International Journal of Information Movement *Vol. 9 Issue I* *(May 2024)*
Website: www.ijim.in *ISSN: 2456-0553 (online)* **Pages 9-15**

PERFORMANCE COMPARISON OF IMAGE SEGMENTATION MODELS in SAM

Er. Anju Saini
M.Tech Scholar
G.R.I.M.T, Radaur
Email Id: reply2ankush@gmail.com

Er. Khushboo Kamboj
Assistant Professor
Department of Computer Science and Engineering, G.R.I.M.T, Radaur
and
Er.Ankush Aggarwal
M.Tech (I.T.)
Engineer I.S.G.E.C Group

Abstract: Food security for the 7 billion individuals on earth requires limiting yield harm by timely identification of crop diseases & illnesses. Most deep learning models for automated recognition of illnesses in plants experience the ill effects of the tragic defect that once tried on independent data, their output drops significantly [1]. Because of this, datasets accessible internet based like plant town comprise of 50000 pictures. These web-based pictures when segmented through different covering strategies, the number of lesions identified from two picture segmentation models showed a huge parameter distinction rate in their outcomes. This examination paper shows that disease forecast results rely upon the nature of the picture. Huge Model performed better compared to the Base Model.

Keywords: Image Segmentation, Disease Prediction, Lesion, Performance parameters

1.0 Introduction

Increasing population is putting an ever-increasing pressure on world agriculture with the population increasing by 1.7 billion in the last 23 years and predicts to increase by 2 billion in the next 28 years. One of the biggest challenges facing the world's population is food security. About 53% of Indians are engaged in agriculture. By leveraging machine learning and deep learning techniques, agriculture stakeholders can enhance disease detection accuracy, optimize resource allocation, and ultimately improve crop yields and profitability while reducing the environmental impact of disease control measures. Automatic disease detection using visible symptoms on leaves is becoming more and more important. The algorithms can train itself, which means that the accuracy can increase with usage.

2.0 Crop Disease Prediction

Machine learning methods have been used in recent years for crop disease prediction and these efforts have been proved worthwhile. They revealed higher accuracy compared to the traditional statistical methods like regression analysis. These methods deal well with noisy and multi-faceted data. There are several factors like soil quality, crop rotation cycle, seed quality etc. which can lead to poor health and diseases in crops. Machine learning algorithms effectively take into consideration all the possible factors, historic data as well as satellite/sensor data of fields to provide valuable disease classifiers. Disease detection using images of crop leaves has been implemented using pattern recognition branch of machine learning. It works by obtaining patterns from input data and separating them into classes of diseases.

2.1 Stages in Image Processing in Disease Detection

a) Image Recognition: Cameras installed in fields can capture images of crops. Machine learning algorithms can then analyze these images to detect visual symptoms of diseases such as discoloration, lesions, or unusual growth patterns.

b) Data Analysis and Predictive Modeling: By applying data analytics and predictive modeling techniques, patterns indicative of disease outbreaks can be identified. This can enable farmers to take preventive measures before diseases spread extensively.
c) Precision Agriculture: IoT technologies enable precision agriculture practices, allowing targeted approach helps in managing diseases effectively while minimizing environmental impact and input costs.

3.0 **Impact On Yield Information**
Most foliar diseases accelerate senescence of the top three leaves and so reduce yield. Fungicide sprays during canopy growth prevent green leaf area loss during grain filling.

a) **Construction Phase, Infection and Development**

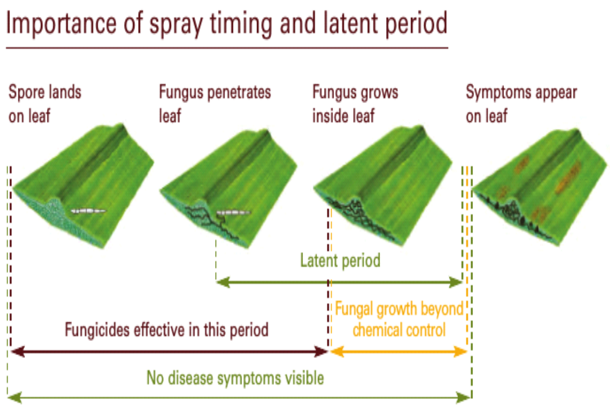


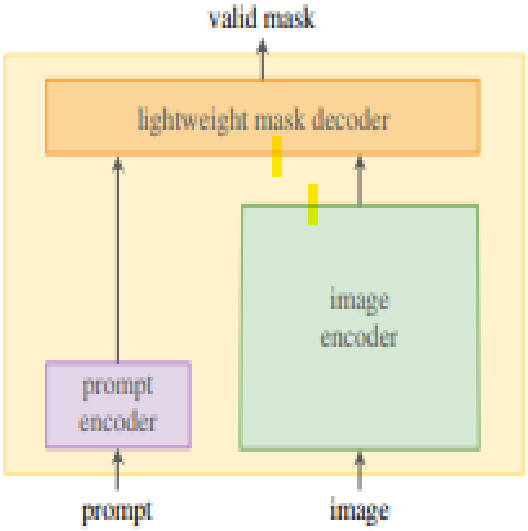
Fig 1. Infection and Development.

b) **Initial infection:** Infection usually results from spores moving into the crop. When this occurs depends on the disease.

c) **Disease Development:** Infection is followed by a 'latent period' when the fungus grows within the leaf, but the leaf exhibits no symptoms. The cycle of leaf emergence, infection, latent period, and symptom expression applies to all foliar diseases. The latent period varies considerably between pathogens and is affected by temperature. At higher temperatures, latent periods are shorter.

d) **Disease Prediction and Analysis**

4.0 Working of model:
4.1 Segment Anything Model (SAM): SAM provides three models. One is BASE, Large and HUGE from Segmentation Anything Model. These models perform in increasing order at the cost of inference time respectively because our images are of low quality. We anticipated all the models would struggle. So we decided to use the HUGE model even if the model performed slower.
We selected two different prompts for Segment Anything. One way to work on SAM is "Prompt engineering". One way is clicking, another one is Bounding Box and the next is equally spaced points, We have selected the strategy of choosing two prompts of equally spaced points i.e 32*32 and 64*64. It is not possible to implement many files processing manually and that's why we have used this method strategy. Points per region is the to remove the regions outside the leaf, ROI is done, First we used 32*32 and 64*64.



4.2 Image Dataset: One source of images for the dataset is the Plant Village database, prepared by Hughes et al. (Hughes and Salathe 2015), which contains more than 50,000 images of more than 35 diseases of 16 plant types. Another field-based dataset of 7,000 images was collected from fields across North-West India for 4 plant types. Lastly, a total of 10,000 images were collected from Internet for the diseases. Special care was taken to ensure random backgrounds and different stages of infection / damage. Table 1.1 gives an overview of the number of images for different diseases and plant types.

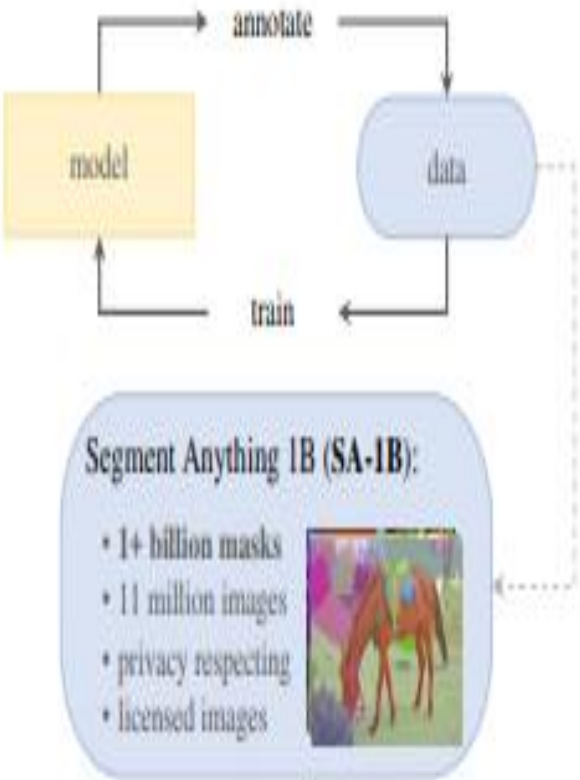


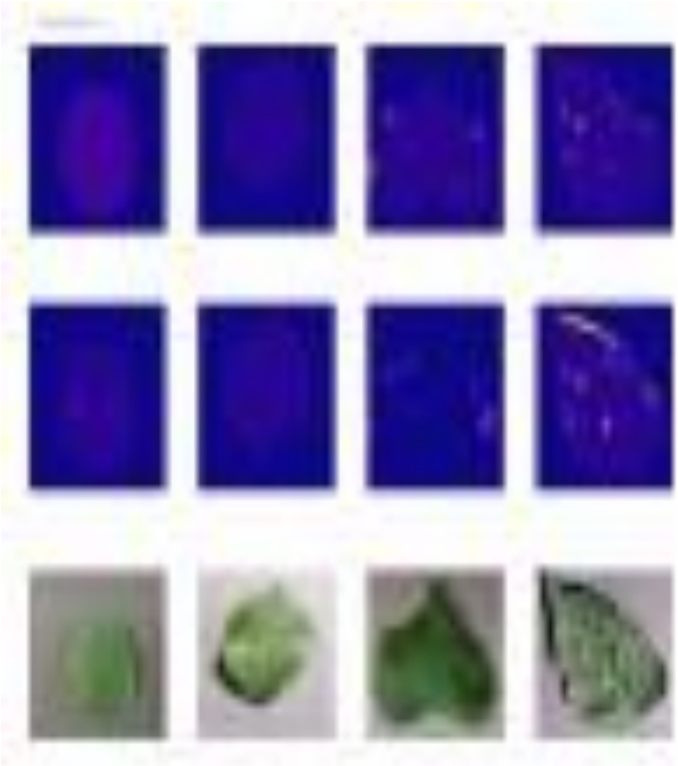
Fig 2. Working of Model

We have used Plant Village consisting of 50000 image and 10000 diseased. Four types of leaf images are used:-

i. Pepper
ii. Tomato
iii. Potato
iv. Apple

Results of the models are on Google Colab.Colab is a hosted Jupyter Notebook service that requires no setup to use and provides free access to computing resources, including GPUs and TPUs. Colab is especially well suited to machine learning, data science, and education.

Tesla T4 GPU is used, and they required 16 GB RAM.GPU is important because of speed and image processing is faster than CPU. Two images' models 32*32 and 64*64. This is shown in Fig



Two Comparison of images model fig 3.

Based on these models, we have made a machine model analysis table based on four parameters

i. True positive: - A true positive is an outcome where the model correctly predicts the positive class

ii. True negative: - A true negative is an outcome where the model correctly predictthe negative class.

iii. False positive: - A false positive is an outcome where the model incorrectly predicts the positive class.

iv. False negative:- A false negative is an outcome where the model incorrectly predicts the negative class.

True Positive (TP):	False Positive (FP):
• Reality: A wolf threatened. • Shepherd said: "Wolf." • Outcome: Shepherd is a hero.	• Reality: No wolf threatened. • Shepherd said: "Wolf." • Outcome: Villagers are angry at shepherd for waking them up.
False Negative (FN):	**True Negative (TN):**
• Reality: A wolf threatened. • Shepherd said: "No wolf." • Outcome: The wolf ate all the sheep.	• Reality: No wolf threatened. • Shepherd said: "No wolf." • Outcome: Everyone is fine.

For example, we have analysis on the images of Bell pepper, this is shown in Table 1.1

		Model 1				Model 2			
FileNr	Real number of spots	True Positives	True Negatives	False Positives	False Negatives	True Positives	True Negatives	False Positives	False Negatives
9241	3	1	1	3	2	1	1	4	2
3132	10	9	1	11	1	10	1	1	0
1964	13	7	1	2	6	10	1	1	3
9177	1	1	1	2	0	1	1	1	0
9076	14	9	1	2	5	3	1	3	11
1799	9	5	1	1	4	8	1	3	1
3162	8	8	1	4	0	2	1	5	6
3272	8	7	1	1	1	8	1	1	0
3369	13	8	1	2	5	8	1	2	5
3244	8	6	1	3	2	0	1	6	8
9123	5	1	1	0	4	3	1	0	2
8192	4	3	1	3	1	1	1	1	3
3176	5	2	1	2	3	4	1	1	1
1827	8	7	1	2	1	2	1	2	6
1825	1	0	1	2	1	1	1	3	0
9060	10	7	1	4	3	3	1	7	7
1874	5	0	1	4	5	2	1	4	3
3234	4	1	1	1	3	1	1	1	3
1862	7	0	1	0	7	0	1	0	7
8970	6	5	1	1	1	6	1	0	0
9145	10	6	1	1	4	8	1	1	2

Based on this ,machine learning performance parameters are

Accuracy:-
Accuracy is a metric that measures how often a machine learning model correctly predicts the outcome. You can calculate accuracy by dividing the number of correct predictions by the total number of predictions.

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{All predictions}}$$

Recall: -
Recall is a metric that measures how often a machine learning model correctly identifies positive instances (true positives) from all the actual positive samples in the dataset. You can calculate recall by dividing the number of true positives by the number of positive instances. The latter includes true positives (successfully identified cases) and false negative results (missed cases).
Precision: -
Precision is a metric that measures how often a machine learning model correctly predicts the positive class. You can calculate precision by dividing the number of correct positive predictions (true positives) by the total number of instances the model predicted as positive (both true and false positives).

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$$

F1-Score :-
The F-score, also called the F1-scoreis a measure of a model's accuracy on a dataset. It is used to evaluate binary classification systems, which classify examples into 'positive' or 'negative'. The F-score is a way of combining the precision and recall of the model, and it is defined as the harmonic mean of the model's precision and recall.

$$\text{F1} = 2 \times (\text{Precision} \times \text{Recall}) / \text{Precision} + \text{Recall}$$

5.0 Result And Discussion
Based on the Analysis, Model 1 parameters (64*64) are performed much better than .32*32. Precision and Accuracy showed improvement of model 1 by 7 percent whereas Recall and F-1 showed a drastic improvement of above 11 percent. The major failure of less accuracy dataset image quality is not good. If the image quality is from high resolution camera, then accuracy would have turned much higher as compared to these results.

6.0. References

i. Gollin, Douglas, (2010). Agricultural Productivity and Economic Growth.

ii. Loayza, Norman V. & Raddatz, Claudio, 2010, "The composition of growth matters for poverty alleviation," Journal of Development Economics, Elsevier, vol. 93(1), pages 137-151, September.

iii. Sucheta Yadav and Subroto Dutta,2019, “A Study of Pesticide Consumption Pattern and Farmer’s Perceptions towards Pesticides: A Case of Tijara Tehsil, Alwar (Rajasthan)”, International Journal of Current Microbiology and Applied Sciences, ISSN: 2319-7706 Volume 8 Number 04 ,pp.96-104.

iv. Hughes, David & Salathe, Marcel. (2015),An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowd sourcing.

v. Hamadttu Abdel Farag El-Shafie (March 15th 2019). Insect Pest Management in Organic Farming System [Online First], IntechOpen, DOI: 10.5772/intechopen.84483..

vi. Gnanavel, 2015. Eco-Friendly Weed Control Options for Sustainable Agriculture. Science International,3:3747.DOI: 10.17311/sciintl.2015.37.4

vii. Kulkarni, Gurudatt & JADHAV, MAHESHCHANDRA & Bhuse, Sadanand & Bankar, Hemant. (2013). COMMUNICATION AS SERVICE CLOUD. International Journal of Computer Networking, Wireless and Mobile Communications (IJCNWMC). Vol. 3. 149-156.

viii. J. D. Owens, M. Houston, D. Luebke, S. Green, J. E. Stone and J. C. Phillips, "GPU Computing," in Proceedings of the IEEE, vol. 96, no. 5, pp. 879-899, May 2008, doi: 10.1109/JPROC.2008.917757.

ix. Ayaz, Muhammad & Uddin, Ammad & Sharif, Zubair & Mansour, Ali & Aggoune, el-Hadi. (2019). Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk. IEEE Access. PP. 1-1. 1109/ACCESS.2019.2932609.