International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Plant Based Disease Detection Using Cnn And Sam

Dhairya Patel[1], Rishab Kate[2], Mohit Solanki[3], Shritika Wayker[4], Kevin Mayani[5], Nalini Jagtap[6]

[1,2,3,4,5,6]Department of computer science & engineering, Dr. D.Y. Patil Institute Of Engineering Management & Research, Pune, India

Abstract

Crop disease detection is pivotal for ensuring food security and sustainable agriculture. Traditional methods often struggle to accurately identify diseased plants, resulting in substantial yield losses. In agricultural contexts, detection of disease is very important so that we get maximum yield and ensures the crop quality or crop health. As we know that for any work related to images we often use CNN convolutional neural network as it work really great due to its architecture thus its use is often seen in leaf disease detection and mostly this traditional approaches use raw leaf image and feed it to CNN to train which may not work if the dataset is very low or we may not get satisfactory accuracy this is because it is not able to capture that pattern, and also in some scenarios diseases spots manifest as light or closely resemble the background color of the leaf thus it requires more data to discern such a subtle patterns.

In this study, we proposed a great approach, that leverages the SAM (Segment Anything Model) [13] for leaf segmentation, followed by CNN training for disease detection which uses the segmented images.

Our approach involves by collecting the data, we needed the dataset of leaf disease in which the disease spots resemble the background color of leaf, after collecting it we have pre-process the images using SAM model, here it segments each part of the leaf and annotate color to it which highlights the diseased part after preprocessing it the segmented images are now ready for training the CNN model on it. Remarkably, with just 300 images, our approach achieved significantly higher accuracy compared to traditional CNN approaches that use raw images.

As SAM model is pre trained on more than 11 million images for segmentation its accuracy to segment small disease spots is remarkable and thus CNN focus on relevant features for disease detection. By segmenting the leaves, our model gains an enhanced understanding of the leaf structure, enabling more precise detection of disease symptoms.

Our experimental results demonstrate the superiority of our approach over traditional methods, highlighting the importance of segmentation and use of segmentation model in improving disease detection accuracy. Furthermore, the advantage of using this approach is that it requires a smaller number of images for training while achieving superior performance, underscores it practical utility in real world agricultural applications.

This research advances the agricultural diagnostics by presenting the innovative and novel method that integrates
segmentation with deep learning to enhance the precision and efficiency of leaf disease detection.

Keywords: Component, Formatting, Style, Styling, Insert

INTRODUCTION

As we are aware of that the global agricultural economy is highly influenced by the quality and health of the crops, due to disease posing significant threats to economic stability, food security as well as farmer livelihoods. Crop disease can lead to severe loses, it also impacts the availability and prices of essential food products, which leads to disturbing the economies worldwide. So, the early detection of leaf is very important for the developing countries where agriculture forms the backbone of the economy and supports the livelihood of a large portion of population.

When we talking about the global economic impact of crop diseases, it has devastating effects on agricultural productivity. According to the Food and Agricultural Organization (FAO), plant diseases cause global crop loses worth approximately 220$ billion annually. These losses result into higher food prices and which increases food insecurity, especially regions which heavily dependent on agriculture. For example, the outbreak of wheat rust disease can destroy up to 100% of affected crops, leading to substantial losses for farmers.

The effect of crop disease extends beyond the agricultural sector to the economic instability. Reduced agricultural output can lead to increased import of food which negatively impacting trade balances. In countries Where agriculture constitutes a significant portion of GDP, the economic stability is compromised, which result in reduced national income and heightened poverty levels in developing countries.

India, with its vast agricultural landscape, and one of the most fertile lands on the globe is particularly vulnerable to the adverse effects of crop diseases. As it is a big player in agricultural sector it is crucial to take future steps to safeguard our crops production. Traditional methods of disease detection involve manual inspection which is lot time consuming as well labour intensive, also prone to human error.

After advancement in technology particularly in AI and ML there has been a paradigm shift in how plant diseases are detected and managed. Among these all-technological advancements, deep learning has shown immense potential in automating and enhancing the accuracy of disease detection. Here for image-based classification there is neural network in deep learning called CNN convolutional neural network has been extensively used including plant disease detection. These models extract features and identify patterns within it, make them ideal for detecting disease from raw leaf images. However, training CNNs on raw leaf images may not always works if you have very limited data due to complexity and variability of natural environments.

To address the limitations of traditional CNNs, segmentation models are used in between before training the leaf images but there are several ways to segment the diseased part of the leaf and then that segmented dataset to be feed to CNN for training but there are methods for it which is mostly manual and some which is not manual are not able to segment precisely thus segmentation models like SAM (segment anything model) [13] have been used. The SAM model is particularly effective in segmenting leaf images, isolating the diseased part from the healthy ones. This will be beneficial for CNN as an input data it's easy to catch the pattern. This way by focusing on diseased parts of a leaf, segmentation models can provide more reliable and accurate data for training CNNs.

The primary objective of this research is to evaluate the effectiveness of using SAM model for leaf segmentation in improving accuracy of disease detection with CNNs. By comparing the performance of

CNNs trained on segmented images with those trained on raw images, we aim to demonstrate the potential benefits of incorporating segmentation into the preprocessing stage.

This research holds significant implications for the agricultural sector, particularly in countries like India, where it is crucial to detect disease early and accurately which can lead to substantial economic benefits. By reducing crop losses and improving yield quality farmers will benefits financially and also contribute the overall growth of the country.

In this study, we employ a comprehensive methodological approach to evaluate the impact of segmentation models on CNN-based disease detection. The process begins with the collection of a dataset comprising leaf images as in here we have used readymade dataset which is present on the Kaggle that is NEW PLANT DISEASE DATASET which comprised of around 87K RGB images but just getting this is not enough we have to find the dataset of particular plant whose disease is difficult to classify for instance the background colour of the leaf resembles the diseased spots. Now these images undergo preprocessing using the SAM model[13], which segments the leaves into distinct regions now after that we have used Supervision library of Python which annotates random colour to the segmented parts of leaves. This segmentation step is crucial as it isolates the regions of interest, making it easier for the CNN to focus on relevant features.

Now these transformed data are then used to train CNN model. The architecture of the CNN carefully fine-tuned to ensure optimal performance and also try to design in such a way that the number of parameters will be less so as to reduce the complexity of CNN architecture and also for processing time. The model is trained using a supervised learning approach, with annotated images providing the necessary labels for classification. Various data augmentation techniques used here such as rotation, scaling and flipping, are applied to increase the robustness of the model and prevent overfitting.

To assess the effectiveness of the segmentation-enhanced CNN, we conduct a series of experiments comparing its performance with a Normal CNN which is trained on raw images. Also, performance metrics such as Training Accuracy as well testing accuracy is used to evaluate models.

LITERATURE SURVEY

The research paper titled "Detection and Classification of Leaf Disease Using Artificial Neural Network" [1] explores the application of artificial neural networks (ANN) in identifying cotton leaf diseases. With an achieved accuracy of 80%, the study presents a promising approach for early and accurate detection of diseases, crucial for agricultural productivity.

The research paper presents an innovative approach combining Artificial Neural Networks (ANN) with the Chan- Vese (CV) algorithm for plant disease detection and classification. [2] Through extensive experimentation, the proposed system achieves remarkable accuracy rates, reaching up to 98.22% accuracy in disease classification. This performance surpasses traditional methods such as RFDCNN, RCNN, SVM, CNN, and DT models, which typically achieve lower accuracy percentages. The study contributes to advancing precision agriculture by leveraging machine learning techniques to accurately diagnose plant diseases, thereby enabling timely interventions and reducing potential crop losses.

The research paper "Plant Disease Detection Using CNN" by Nishant Shelar et al. [3] surveys various approaches in plant disease detection, highlighting the use of convolutional neural networks (CNNs). It discusses multiple studies employing CNNs to classify diseased leaves accurately. Among these, Sladojevic et al. achieved precision ranging from 91% to 98% for plant disease identification, while Garima Shrestha et al. reached an accuracy of 88.80% for classifying 12 plant diseases. Additionally, the document presents methods utilizing advanced architectures like VGG- 19, demonstrating a 95.6% accuracy rate in detecting plant diseases.

The literature surrounding leaf disease classification using artificial neural networks highlights the significance of employing technology to address agricultural challenges. This research, conducted by Syafiqah Ishak et al.,[4] focuses on classifying healthy and unhealthy leaves of Phyllanthus Elegans Wall (Asin-Asin Gajah) using image processing and neural networks. They achieved promising accuracy rates, with the multi-layer perceptron (MLP) achieving up to 99.15% accuracy and the radial basis function (RBF) reaching up to 99.2% accuracy, demonstrating the effectiveness of the approach in accurately identifying leaf health status.

The research paper "Leaky Rectilinear Residual Network (LRRN) for Plant Disease Detection" proposes a novel approach using Leaky Rectilinear Residual Network (LRRN) to detect plant leaf diseases.[5] Through evaluation on the Plant Village dataset, the proposed model achieved an impressive accuracy of 94.56%, surpassing existing techniques such as HRF-MCSVM, MF3 R-CNN, OMN- CNN, and CNN-VGG19. This high accuracy underscores the efficacy of the LRRN model in accurately predicting plant leaf diseases, highlighting its potential for practical implementation in precision agriculture and crop management.

The research paper shows a comprehensive exploration of methodologies for plant disease detection. Notably, Khirade et al. (2015) utilized digital image processing coupled with neural networks, achieving promising results [6]. Madiwalar and Wyawahare (2017) explored color and texture features, achieving an accuracy of 83.34%. Moghadam et al. (2017) demonstrated hyperspectral imaging, albeit with higher costs, achieving accuracies up to 93%. Shrestha et al. (2020) employed Convolutional Neural Networks (CNNs), achieving 88.80% accuracy. However, the proposed system in this research surpasses these methodologies, achieving an impressive average accuracy of 93%, thus offering a cost- effective and efficient solution.

The research paper titled "Plant leaf disease using CNN and transfer learning"[7] explores the application of deep learning techniques for the early detection and identification of plant diseases. Through the utilization of convolutional neural networks (CNNs) and transfer learning, the authors achieved remarkable accuracy rates, with the EfficientNetB0 model reaching an impressive accuracy rate of 99.56%. Their study not only demonstrates the effectiveness of deep learning in plant disease detection but also highlights the potential for real-world applications in agriculture, paving the way for more efficient and accurate disease diagnosis systems.

The research paper presents a comprehensive approach to plant disease identification using deep learning models [8]. By integrating methods like the RPN algorithm, CV algorithm, and TL algorithm, the proposed model achieves significant advancements in accuracy, surpassing traditional methods. With an average correct rate of 83.75%, notably better than the 42.5% achieved by the ResNet-101 model, the proposed model demonstrates its efficacy in accurately identifying various plant diseases. This improved accuracy holds promise for enhancing agricultural productivity by enabling rapid and precise disease diagnosis, contributing to sustainable agricultural practices.

The research paper proposes a ResNet-based approach for the detection and classification of plant leaf diseases [9], achieving remarkable accuracy. Trained on a dataset containing 15200 images, the ResNet34 model demonstrates an impressive accuracy of 99.40% on a test set, underscoring its efficacy in automated disease detection. This accuracy outperforms several traditional and deep learning models previously employed for similar tasks, highlighting the superiority of the proposed approach in precision agriculture and crop disease management.

The research paper focuses on using artificial neural networks (ANNs) to classify rice leaf diseases [10], particularly brown spot and leaf smut, based on leaf images.

It explores various ANN architectures and features extracted from the images to achieve accurate classification. The study reports an accuracy of 66.3% during the training phase and 76.7% during the testing phase for the selected ANN architecture. Previous studies have employed different techniques like SVM and ANN back propagation, achieving high accuracy rates, but this research emphasizes the use of minimal features for classification, highlighting the potential for improvement by increasing the number of input features and hidden layers.

The research paper presents a novel approach to leaf segmentation utilizing a fusion of YOLOv8 and DeepLabv3+ [11]. Through comparative analysis, the proposed model, DeepLabv3+ (DenseASPP + SP), achieves remarkable segmentation accuracy, surpassing traditional models such as FCN, LR-ASPP, PSPnet, U-Net, and DeepLabv3. Leveraging DenseASPP and SP networks alongside YOLOv8 processing, the model attains an increase of 1.8 percentage points in mIoU compared to non-YOLOv8 based approaches. Additionally, on the test set, the model demonstrates robust generalizability, outperforming other segmentation models with an mIoU of 88.1% and mPA of 93.0%.

The research paper explores various techniques for detecting leaf diseases using artificial intelligence methods. It presents a comprehensive literature review encompassing diverse approaches such as image processing, machine learning, and deep learning. The surveyed studies demonstrate remarkable accuracy rates in disease detection and classification, ranging from state-of-the-art convolutional neural networks to evolutionary and machine learning methods [12]. Achieved accuracies often exceed 90%, showcasing the effectiveness of these techniques in automated plant health monitoring and diagnosis.

PROPOSED SYSTEM

Before you begin to format your paper, first write and save the content as a separate text file. Complete all content and organizational editing before formatting. Please note sections A-D below for more information on proofreading, spelling and grammar.

Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

A. Data set Information

For this study, we had chosen the images of leaf of various crops from the dataset called “NEW PLANT DISEASE DATASET” which comprised of around 87K RGB images from which certain images of different variety of crops have been collected such a way that the disease spot of the leaf resembles to the background colour of the leaf this we have collected around 420 images for each healthy and unhealthy leaves which includes blight, mildew, rust and leaf spots. There is important to consider that the images must be of better quality such that the spots can b seen through naked eye.

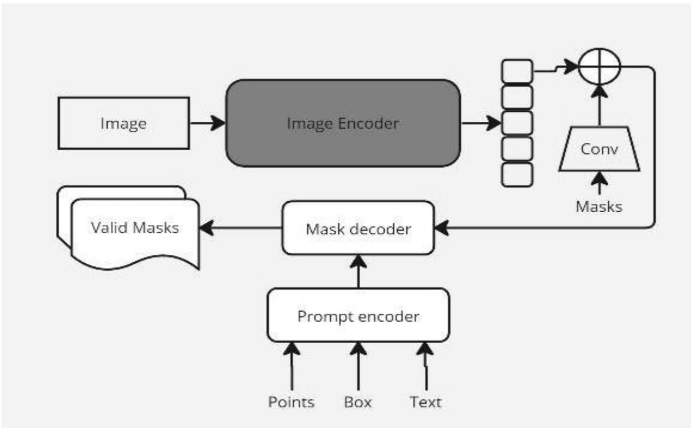
Healthy leaf *Unhealthy leaf*

B. Image pre-processing

Effective image preprocessing is crucial for enhancing the performance of machine learning models, particularly in the context of leaf disease detection. The preprocessing steps are as follows:

1. Resizing: All images were resized to a uniform dimension it can be anything like 256x256 pixels to ensure consistency and reduce computational complexity.
2. Normalization: The pixel values of the images were normalized to a range of 0 to 1 to standardize the input data to improve the training efficiency of the neural network.
3. Image Enhancement: Noise cancellation is a technique used in the process of image enhancement. The process of adjusting pixel values that do not accurately reflect the accurate intensities of the actual scene is known as noise
4. Segmentation Head: The segmentation head is the final component that generates the segmentation masks. It combines the features extracted by the convolutional layers and refined by the attention mechanisms to produce precise and accurate masks.

The integration of these components allows the SAM model to perform high-quality segmentation, making it an ideal choice for our leaf disease detection system.



SAM MODEL ARCHITECTURE

The Segment Anything Model (SAM) incorporates several key mathematical formulations to achieve its segmentation capabilities.

A convolutional layer applies a convolution operation to the input data to extract features. The operation can be mathematically expressed as:

$(I * K)\,(x, y) = \Sigma^{m-1}\Sigma^{n-1} I(x + i, y + j) \cdot K(i, j)$

cancellation.

C. Image Segmentation and data preparation

These raw images cannot be feed to the CNN model after

Where: i=0

j=0

all this preprocessing done on images now it goes for image segmentation, pretrained model called SAM model [13] has been used here.

The Segment Anything Model (SAM) is an advanced image segmentation model designed to segment each part of image allowing for precise analysis of specific regions. What it does is each segment all the parts of leaves and store it in dictionary form which includes 'segmentation', 'area', 'bbox', 'predicted_iou', 'point_coords', 'stability_score', 'crop_box'. Now there is python library called supervision which is used to annotate color to each segmented part and all the colours assign to it are unique and random. After segmenting each image, it is ready for CNN model to train on it.

The architecture of the SAM model is built on a combination of convolutional layers and attention mechanisms, allowing it to capture both local and global features within an image. Key components of the SAM model include:

1. Convolutional Layers: These layers are responsible for extracting low-level features such as edges, textures, and colors from the input image. Multiple convolutional layers are stacked to capture increasingly complex patterns.
2. Attention Mechanisms: Attention mechanisms help the model focus on relevant parts of the image, effectively weighting the importance of different regions. This is crucial for segmentation tasks where the model needs to accurately delineate boundaries between different segments.

- I is the input image or feature map.
- K is the kernel or filter.
- (x, y) are the coordinates of the output feature map.
- m and n are the dimensions of the kernel.

This equation describes how the kernel slides over the input image, performing element-wise multiplication and summing the results to produce the output feature map.

The attention mechanism in SAM helps the model focus on relevant parts of the image. The attention score for each pixel is computed using:

Attention (Q, K, V) = SoftMax $(\frac{Qk^T}{\sqrt{dk}})\, V$

Where:

Q (Query) and K (key) are transformed representations of the input.

V (value) is another transformed representation of input

d_k is the dimension of the key vectors, used for scaling.

This equation shows that the attention scores are computed by taking the dot product of the query and key vectors, scaling by the square root of the dimension, and applying a SoftMax function to obtain the weights. These weights are then used to compute a weighted sum of the value vectors.

The final segmentation mask is predicted by combining the features extracted by the convolutional layers and refined by the attention mechanism. This involves applying a series of transformations and activations to generate the mask. A common approach uses a sigmoid activation function to produce the final mask:

Where:

σ is the sigmoid functionsuch as SoftMax to produce class probabilities or results.

The CNN model involves several mathematical operations to process the input segmented leaf images and make predictions. Here are the following equations involved:

1. Convolutional Operations: The convolution operation is applied to the input segmented leaf

w_k are the weights associated with the featuresimage I using a set of learnable filters W.

Mathematically, it can be represented as: $O\,(i, j)$ =

b is the bias term

(x, y) are the coordinates in the output mask

This equation describes how the model aggregates the weighted features and applies a sigmoid function to produce a binary mask indicating the presence or absence of the target object.

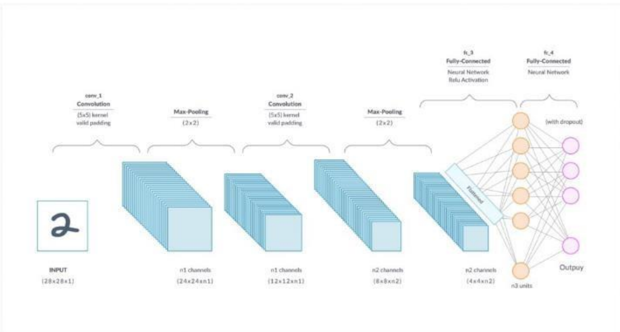
D. CNN(Convolutional neural network) model

$\Sigma_m \Sigma_n I(i+m, j+n) \times W(m, n)$ where $O(i, j)$ is the output feature map, (i, j) are the spatial coordinates, and (m, n) are the filter dimensions.

2. **ReLU Activation:** The ReLU activation function introduces non-linearity to the model by replacing negative values with zero: $f(x) = \max(0, x)$
3. **Max Pooling Operation:** Max pooling down samples the feature maps by selecting the maximum value within each pooling window: MaxPooling$(x, y) = \max(M(x, y), M(x+1, y), M(x, y+1), M(x+1, y+1))$
   where M represents the input feature map and (x,y) are the spatial coordinates of the pooling window.
4. **Softmax Activation:** The softmax activation function is applied to the output of the fully connected layers $e^{fj(X)}$

to produce class probabilities: $P(y = j|\text{X}) = \_\_\_\_\_\_$

$\sum k \ e^{fk(X)}$



CNN ARCHITECTURE

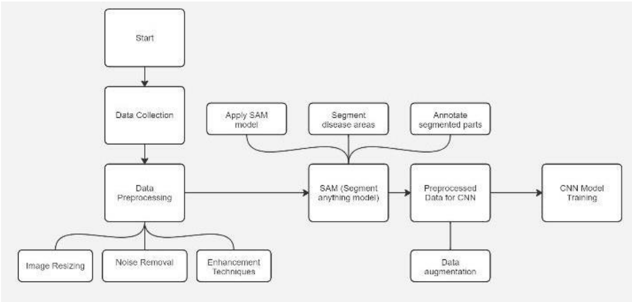
Here CNN leverages the segmented leaf images obtained from SAM (SEGMENT Anything Model) for more accurate and efficient disease classification.

Architecture overview:

The CNN model consists of multiple layers designed to extract features from the segmented leaf images and classify them into diseased or non-diseased leaf. This architecture includes the following:

1. Convolutional layers: These layers perform convolutions on the input segmented images to extract hierarchical features. Each convolutional layer has a non-linear activation function such as ReLU (Rectified Linear Unit) to introduce non- linearity.
2. Pooling layers: Pooling layers reduce the spatial dimensions of the feature maps obtained from the convolutional layers while maintaining the most important information. Max pooling is used to down sample the feature maps.
3. Flattening Layer: This layer flattens the output from the last pooling layer into a one-dimensional vector, preparing it for input into the fully connected layers.

4. Fully Connected Layers: Fully connected layers process the flattened feature vector to make predictions. These layers use activation functions
where $P(y = j|X)$ is the probability of class j given input X, and $f_j(X)$ is the score for class j computed by the model.



An excellent style manual for science writers is [7].

Above image is of whole architecture of how image process and feed to CNN.
As in the diagram first data collection is done then data will be preprocessed which include image resizing, noise removal and other enhancement techniques so that image provided to the model will be clear so as high quality so that it Is easy to extract features as well patterns from the image. Now this image will go through SAM model in which it segments image's part and store it in the dictionary form and after using this dictionary we will assign random color to each segmented part of the leaf using Supervision library of Python. Now after this image go for training it will be feed to CNN.

RESULTS AND DISCUSSION

A. DATASET

In this study, A small set of datasets was used focusing specifically to plants like strawberry leaf in which disease
resembles the background color of the leaf for categorizing into healthy and unhealthy leaves. The dataset covers a diverse array of leaf samples, capturing various disease manifestation which can have variation in colors, texture etc.
Through careful selection, we collected a subset of dataset comprising approximately total 420 images for 2 class and also ensures balanced and robust dataset for training and evaluation purposes.
The dataset compilation process involved careful picking the high-quality images that accurately depict the spectrum of health conditions observed in the leaves on strawberry Using this we aimed to develop and validate our methodology for leaf disease detection with confidence and reliability.

B. Performance Metrics

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.
Accuracy Analysis on training dataset:
The table presents a comprehensive overview of the training dataset accuracy across various classification models, including RCNN, Decision Trees (DT), Support Vector Machines (SVM), conventional Convolutional Neural Networks (CNN), and SAM-CNN, the CNN model augmented with the Segment Anything Model (SAM).
Each row in the table corresponds to a different number of images per class ranging from 100 to 300, enabling a good examination of how model accuracy increases with increasing the size of the dataset

during the training phase.

The RCNN model demonstrates consistent accuracy across the different dataset sizes, showcasing an improvement as the size of the data increases, while Decision Tress (DT) and Support Vector Machines (SVM) exhibit relatively stable accuracy rates, displaying even with smaller dataset sizes.

Conventional Convolutional Neural Network (CNN) display excellent performance, with accuracy rates fluctuating moderately across different dataset sizes. Interestingly SAM-CNN, leveraging the segmentation capabilities of SAM, gives remarkable accuracy enhancements, particularly evident with larger dataset sizes, better than other models and surpass by a substantial margin especially with just 420 images.

No. of Images form each class	***RCNN***	***DT***	***SVM***	***CNN***	***SAM- CNN***
100	80.1	82	82.37	83	91.12
150	79	84.25	85	81.23	92.89
200	81.6	83.21	84.88	83.90	91.99
300	83.1	84.90	88.9	85.4	93.56

Accuracy Analysis on test data:

The table presents a comparative analysis of test data accuracy across various classification models, namely RCNN, Decision Tress (DT), Support Vector Machines (SVM), Conventional Convolutional Neural Networks (CNN), and a CNN model augmented with the Segment Anything Model (SAM) – denoted as SAM-CNN.

The accuracy percentages correspond to different numbers of images per class, ranging from 100 to 300. Each model's performance fluctuates across different dataset sizes, which shows their respective strengths and weakness in handling different volumes of data.

For instance, the RCNN model exhibits consistent accuracy levels across the different dataset sizes, with a increase observed as the dataset size grows. On the other hand, decision tress (DT) demonstrates relatively stable accuracy rates, which shows its robust performance even with smaller datasets.

Support Vector Machines (SVM) display a similar trend, maintaining steady accuracy levels across different dataset sizes. While conventional Convolutional Neural Networks (CNN) shows competitive performance, with accuracy rates slightly fluctuate as dataset sizes vary.

The most outstanding performance is observed in the SAM-CNN model particularly clear with larger dataset sizes. Leveraging the capabilities of the Segment Anything Model (SAM) , significantly boosts accuracy levels, which is better than other models and surpass them with substantial margin, especially with just 420 images for the classes.

No. of Images form each class	***RCNN***	***DT***	***SVM***	***CNN***	***SAM- CNN***
100	78.1	82.33	80.24	83	89.23
150	79	83.89	82.13	84.97	90.10
200	78.6	81.11	80.59	85	87.65

300	77.1	84.23	79.23	81.11	94.44

Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced. Styles named “Heading 1”, “Heading 2”, “Heading 3”, and “Heading 4” are prescribed.

Conclusion

In this paper we provided an introduction to Deep learning and a survey of recent research into its application to the identification of diseases in plant leaves. The development of CNN which integrates with Segment anything model (SAM) for leaf disease detection Represents a significant advancement in technology. Through this research we have explored how combining the deep learning techniques with precise segmentation can be helpful to address critical challenges in crop management and agricultural sustainability.

The integration of Segment anything model (SAM) generated segmented leaf images with the CNN model has given a promising result, significantly enhancing the accuracy and efficiency of disease detection. By leveraging the SAM’s capability to segment diseased regions on the leaves, the CNN model can focus on that highlighted part and can extract features and pattern speedily with less data.

The CNN model's architecture, includes convolutional layers, pooling layers, and fully connected layers, has demonstrated its effectiveness in extracting hierarchical features from segmented leaf images and making accurate disease classification predictions. The mathematical operations involved in the CNN model, including convolution, ReLU activation, max pooling, and SoftMax activation, have been useful in achieving robust classification performance. the proposed system's impact on the global and regional economies, particularly in the context of agriculture will be great. Early and accurate detection of leaf diseases facilitated by the CNN-SAM integration can lead to larger improvements in crop yield, quality and overall productivity of agriculture. By enabling farmers to detect and mitigate disease outbreaks promptly, this system has potential to minimize crop losses and enhance resource efficiency in agricultural practices.

Furthermore, the research conducted in this research underscores the importance of interdisciplinary collaboration between computer science and agricultural engineering.

Looking ahead, future research may focus on refining the CNN-SAM model further, exploring additional image augmentation techniques, and expanding the dataset to encompass a broader range of leaf diseases and plant species. Additionally, efforts to deploy the developed system in real- world agricultural settings, which has user feedback and iterative improvements, will be crucial in ensuring its practical utility and scalability.

In conclusion, the CNN-SAM integrated model represents a paradigm shift in leaf disease detection, offering a potential tool for sustainable agriculture, crop protection, and food security. With continued research and development efforts, this technology holds the promise of transforming the agricultural landscape, empowering farmers, and safeguarding global food supplies for generations to come.

References

1. Ranjan, M., Weginwar, M. R., Joshi, N., & Ingole, A.B. (2015). Detection and Classification of Leaf Disease Using Artificial Neural Network. International Journal of Technical Research and

Applications, 3(3), 331-333.
2. A. Mayuri, V. Rashmi, B. Das, A. Mandal and S. Neelakandan, "Artificial Neural Network (ANN) With Chan-Vese(CV) Algorithm- Based Plant Disease Detection And Classification," 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC), Dharwad, India, 2023, pp. 1-6, doi: 10.1109/ICAISC58445.2023.10199472. keywords:
3. {Training;Productivity;Plant diseases;Image segmentation;Machine learning algorithms;Loading;Crops;plant disease diagnosis;machine learning (ML);artificial neural network(ANN);cv algorithm}
4. IShelar, N., Shinde, S., Sawant, S., Dhumal, S., & Fakir, K. (2022). Plant disease detection using CNN. ITM Web of Conferences, 44, 03049. https://doi.org/10.1051/itmconf/20224403049.
5. Ishak, S., Rahiman, M. H. F., Kanafiah, S. N. a. M., & Saad, H. (2015). LEAF DISEASE CLASSIFICATION USING ARTIFICIAL
6. NEURAL NETWORK. Jurnal Teknologi/Jurnal Teknologi, 77(17). https://doi.org/10.11113/jt.v77.6463
7. Padshetty, S., & Ambika, N. (2023). Leaky ReLU-ResNet for Plant Leaf Disease Detection: A Deep Learning Approach. MDPI. https://doi.org/10.3390
8. Kulkarni, P., Karwande, A., Kolhe, T., Kamble, S., Joshi, A., & Wyawahare, M. (2021). Plant disease detection using image processing and machine learning. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2106.10698
9. Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E. (2021). Identification of Plant-Leaf diseases using CNN and Transfer- Learning approach. Electronics, 10(12), 1388.https://doi.org/10.3390/electronics10121388
10. Guo, Y., Zhang, J., Yin, C., Hu, X., Zou, Y., Xue, Z., & Wang, W. (2020). Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming. Discrete Dynamics in Nature and Society, 2020, 2479172. doi:10.1155/2020/2479172
11. V. Kumar, H. Arora, Harsh and J. Sisodia, "ResNet-based approach for Detection and Classification of Plant Leaf Diseases," 2020
12. International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 495- 502, doi: 10.1109/ICESC48915.2020.9155585. keywords:
13. {Diseases;Agriculture;Feature extraction;Machine learning;Neurons;Computer vision;Task analysis;Leaf disease detection & classification;Convolutional Neural Network (CNN);Deep Learning (DL);Computer Vision;Residual Network (ResNet)},
14. Gunawan, P. A., Kencana, E. N., & Sari, K. (2021). Classification of rice leaf diseases using artificial neural network. Journal of Physics. Conference Series, 1722(1), 012013. https://doi.org/10.1088/1742- 6596/1722/1/012013
15. Yang, T., Zhou, S., Xu, A., Ye, J., & Yin, J. (2023). An approach for plant leaf image segmentation based on YOLOV8 and the improved DEEPLABV3+. Plants, 12(19), 3438. https://doi.org/10.3390/plants12193438
16. Demilie, W. B. (2024). Plant disease detection and classification techniques: a comparative study of the performances. Journal of Big Data, 11(1). https://doi.org/10.1186/s40537-023-00863-9
17. Osco, L. P., Wu, Q., De Lemos, E. L., Gonçalves, W. N., Ramos, A. P. M., Li, J., & Marcato, J. (2023). The Segment Anything Model (SAM) for remote sensing applications: From zero to one

shot. International Journal of Applied Earth Observation and Geoinformation, 124, 103540. https://doi.org/10.1016/j.jag.2023.103540