p. 81, Jan. 2021.
- [7] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Inf. Process. Agricult.*, vol. 4, pp. 4149, Mar. 2020.
- [8] A. Pourreza, W. S. Lee, R. Ehsani, J. K. Schueller, and E. Raveh, "An optimum method for real-time in-eld detection of huanglongbing disease using a vision sensor," *Comput. Electron. Agricult.*, vol. 110, pp. 221232, Jan. 2021.
- [9] T. T. Santos, L. L. de Souza, A. A. dos Santos, and S. Avila, "Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association," *Comput. Electron. Agricult.*, vol. 170, Mar. 2020, Art. no. 105247.
- [10] P. Deivendran, "Liver infection prediction analysis using machine Learning to Evaluate Analytical Performance in Neural Networks by Optimization Techniques," *International journal of Engineering Trends and Technology*, 2023, 7(3), pp. 377-384.
- [11] P. Ganesh, K. Volle, T. F. Burks, and S. S. Mehta, "Deep orange: Mask R-CNN based orange detection and segmentation," *IFAC-PapersOnLine*, vol. 52, no. 30, pp. 7075, 2021.
- [12] Deivendran.P, 2020, "Scalability Service in Data Center Persistent Storage Allocation using Virtual Machines", *International Journal of Scientific & Technology Research*, Vol.9, Issue 02, ISSN:2227-8616 pp 2135-2139, February 2020. Elsevier Publication
- [13] F. Meyer, "Topographic distance and watershed lines," *Signal Process.*, vol. 38, no. 1, pp. 113125, 2020.
- [14] P. Deivendran, "Analysis of Stock Price Fluctuations Accuracy using a Cloud based Recurrent Neural Network's Long Short Term Memory Model," *SSRG International Journal of Electrical and Electronics Engineering* ISSN:2348-379/HTTPS://DOI.ORG/10.14445/23488379/ijee-vi015p103

Journal of Coastal Life Medicine

- [15] D. Morris, "A pyramid CNN for dense-leaves segmentation," in Proc. 15th Conf. Comput. Robot Vis. (CRV), May 2021, pp. 238245.
- [16] Monica.GK, MEMS based Sensor Robot for Immobilized Persons, International Conference on Innovative Data Communication Technologies and Application, ICIDCA 2023, proceedings, 2023, pp.924-929.
- [17] P. Singh, A. Verma, and J. S. R. Alex, "Disease and pest infection detection, in coconut tree through deep learning techniques," Comput. Electron., Agricult., vol. 182, Mar. 2021, Art. no. 105986.
- [18] P. Deivendran, Smart IoT based an Intelligent System for Needy People to Recognition Voice Detection of Obstacle, International Conference on Innovative Data Communication Technologies and application (ICIDCA-2023), IEEE Xplore part number, CFP23CR5 ART, ISBN:979-8-3503-9720-8
- [19] L. M. Tassis, J. E. Tozzi de Souza, and R. A. Krohling, "A deep learning approach combining instance and semantic segmentation to identify diseases and pests of coffee leaves from in-eld images," Comput. Electron. Agricult., vol. 186, Jul. 2021, Art. no. 106191.
- [20] A. Cruz, Y. Ampatzidis, R. Pierro, A. Materazzi, A. Panattoni, L. De Bellis, and A. Luvisi, "Detection of grapevine yellows symptoms in vitis vinifera, L. With artificial intelligence," Comput. Electron. Agricult., vol. 157, pp. 6376, Feb. 2020.
- [21] Selvakanmani.S, Deep learning approach to solve image retrieval issues associated with IOT sensors, Measurement: sensors, 2022, 24, 100458.
- [22] Deivendran, P., Naganathan, E.R., "Scalability Assurance Process in replication and Migration Using Cloud Simulator", International Journal of Networking and Virtual Organisations, Jan 01, 2019, Vol. 21, No. 1, pp. 112-126, DOI: 10.1504/IJNVO.2019.101153; ISSN: 14709503, UG C.SL.NO.1-23221.
- [23] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," in Proc. Int. Conf. Mach. Learn., 2021, pp. 61056114.
- [24] Software engineering techniques for block chain technology, Rathish Babu, T.K.S., Balaji, V., Krishna, A., International Journal of Recent Technology and Engineering, 2022, 8(2), pp. 3672-3675
- [25] Deivendran.P, Scalability and security requirements for the Internet of Things architecture, Artificial Intelligence for Internet of Things: Design Principle, Modernization, and Techniques, 2022, pp.109-147.
- [26] J. Chen, H. Yin, and D. Zhang, "A self-adaptive classification method for plant disease detection using GMDH-logistic model," Sustain. Comput., Informat. Syst., vol. 28, Dec. 2020, Art. no. 100415.
- [27] Muthukaruppasamy.S, Evaluation of additional power loss reduction in DG integrated optimal distribution network, Control Engineering and applied informatics, 2022, 24(1)
- [28] Model predictive controller-based quadratic boost converter for WECS applications Nandha Gopal, J., Muthuselvan, N.B., Muthukaruppasamy, S., International Transactions on Electrical Energy Systems, 2021, 31(12), e13133
- [29] Shanmuganathan.C, Enabling security in MANETs using an efficient cluster based group key management with elliptical curve cryptography in consort with sail fish optimization algorithm, Transactions on Emerging Telecommunications Technologies, 2023, 34(3), e4717
- [30] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using efficientnet deep learning model," Ecol. Informat., vol. 61, Mar. 2021, Art. no. 101182.
- [31] Shanmuganathan.C, Copy paste forgery detection using deep learning with error level analysis, Multimedia Tools and applications, 2023,.
- [32] P Deivendran, "Machine Learning approach for Gesticulation system using Hand, International conference on innovative Data Communication Technologies and application, ICIDCA 2023, PP, 78-83
- [33] L. Goyal, C. M. Sharma, A. Singh, and P. K. Singh, "Leaf and spike wheat disease detection & classification using an improved deep

- convolutional architecture,” *Inform. Med. Unlocked*, vol. 25, Jan. 2021, Art. no. 100642.
- [34] Rathish Babu, T.K.S., Balamurugan, N.M., Suresh, S., Sharmila, L., Retraction notice to “An assessment of software defined networking approach in surveillance using sparse optimization algorithm” [*Comput. Commun.* 151 (2020) 98–110] (*Computer Communications* (2020) 151 (98–110), (S0140366419315907), (10.1016/j.comcom.2019.12.061)), *Computer Communications*, 2021, 177, pp. 265
- [35] Deivendran, P., Naganathan, E.R., 2017, ‘Scalability In Dynamic Performance And Utilization Techniques In Scalable Cloud Computing’, *Journal of Advanced Research in Dynamical and Control Systems* Vol. 9. pp.2975-2996, ISSN. 1943-023X, UGC.SLNO.1-2630.
- [36] P. Deivendran, Scalability and Security requirements for the Internet of Things architecture, *Artificial intelligence for internet of things: design principle, modernization, and techniques*, 2022, pp.109-147.
- [37] S. Sood and H. Singh, “An implementation and analysis of deep learning models for the detection of wheat rust disease,” in *Proc. 3rd Int. Conf. Intell. Sustain. Syst. (ICISS)*, Dec. 2020, pp. 341–347.
- [38] V. Kukreja and D. Kumar, “Automatic classification of wheat rust diseases using deep convolutional neural networks,” in *Proc. 9th Int. Conf. Rel., Infocom Technol. Optim. (Trends Future Directions) (ICRITO)*, Sep. 2021, pp. 1–6..
- [39] Srinivasan, G., Senthil Kumar, R., Muthukaruppasamy, S., Evaluation of additional Power loss reduction in DG integrated optimal Distribution Network Control Engineering and Applied Informatics, 2022, 24(1)
- [40] Boominathan perumal, Music genre classification using federated learning, *Smart innovation, Systems and Technologies*, 2023, 324, pp.251-262.
- [41] Kaliappan, S., Factors influencing the gas porosity formation in A438 alloy wheels produced by gravity die casting, *AIP Conference proceedings*, 2023, 2747, 030003
- [42] Anbazhagan, K., Earthquake damage prediction using machine learning, 13th international Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT 2022, 2022, 8, pp.821-8277.
- [43] Deivendran, P., Naganathan, E.R., 2015, ‘Scalability Services in Cloud Computing Using Eyeos’, *Journal of Computer Science*, Science Publication, Volume 11 No. 1, 2015, 254-261, <https://doi.org/10.3844/jcssp.2021.254.261>; ISSN: 254-261;
- [44] A. Hussain, M. Ahmad, and I. A. Mughal, “Automatic disease detection in wheat crop using convolution neural network,” in *Proc. 4th Int. Conf. Next Gener. Comput.*, 2020, pp. 1–4.
- [45] Shanmuganathan, C. Enabling security in MANETs using an efficient cluster based group key management with elliptical curve cryptography in consort with sail fish optimization algorithm, *Transactions on Emerging Telecommunications Technologies*, 2023, 34(3), e4717
- [46] M. Schirrmann, N. Landwehr, A. Giebel, A. Garz, and K.-H. Dammer, “Early detection of stripe rust in winter wheat using deep residual neural networks,” *Frontiers Plant Sci.*, vol. 12, p. 475, Mar. 2021.
- [47] P Deivendran, Machine Learning Approach for Gesticulation System Using Hand, *International Conference on Innovative Data Communication Technologies and Application (ICIDCA-2023) IEEE Xplore Part Number: CFP23CR5-ART; ISBN: 979-8-3503-9720-8.*