American Journal of Psychiatric Rehabilitation

Expert Opinion Article

Vegetable Plant Leaf Disease Image Classification Using Convolutional Neural Network

Chappa Vasantha[1*], Sajja Tulasi Krishna[2]

[1*]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur, AP, Email:chappavasanta@gmail.com
[2]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur, AP, Email: tulasisajja788@gmail.com

Abstract
Vegetables have a wealth of minerals, vitamins and calcium, hence numerous health benefits. In order to fully exploit such advantages, Different sorts of vegetables must be differentiated from one another. One of the means of doing this is to examine their images. In this paper, a total of 7226 RGB images composed of 25 kinds of vegetable leaf samples have been gathered. These images were used through the machine learning process specifically through the Convolutional Neural Networks (CNN) in order to build different models. Neural networks such as CNN, which learns a hierarchy of features as it sees more and more of the images, thus can classify images. Subsequently, the different models constructed were evaluated for four performance metrics, namely, precision (Pr), recall (Re) and F1 score (F1-S). The result revealed that CNN outperformed another classifiers with accuracy performance of 93.66%.

Keywords: Convolutional Neural Networks (CNN), Vegetative Leaf dataset; Machine Learning, RGB Images, Classification, Performance-oriented

1. Introduction

The primary activity on which human beings depend for survival is agriculture since it provides food as well as other services critical for our wellbeing. Of all the agricultural products, most foodstuff comes from vegetables which are, however, more useful than simply being energy-giving foods [1]. Therefore, it is crucial to focus on the factors that will enable effective and quick identification of vegetable leaves. In general, vegetable leaves can be classified into two classes based on the main associated causative agent: infectious and non-infectious classes. In order to help this identification process, Machine Learning algorithms are being employed increasingly. These, as [2] noted, allow one to distinguish various vegetables in a short period of time.

One of the most successful methods in machine learning for this task, is the implementation of Convolutional Neural Network (CNN) based approach. A convolutional neural network is a deep learning algorithm which is particularly designed for images or data which is arranged in a grid like fashion. These networks are specially designed for classification of objects in images because they automatically and adaptively learn spatial hierarchies of different features in the images provided as input. The common architecture of a CNN comprises several layers; convolutional layers, pooling layers and fully connected layers. In the convolutional layers, the input image is processed with different filters to find different elements. The pooling layers reduce the size of the features, hence making the operation less expensive. After this, the features are sent to fully connected layers where they are again processed for the purpose of classifying the image.

2. Literature Review

It is amazing to use Extreme Learning Machine (ELM) for classification of plant diseases in relations to diseases in leaves. [3] It is of great value for feature engineering to use image features from both the HSV color space and Haralick textures. An accuracy of 84.94% is not low at all, since the issue of distinguishing between similar plants in agriculture is a serious one.

Especially,[4] it is a remarkable work to develop a mobile application to identify plants in Sri Lanka using machine learning algorithms due to the fact that there are difficulties in manual identification and also less knowledge on plant species is possessed. The Picture Ranking System which is the mobile application described in this research is systematic in nature as it contains pre-processing, features extraction and classification.

The ability to use Convolutional Neural Networks (CNNs) for diagnosing and managing tomato diseases and pests is a big milestone in the field of agriculture, more so, considering the importance of tomatoes in food production index. [5]. have identified the importance of early detection of diseases on tomato plants and how it reduces the effects on yield and quality which is advantageous to farmers as well as consumers.

[6] Compact convolutional networks (CNN) for classification and identification of plants is an important improvement in precision farming technology especially within the automation systems. Their application, together with transfer learning of AlexNet, shows an innovative way of exploiting the available designs for better performance.

This workflow, which starts with image acquisition, suggests pre-processing, and ends with the zeroth screening stage of the visual inspection of diseased plant leaf surfaces shows that there is order in looking for and studying where the diseases occur on the green parts of the plants. Employing biological optimization techniques for the purposes of component region extraction combined with Support Vector Machine SVM classifiers for imagery classification enhances the sophistication of the system which might in turn improve the precision of disease detection mechanisms[7].

Artificial Intelligence (AI) approaches for plant leaf disease classification based on deep learning architectures such as EfficientNet comes with exciting prospects in agricultural technology. With the models based on deep learning theory, which can discover intricate patterns from unstructured information on their own, [8] less effort is needed for manual feature extraction thus enhancing the speed and precision of classifying images.

The application of deep learning approaches based on convolutional neural networks (CNNs) in the diagnosis of plant diseases with the help of leaf images is a remarkable enhancement in agriculture. Disease detection is now more efficient and precise with the new generation of CNNs, [9] leading to better practices of crop management.
The study of plant leaf diseases using image processing techniques has drawn more attention in recent years, particularly in agriculture, where early detection and management of accurate classifications can save substantial amounts of crop losses and increase yields. In this paper, the authors discuss the review of the recent trends in the literature related to the diagnosis and the treatment of plant leaf diseases using various imaging modalities[10].

The combination of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for improving the assessment of vegetables in intelligent agriculture is a very exciting one.[11] This is because, while CNNs are good at high-level feature extraction of images, SVMs work better when there is less data but more instances which creates a complementarity between the two.

The utilization of image processing and Convolutional neural Networks (CNNs) in recognition of plant leaf diseases is a suggestion that is quite encouraging on the needs of the farmers, more so those in the rural and isolated regions. [12] Leaf diseases are one of the major causes of concern in the agricultural growth and even the global food security, and their early detection offers the best remedy to yield losses.

[13] Adopting systems that are deep learning-based for the purposes of detecting diseases in tomato plants by means of images is a major leap in the agricultural sector. Plant disease monitoring by agricultural specialists is also complicated as it requires a lot of time, and may contain numerous mistakes. Another approach to tackling this problem would be to resort to machine vision for artificial intelligence which would be beneficial in alleviating the difficulties and restraining the impact of diseases.

The creation of a comprehensive model for disease detection in vegetables in field conditions is a notable breakthrough in the field of smart agriculture. Most existing models that are based on Deep Convolutional Neural Networks (DCNNs) have a problem with performance in terms of resolution with complex backgrounds,[14] thus limiting their effectiveness and reliability.

When image processing and Densenet convolution neural networks (CNN) systems are incorporated into digital farming practices, the opportunity to combat and prevent plant diseases in any agricultural setup becomes very high.[15] Farmers, particularly in the rural places, physically assessing crops can be a costly venture since the inspection for disease may come late or miss entirely. With the help of new and sophisticated technologies such as deep learning and image processing, farmers are able to pinpoint the disease affecting a crops parts mix which can be heady and time wasting for many allowing prevention in advance.

Plant phenotyping as one of the parameters involved in assessing the growth of plant development can analyzing soil condition and cover vegetation whilst imaging of intact, injured or diseased leaves processed using machine learning classification methods.[16] The onset of many diseases is seen on the leaves and characters such as brown or black spots can be associated with the lack of green chlorophyll and can be captured using classification, feature extraction and image restoration and segmentation.

In current times,[17] it is particularly important to look at the aspects of plant disease detection in agriculture which has been the core aim of the work presented in the paper so as to avoid losses in crops. Therefore, the objective of this particular section is to introduce the novel application of Convolutional Neural Networks, such as the VGG16 model, and its relevance to the field of agriculture. CNN's are highly in application when it comes to images classification and has proved to be very helpful in numerous other fields including plant diseases recognition.

Considering the fact that agriculture is a central part of the economy of India, the proposed machine learning based approach for segmenting vegetable leaves and spotting their imperfections is considerable in improving the surveillance of crops and protection against their diseases. The automated image analysis and classification system attempts to collect a variety of vegetable leaf images and performs recognition and classification of their diseased condition due to bacteria, viruses and insects[18].

The paper presents an analysis of plant diseases that is all the more keen because of the need to ensure a turnaround within the shortest time possible in food production as well as prevent unnecessary losses in the agricultural sector.[19] CNN's are deep learning models that have gained many important applications and this study explores the use of such models which have been trained on other datasets for the purposes of identifying different plant diseases.

The norms or rather guidelines have been necessitated by the importance of maize in people's diets. Hence, there is need to come up with automated systems for early detection and control of maize leaf diseases to maintain high quality and yield of maize crops. In most cases, it is very important to detect such diseases in their early stages. Even though very challenging due to many factors. In this research project, we propose to extend the k-nearest neighbor (KNN) model in order to get information on different types of maize leaf diseases[20].

Terwijl plantenziekten verder blijven veroorzaken problematiek en strife towards global agricultural development , concernable regards from food insecurity going along with crop production. [21] Prevention of yield losses and ensuring a constant food supply requires occupation. Within the presented work, we focus on transfer learning, one of the advanced techniques in deep learning, in aiding image classification for plant disease prediction. [22,23,24] The suggested crop disease detection technique using computer vision and machine learning has taken agricultural practice a step ahead. Timely assessment of crop diseases is a very important aspect of agriculture, however, if the assessment has to quality, then there is need for expert manpower. This translation would sooner or later require the promising advancements in computer vision and machine learning to solve the problem adequately and conveniently by itself.

3. Methodology

Dataset: A dataset in the form of RGB image is captured and stored in the system. At the very beginning, the image has to be resized. Thus images are prepared for analysis in 250 × 250 dimensions. It comprises a data set of 7226 RGB images of Vegetable leaves belonging to 25 classes. Let $V = \{V_i^k, y_i\}_{i=1}^{k}$ be defined as the set of all the RGB images that have been recorded. Here, Vi indicates the correspondence of each sample i in the data set with label $y_i \in Y$ i.e. $Y = \{y_i\}_{i=1}^{k}$, where i = {1, 2, 3,...,k} and numbers of elements in the dataset are k. An example can be defined using a matrix $h^{(h \times w \times b)}$ a for each $V_i \in V$.

Here, row (i) and column (j) of this matrix (M) give the output as M_{ij}.Where h, w, b corresponds to height, width and batch size respectively. The required scaled dataset $\{V_i^k, y_i\}_{i=1}^{k}$ may be constructed by using the resized function $f_x()$ in Equation

$$V^t = f_x\left(\{V_i^k, y_i\}_{i=1}^{k}, p \times q\right)$$

Experiment: The total dataset of plant leaf pictures comprises of 7226 RGB images and is further divided into 25 subcategories, which are images of vegetable plants leaves. In Figure 1, [25]. Vegetable plants based leaves of various kinds have been used for example eggplant, onion, cabbage, beet root etc. Every category consists of no less than 250 photos. For the case of the tests, all photographs in a class are taken on plain white dataset numbers in different classes are shown below each image. The image dataset is divided into three specific subsets of data, which are training, testing, and validation. Each category of the training dataset consists of over 150 samples while recruiting and testing datasets are 50 samples each.

Figure 1. Assembled all 25 classes of vegetable plant leaves with their respective images, common names preparation techniques

Experiment Design: In terms of the experiment Figure 2, [26]. The depiction of the experimental flowchart of data regarding vegetable leaf images especially deals with the process of data collection and the classification of the different vegetable plants. The process of data acquisition is the initial step and this work has collected roughly two hundred fifty images of leaves per each of the twenty five types of vegetable plants. Whereas in the previous section, the dataset was collected from different areas, here the dataset is prepared for further work which includes cropping and scaling down the pictures. Images for evaluation are resized to 250 x 250 pixels. Images are color oriented. The images were taken by a mobile phone with the camera of sixteen megapixels. This is cluster-based approach. The cluster based approach yields superior results on the completion of the feature extraction. The image attributes are extracted and provide support to the classifier in giving the accurate outcome. The classifier used in this case is Convolution neural networks. An evaluation of classifiers' performance can be performed on Acc, Pr, Re, F1-S etc. Finally, the findings are demonstrated in the form of a bar graph and box graph.

Figure 2. Classification of vegetable leaves using image processing flow chart

4. Results and Analysis

Bar plot of classifiers Figure 3. Traditional classifiers can achieve levels between 80 and 90 percent accurate rates. This depends on the particular strategy that is in play and how much it has been optimized. But there is no comparison with CNNs as they can easily cross the 90-99 accuracy percentage level. This is due to the nature of imaging and how well they learn. Even in more advanced datasets like CIFAR-10 or ImageNet, a very clear performance gap exists between classical classifiers and CNNs.

Classification box diagram Figure 4, [30]. The aforementioned box diagram depicts the accuracy ranges for a few classifiers such as Logistic Regression, Decision Tree, SVM, Till K-NN, and a Convolutional Neural Network (CNN) with respect to the CIFAR-10 data. Each box plot shows the IQR of accuracy values of 100 repetitions of training and testing, while the line within each box shows the mean accuracy. From the figure, it is apparent that CNN performs better when compared with traditional classifiers which have a median accuracy of about 93.66%.

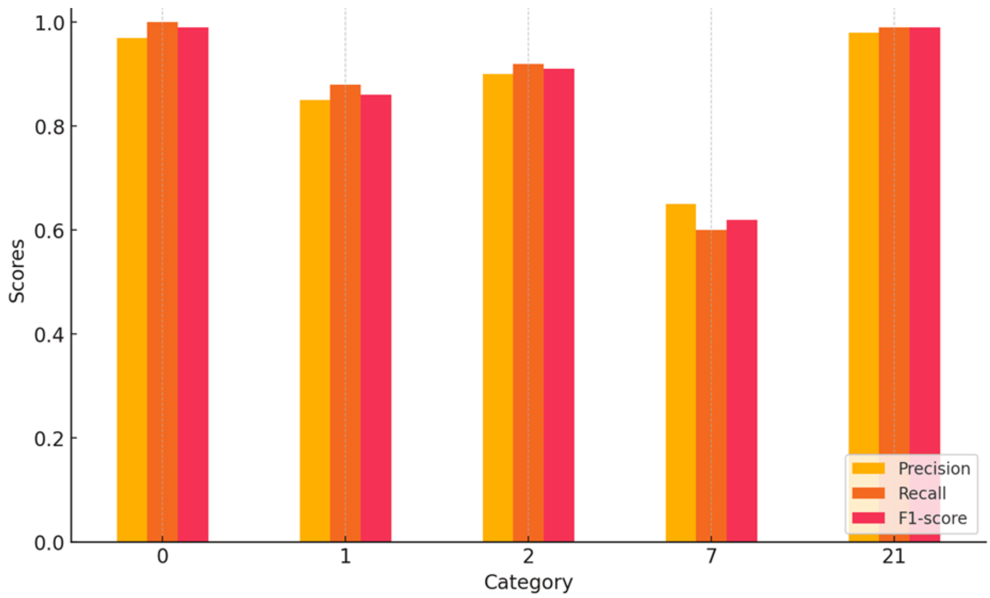

Figure 3. Bar plot showing the performance of CNN classifier

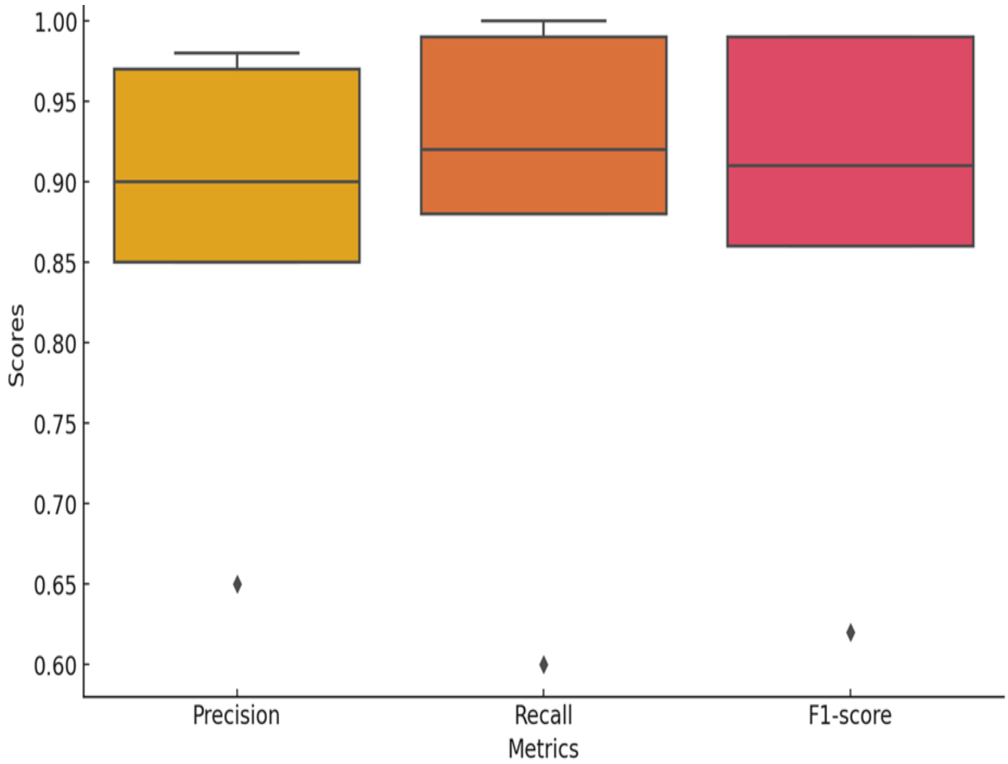

Figure 4. Box plot depicting the performance of the CNN classifier

Using the Heat-Mapped Confusion Matrix in Figure 5, [27]. This heat-mapped confusion matrix is presented for the vegetable plant leaves image dataset. On the extreme right, there is a scale which ranges from 0-4.5, indicating the extent of boxer classers correlation. In exponentiated scale values, one displays a sufficient degree of association between two measured variables. Also, for the scale which is low or 0, the two variables measured do not have any relation.

Now in Figure 3. The part where both the actual and predicted outputs are reference is the strongest correlated one, which is also the diagonal. This means the classifier has been able to classify data successfully. However, if the color of the cells along the main diagonal is much darker (closer to 0), It means that the classifier has made a lot of misclassifications in classification. A lot of dark shades close to 0 will, except for this colorful diagonal cell, hold it the other way around. The color, however, indicates the significance that particular class has with respect to the other vegetable plant leaf classes.
The various fold approaches concerning precision, recall, and F1-s performance. In fact, all the performance results, according to the work in this section, are provided in Table.1 of the section. According to data depicted in Table 1, The tomato plant leaf recorded the highest score across precision (0.97), recall (1.00) and F1-s (0.99) performance measures. Support has the highest Pr, Re, and F1-s in terms of each specific category performance. Conversely, the highest version of tomato and there is the least performance for majority radish. Hence it is seen that in this case, the performance of the CNN classifier is the highest for this category.

Final thoughts of the previous analysis Based on the results in this research work, it is observed that the CNN classifiers have surpassed all other models in accuracy as evidenced by the bar and box plots. The SVM and LR classifiers ranked second and third corresponding to the accuracy rank, respectively. Hence, Precision, Recall and F1- Score are the main performance metrics which are used for analyzing the classification performance, and it is clear that the (TOMATO) demonstrates the highest performance across all the CNN classifiers.

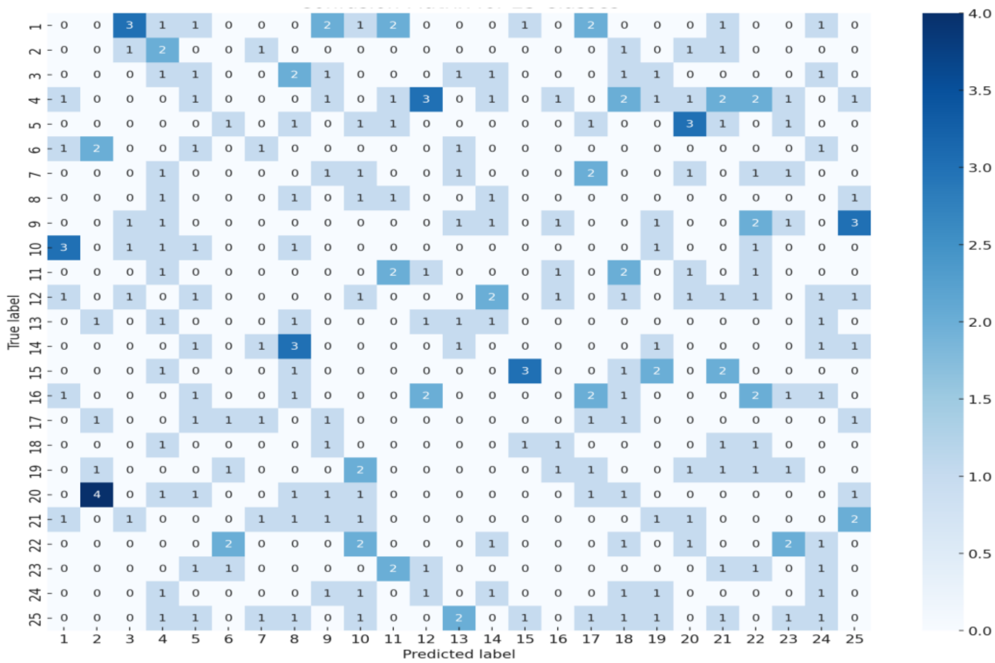

Figure 5. Heat-map Confusion Matrix of CNN

Table 1. Performance of the CNN classifier in terms of Pre, Re, F1-S

CATEGORY	PRECISION	RECALL	F1-SCORE
Onion	0.88	0.89	0.88
Brinjal	0.9	0.89	0.9
Beetroot	0.92	0.93	0.92
Cauliflower	0.9	0.89	0.89
Cabbage	0.89	0.9	0.89
Sword bean	0.87	0.86	0.88
Wild spinach	0.94	0.95	0.94
Lvy gourd	0.92	0.9	0.9
Kumda	0.86	0.89	0.88
Carrot	0.88	0.85	0.86
Hyacinth bean	0.89	0.89	0.9
Pumpkin	0.9	0.91	0.9
Sponge gourd	0.86	0.89	0.89
Bitter gourd	0.87	0.86	0.84
Drum stick	0.9	0.91	0.93
Lima bean	0.87	0.86	0.86
Green pea pinum	0.9	0.87	0.88
Radish	0.85	0.84	0.84
Tomato	0.97	1.0	0.99
Potato	0.91	0.9	0.9
Spinach	0.94	0.95	0.94
Samarkand	0.95	0.92	0.96
Printed gourd	0.88	0.85	0.89
Horse bean	0.87	0.9	0.9
Yardlong bean	0.94	0.95	0.95

Prior to considering the findings reported in the Figure 6, [28]. it is evident from the accuracy bar and box plots that the CNN classifiers have outperformed all other models. Hence, the SVM and LR classifiers also appear consecutively in terms of accuracy being ranked as two and three. Thus, Pr, Re, and F1-S become the very important parameters to evaluate the effectiveness of classification and it is clear that the category - (TOMATO) demonstrates the highest performance across all the CNN classifiers [29].

Figure 6. Tomato leaf classifier

5. Summary

Machine learning based techniques can now outperform doctors in a number of diagnosis tasks Attained an accuracy of 93.66 percent on the blind test dataset with the Convolutional Neural Network model. This high accuracy emphasizes the model's capability of classifying a series of diseases with respect to the medical images and their visual features. To comprehend the performance of the model in detail, we examined the confusion matrix again and assessed the other performance metrics such as precision, recall, F1-score in the case of each disease class. Such analysis proved beneficial in understanding the pros and cons of the CNN, as it was able to determine the diseases that the CNN was good at, and the ones that the CNN had a high degree of misclassification. These results are useful to foresee further steps, aimed at the model improvement in the diseases that are, at present, hard to classify with the model. Based on the damages, it will help improve the deformation quantifying model.

References

[1] Toor, G. S., Yang, Y. Y., Das, S., Dorsey, S., & Felton, G. (2021). Soil health in agricultural ecosystems: current status and future perspectives. Advances in Agronomy, 168, 157-201. http://dx.doi.org/10.1016/bs.agron.2021.02.004

[2] Tripathi, M. K., & Maktedar, D. D. (2021). Detection of various categories of fruits and vegetables through various descriptors using machine learning techniques. International Journal of Computational Intelligence Studies, 10(1), 36-73. http://dx.doi.org/10.1504/IJCISTUDIES.2021.113819

[3] Xian, T. S., & Ngadiran, R. (2021, July). Plant diseases classification using machine learning. In Journal of Physics: Conference Series (Vol. 1962, No. 1, p. 012024). IOP Publishing. http://dx.doi.org/10.1088/1742-6596/1962/1/012024

[4] Dissanayake, D. M. C., & Kumara, W. G. C. W. (2021). Plant leaf identification based on machine learning algorithms.

[5] Trivedi, N. K., Gautam, V., Anand, A., Aljahdali, H. M., Villar, S. G., Anand, D., ... & Kadry, S. (2021). Early detection and classification of tomato leaf disease using high-performance deep neural network. Sensors, 21(23), 7987. http://dx.doi.org/10.3390/s21237987

[6] Wagle, S. A., Harikrishnan, R., Ali, S. H. M., & Faseehuddin, M. (2021). Classification of plant leaves using new compact convolutional neural network models. Plants, 11(1), 24. http://dx.doi.org/10.3390/plants11010024

[7] Sathyaa, S. P. A., Ramakrishnana, S., Shafreena, M. I., Harshini, R., & Malinia, P. (2022, April). Optimal plant leaf disease detection using SVM classifier with Fuzzy System. In Workshop on Intelligent Systems (pp. 22-24).

[8] Atila, Ü., Uçar, M., Akyol, K., & Uçar, E. (2021). Plant leaf disease classification using EfficientNet deep learning model. Ecological Informatics, 61, 101182. http://dx.doi.org/10.1016/j.ecoinf.2020.101182

[9] Hridoy, R. H., Tarek Habib, M., Sadekur Rahman, M., & Uddin, M. S. (2022). Deep neural networks-based recognition of betel plant diseases by leaf image classification. In Evolutionary Computing and Mobile Sustainable Networks: Proceedings of ICECMSN 2021 (pp. 227-241). Singapore: Springer Singapore. http://dx.doi.org/10.1007/978-981-16-9605-3_16

[10] Jasim, M. A., & Al-Tuwaijari, J. M. (2020, April). Plant leaf diseases detection and classification using image processing and deep learning techniques. In 2020 International Conference on Computer Science and Software Engineering (CSASE) (pp. 259-265). IEEE. http://dx.doi.org/10.1109/CSASE48920.2020.9142097

[11] Nurrani, H., Nugroho, A. K., & Heranurweni, S. (2023). Image Classification of Vegetable Quality using Support Vector Machine based on Convolutional Neural Network. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 7(1), 168-178. http://dx.doi.org/10.29207/resti.v7i1.4715

[12] Nagamani, H. S., & Sarojadevi, H. (2022). Kh . International Journal of Advanced Computer Science and Applications, 13(1).

[13] Shoaib, M., Hussain, T., Shah, B., Ullah, I., Shah, S. M., Ali, F., & Park, S. H. (2022). Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease. Frontiers in Plant Science, 13, 1031748. http://dx.doi.org/10.3389/fpls.2022.1031748

[14] Feng, X., Zhao, C., Wang, C., Wu, H., Miao, Y., & Zhang, J. (2022). A vegetable leaf disease identification model based on image-text cross-modal feature fusion. Frontiers in Plant Science, 13, 918940. http://dx.doi.org/10.3389/fpls.2022.918940

[15] Tirupati Rao, S., Reddy, L., & Dileep, P. (2023). Disease Detection of a Plant Leaf using Image Processing and CNN with Preventive Measures. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 14(2), 972-979.

[16] Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), 305-310. http://dx.doi.org/10.1016/j.gltp.2022.03.016

[17] Rinu, R., & Manjula, S. H. (2021). Plant disease detection and classification using CNN. International Journal of Recent Technology and Engineering (IJRTE), 10(3), 152-156.

[18] Tippannavar, S., & Soma, S. (2017). A machine learning system for recognition of vegetable plant and classification of abnormality using leaf texture analysis. Int. J. Sci. Eng. Res, 8(6), 1558-1563. http://dx.doi.org/10.14299/ijser.2017.06.008

[19] Eunice, J., Popescu, D. E., Chowdary, M. K., & Hemanth, J. (2022). Deep learning-based leaf disease detection in crops using images for agricultural applications. Agronomy, 12(10), 2395.

[20] Noola, D. A., & Basavaraju, D. R. (2022). Corn leaf image classification based on machine learning techniques for accurate leaf disease detection. Int. J. Electr. Comput. Eng, 12(3), 2509-2516. http://dx.doi.org/10.11591/ijece.v12i3.pp2509-2516

[21] Dubey, D., Gupta, N. K., & Gupta, S. (2022). Image Classification For Plant Disease Prediction Using Ensemble Deep Transfer Learning. Journal of Survey in Fisheries Sciences, 577-583. http://dx.doi.org/10.53555//sfs.v9i1.1758

[22] Zamani, A. S., Anand, L., Rane, K. P., Prabhu, P., Buttar, A. M., Pallathadka, H., ... & Dugbakie, B. N. (2022). Performance of machine learning and image processing in plant leaf disease detection. Journal of Food Quality, 2022, 1-7. http://dx.doi.org/10.1155/2022/1598796

[23] Sachdeva, G., Singh, P., & Kaur, P. (2021). Plant leaf disease classification using deep Convolutional neural network with Bayesian learning. Materials Today: Proceedings, 45, 5584-5590. http://dx.doi.org/10.1016/j.matpr.2021.02.312

[24] Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. Agriculture, 12(8), 1192. http://dx.doi.org/10.3390/agriculture12081192

[25] Kumar, C., & Kumar, V. (2023, March). Vegetable plant leaf image classification using machine learning models. In Proceedings of Third International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2022 (pp. 31-45). Singapore: Springer Nature Singapore. http://dx.doi.org/10.1007/978-981-19-9228-5_4

[26] Mahmood ur Rehman, M., Liu, J., Nijabat, A., Faheem, M., Wang, W., & Zhao, S. (2024). Leveraging Convolutional Neural Networks for Disease Detection in Vegetables: A Comprehe nsive Review. Agronomy, 14(10), 2231. http://dx.doi.org/10.3390/agronomy14102231

[27] Ashwinkumar, S., Rajagopal, S., Manimaran, V., & Jegajothi, B. (2022). Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks. Materials Today: Proceedings, 51, 480-487. http://dx.doi.org/10.1016/j.matpr.2021.05.584

[28] Omar, S., Jain, R., & Bali, V. (2022, May). Leaf disease detection using convolutional neural network. In 2022 international conference on machine learning, big data, cloud and parallel computing (COM-IT-CON) (Vol. 1, pp. 53-56). IEEE. http://dx.doi.org/10.1109/COM-IT-CON54601.2022.9850950

[29] Rao, E. G., Anitha, G., & Kumar, G. K. (2021, June). Plant Disease Detection using Convolutional Neural Networks. In 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 1473-1476). IEEE.

[30] Mahanty, M., Vamsi, B., Srilatha, Y., Doppala, B.P. (2024). Prediction of Rice Leaf Diseases at an Early Stage Using Deep Neural Networks. In: Lin, F.M., Patel, A., Kesswani, N., Sambana, B. (eds) Accelerating Discoveries in Data Science and Artificial Intelligence I. ICDSAI 2023. Springer Proceedings in Mathematics & Statistics, vol 421. Springer, Cham. https://doi.org/10.1007/978-3-031-51167-7_6