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"TomatoHub": An Analysis of Plant Disease Detection Using Mask-RCNN.

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ABSTRACT:

Tomatoes, being a vital component of global food systems, face numerous challenges ranging from cultivation intricacies to disease susceptibility. Inefficient production methods and lack of awareness contribute to suboptimal yields, hindering food security and economic sustainability. Moreover, undetected diseases can wreak havoc on tomato crops, leading to extensive losses due to delayed intervention. Recognizing the urgency of these challenges, "TomatoHub," an Android application tailored to address these issues comprehensively. With the overarching goal of enhancing tomato cultivation practices, TomatoHub endeavors to educate individuals about optimal production techniques. By offering insights into soil conditions, irrigation strategies, fertilization routines, and climate considerations, the app aims to empower cultivators to make informed decisions and boost yields. Disease detection forms a main aspect of TomatoHub. The application harnesses the potential of deep learning, particularly mask Region-based Convolutional Neural Networks (M-RCNN), to enable timely disease identification through image analysis. This innovation promises to revolutionize disease management by providing users with a tool to recognize and categorize diseases swiftly. Timely intervention could substantially mitigate losses caused by disease outbreaks and reduce the need for extensive pesticide application. Also our research suggest which pesticides should be used for detected diseases. In bridging the gap between cultivation knowledge and disease management, TomatoHub emerges as a holistic solution. By consolidating production insights, advanced disease detection methodologies, and preservation techniques, the application strives to equip users with the essential tools for successful tomato cultivation. By fostering a harmonious balance between sustainable practices and technological innovation, TomatoHub aspires to contribute to enhanced agricultural productivity and reduced food waste.

Keywords: Mask Region-based Convolutional Neural Network (M-RCNN).

1. INTRODUCTION:

The global agricultural landscape stands at a crossroads, where the search for sustainable food production intersects with the rapid advancements in technology. Among the myriad crops that comes under our food systems, tomatoes hold a prominent place due to their nutritional value and culinary versatility. However, the journey from seed to production is fraught with challenges from intricate cultivation practices to the looming threat of diseases. Addressing these challenges is paramount for ensuring food security, economic stability, and sustainable agricultural practices."TomatoHub" emerges as a pioneering solution in this context, a groundbreaking Android application that encapsulates a comprehensive approach to tackle the intricate web of challenges faced in tomato cultivation. By seamlessly integrating essential cultivation insights, cutting-edge deep learning disease detection techniques, and preservation methodologies, TomatoHub envisions a future where tomatoes flourish as a resilient crop, fostering a balanced coexistence between nature and technology.

TomatoHub aims to empower cultivators, be they novices or seasoned experts, with a comprehensive understanding of these critical variables. By offering insights into optimal soil conditions, efficient irrigation strategies, tailored fertilization regimens, and climate considerations, the application equips users with the necessary knowledge to navigate the complexities of successful tomato cultivation.
A looming specter in tomato cultivation is the incursion of diseases that can swiftly devastate crops. TomatoHub brings forth a transformative solution by harnessing the power of deep learning, specifically Mask Region-based Convolutional Neural Networks (M-RCNN), for disease detection. Through image analysis, the application enables users to identify diseases in real time, promising a paradigm shift in disease management. Swift recognition and accurate categorization offer the potential for timely interventions, thereby mitigating losses caused by disease outbreaks and reducing the reliance on excessive pesticide application. The story of tomato cultivation extends beyond the harvest. Post-harvest preservation techniques play a crucial role in minimizing food waste and sustaining produce quality. TomatoHub extends its holistic approach by offering comprehensive guides on preservation methods like canning, drying, and proper storage. By imparting knowledge on these techniques, the application ensures that the fruits of labor endure, contributing to food security and sustainable agricultural practices.

"TomatoHub" represents an embodiment of knowledge, innovation, and resilience in the face of agricultural challenges. As the world seeks harmonious solutions that blend traditional wisdom with technological gallantry, TomatoHub envisions a future where tomato cultivation is fortified by both, ensuring that the tables of tomorrow are graced by nutritious, sustainably cultivated tomatoes.

2. OBJECTIVES:

1) To detect diseases on tomato plants with highest accuracy so that we can mitigate the loss due to tomato disease.
2) To increase tomato crop yield by a certain percentage by optimizing cultivation practices through the application's insights and recommendations.
3) To decrease crop losses caused by diseases by implementing timely interventions enabled by the disease detection capabilities of TomatoHub.
4) To encourage adoption of sustainable agricultural practices among cultivators by providing guidance on efficient resource utilization and reducing reliance on pesticides.
5) To equip both novice and experienced cultivators with the necessary knowledge and tools to improve their tomato cultivation practices and increase economic stability.
6) To showcase the successful integration of deep learning techniques, i.e. M-RCNN, in agriculture for disease detection and management, setting a precedent for future technological applications in farming.

3. METHODOLOGY:

3.1 Machine learning VS Deep Learning:

Deep learning models, have emerged as the preferred approach for object detection over traditional machine learning models. This is primarily due to their ability to automatically learn and extract meaningful features from raw data, such as images, without the need for manual feature engineering. Deep learning models excel in feature learning and representation. Unlike traditional machine learning where manual feature engineering is a critical step, deep learning models learn relevant features directly from the data. Deep learning model has the architecture for object detection, have multiple layers that hierarchically extract features, allowing for a comprehensive understanding of the objects being detected.

Moreover, deep learning models demonstrate adaptability and generalization, being capable of learning from diverse datasets and generalizing well to unseen data. This adaptability is crucial for accurate object detection, especially in real-world scenarios where objects may vary in appearance, size, or orientation. The end-to-end learning approach in deep learning simplifies the development pipeline, enabling the model to directly map raw input data to the desired output (e.g., bounding boxes and object classes). Additionally, the availability of large-scale labeled training data and advancements in computational power, such as GPUs and TPUs, has significantly contributed to the success of deep learning models in achieving state-of-the-art results for object detection tasks. Deep learning models' ability to automatically learn features, adapt to diverse data, and leverage large-scale labeled datasets, coupled with advancements in computational resources, makes them superior for object detection compared to traditional machine learning models. Also various research including [1] states that machine learning model is less accurate when it comes to object detection in comparison with deep learning model. By considering all the scenario our proposed model is based on deep learning algorithms.

3.2 Problem of object detection:

Object detection in deep learning involves identifying and localizing objects within an image. While deep learning models have significantly advanced object detection capabilities, several challenges persist. One major issue is related to scale and resolution. Objects in images can vary in size and may appear differently due to perspective or distance from the camera. Deep learning models need to effectively handle these variations and accurately detect objects of varying scales. Also there are occlusions and clutter pose significant challenges. Objects may be partially obscured or overlap with other objects, making accurate detection complex. Dealing with occlusions and clutter requires the model to have robust features and contextual understanding to accurately identify objects in such scenarios. Another problem lies in handling diverse object categories. Object detection models need to generalize well across a wide range of object types, each with unique features and characteristics. Training the model to recognize and differentiate between a broad array of objects requires substantial data and robust architectures. Furthermore, achieving real-time processing is a crucial concern, especially in applications like autonomous driving or video surveillance. The model needs to be efficient and fast to detect objects in near real-time while maintaining high accuracy. Balancing speed and accuracy remain a constant challenge in the development of object detection models.

There is the issue of annotation and data availability. Training deep learning models for object detection necessitates large amounts of annotated data, which can be time-consuming and expensive to acquire. Additionally, ensuring the accuracy and consistency of annotations is crucial for model performance. Addressing these challenges involves ongoing research and innovation, focusing on refining architectures, data augmentation techniques, training strategies, and developing novel approaches to improve object detection in deep learning models. So, we need to find model that can solve problems.

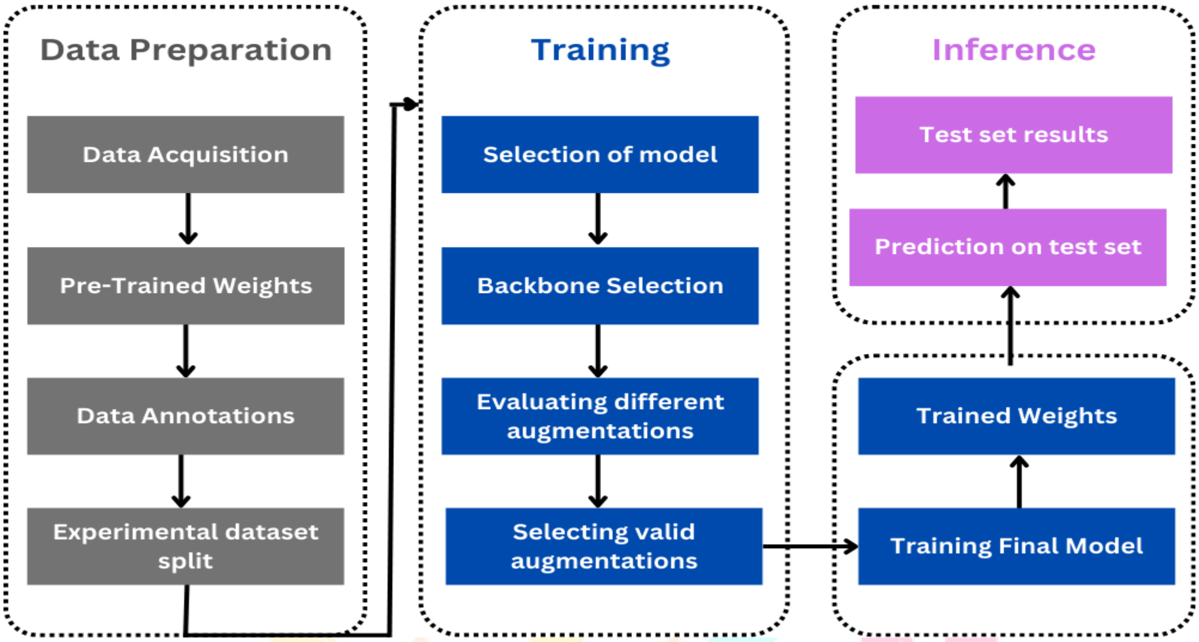

Fig. No. 1 Flowchart for developing a system to detect tomato diseases.

Above flowchart shows the complete step-wise procedure from data preparation to training our disease detection model. Data preparation involves processes like data acquisition, data annotations, splitting of data. After data preparation this prepared data is use for training model. For training our disease detection model which involves feature extraction, backbone selection, segmentations etc. Once model is trained then it is tested by validation dataset.

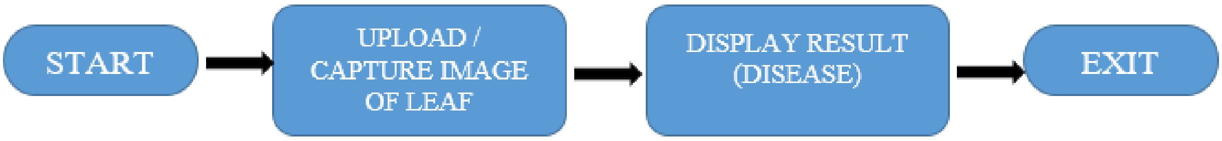

Fig. No. 2 Working of disease detection system

3.3 Data Preparation:

Although various models have been developed to perform object detection for multiple diseases in tomatoes, there is much to be desired when it comes to datasets allowing fine- grained instance segmentation of multiple diseases and pests in tomatoes. In an attempt to fill that void, we used the dataset that allows users to segment ten different kinds of tomatoes diseases. Since our dataset consists of images that are collected in real fields/greenhouses instead of a laboratory, it introduces multiple challenges such as having background variations, complex field conditions, different illumination settings, etc. As a result, these variations allow us to design models that have a higher capacity to be more robust and generalizable.

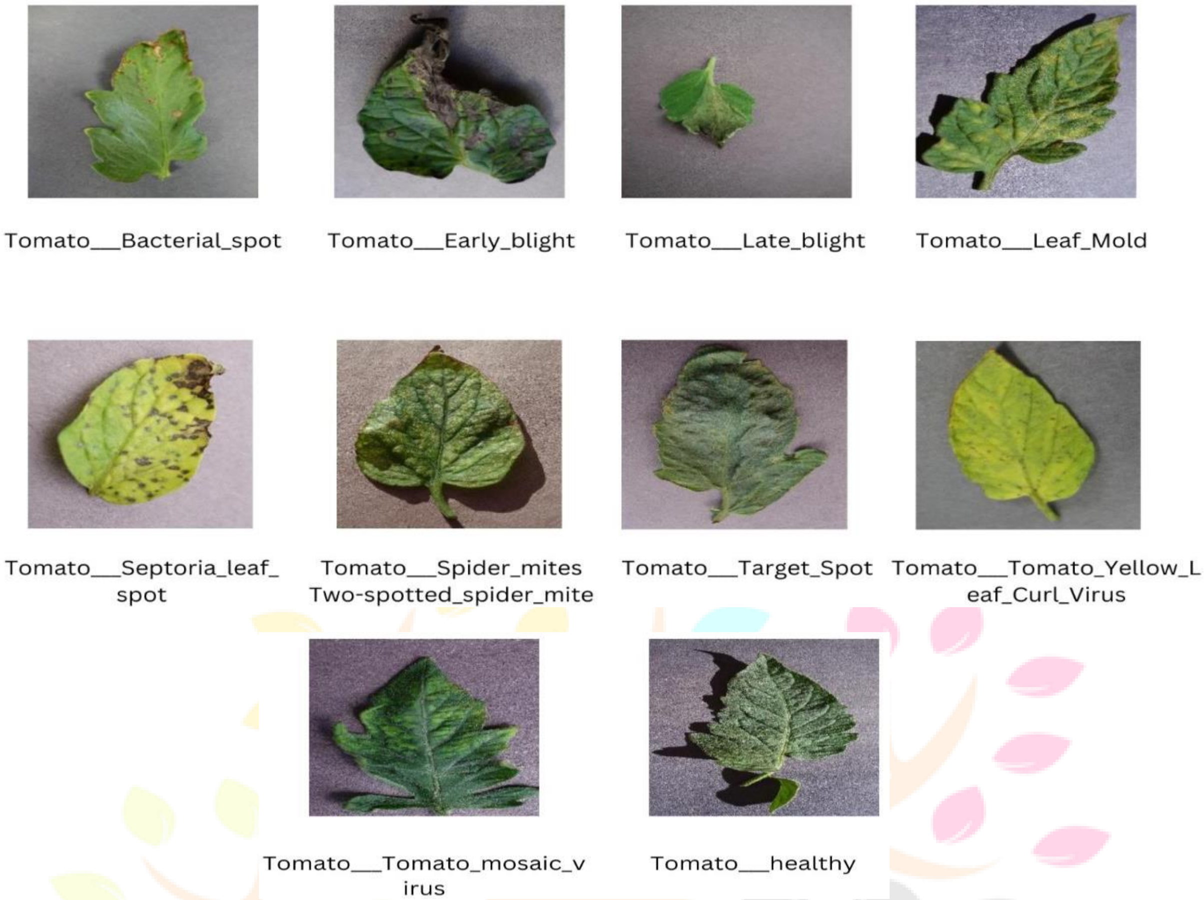

Fig no. 3: Ten classes of tomato leaf diseases

Above figure shows the ten types of diseases that found in tomato. Dataset consists of 1000 images for each class. So, for each class we trained our model with 1000 images so that our model can accurately predict the diseases.

Running a deep learning model with an unprepared dataset may result in unsatisfactory classification performances, whereas a pre-processed and fully prepared dataset will increase the efficiency. In our experiment, several measures have been taken to prepare the dataset for training.

- Data acquisition: The dataset contains 11,000 images for tomato disease. Our dataset is collected form Kaggle website which is licensed data. Dataset consists of ten different types of tomato disease, with images ranging from initial, middle and final stages of the diseases. An example case for all ten tomato diseases is visualized in figure 2.
- Removing Outliers: The whole dataset was checked thoroughly for outlier images as outliers can create variability which directly affects the model performance.
- Resizing Images: For better approach, all of the images were resized to a fixed resolution of 256 X 256 pixels.
- Dataset Normalization: Deep learning-based architectures always work better for normalized data. Pixel values in an image can vary from 0 - 255. So, the pixel values of the images were normalized by min-max normalizer.
- Data Augmentation: Different types of data augmentation methods have been used to expand the training data as the more data can be fed into a model the better the result is. Image manipulation techniques like shearing, zooming, rotating, flipping, etc. have been applied to the training data to diversify the dataset and make the model robust. The main purpose of data augmentation is to assign boundaries to images. For that we have used VGG16 framework. This framework takes an image as

an input and generate augmented image as an output.

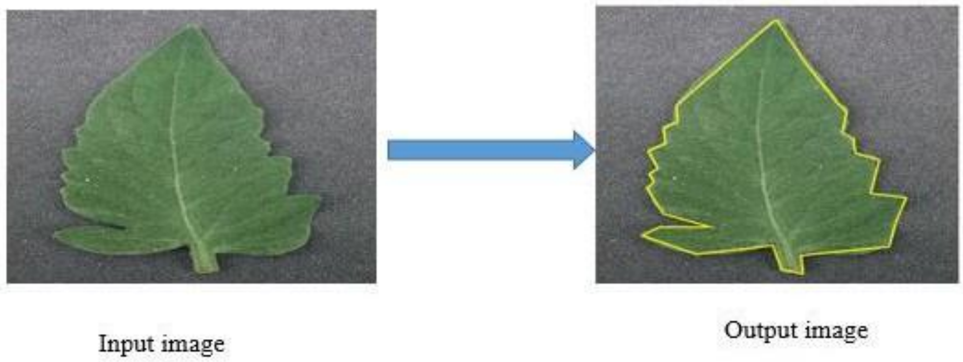

Fig no. 4: Data augmentation by using VGG16 image annotator.

Above image depicts how data augmentation is performed on the image. Our complete data undergo this process. Basically, it is adding segments to the images.

- Experimental dataset split: The dataset which is 11000 images are splits into 10000 images for training and 1000 images for validation and testing.

- Class Label Encoding: Numeric data is always preferable for a deep learning model rather than texts. Hence, each of the class labels mapped to an integer value using one-hot encoding. Labels from 1 to 10 is assign to each class of tomato disease. These are some methods that are involve in data preparation.

Category of data	**No. of images**
Training data	10000
Testing data	1000
Total data	11000

Table no. 1: Distribution of data

3.4 Classification techniques:

Various techniques have been proposed for detecting plant disease. These techniques primarily rely on deep learning methods, such as CNN, faster RCNN, mask RCNN etc. The best technique is Mask-RCNN which is explained below.

Mask RCNN model:

Mask RCNN is an updated version of faster RCNN. It is highly recommended for object detection because of its instance segmentation feature which is explained below.

A) Detection Approaches: Mask R-CNN employs a two-stage detection approach. In the first stage, it uses a Region Proposal Network (RPN) to generate region proposals by suggesting potential object bounding boxes. In the second stage, it refines these proposals and classifies them into specific object categories using a classifier and predicts more precise bounding boxes. Additionally, Mask R-CNN introduces a mask head that predicts pixel-wise object masks for each region proposal, achieving instance segmentation. The mask head consists of convolutional layers and a region-based ROI Align pooling layer, which aligns extracted features with the mask prediction. The model optimizes multiple losses, including classification loss, bounding box regression loss, and mask segmentation loss, improving both detection and segmentation accuracy. This two-stage approach effectively combines object detection with pixel-level segmentation, making Mask R-CNN a versatile framework for tasks like object detection, instance segmentation, and related computer vision applications.

B) Segmentation Approaches: In Mask R-CNN, the segmentation approach involves a specialized segmentation head integrated into the architecture. This head is responsible for generating precise pixel-wise masks for each detected object instance in the image. To achieve this, region-of-interest features obtained from ROIAlign, which aligns features with the proposed regions, are fed into a small Fully Convolutional Network (FCN). The FCN refines these features through a series of convolutional layers, transforming them into high-resolution binary masks corresponding to the shapes of the objects. During training, a pixel-wise binary cross-entropy loss is utilized to optimize the mask predictions. Importantly, this segmentation process operates independently alongside the detection process, enhancing the model's ability to localize objects accurately while providing detailed pixel-level segmentation. By combining object detection with precise instance segmentation, Mask R-CNN stands as a powerful and versatile model for a wide array of tasks requiring precise object delineation and segmentation.

C) Mask RCNN architecture: Mask R-CNN is an update to the previous Faster R-CNN system. It is a simple yet efficient algorithm. It enables instance segmentation for an application. Mask R-CNN brings together Faster R-CNN and FCN for both object detection and instance segmentation. For our final model, we first use a ResNet101 MS-COCO pre-trained backbone for extracting the feature maps from an input image. Treating the extracted features as the bottom-up pyramid, the top-down feature pyramid is generated using lateral connections to obtain multi-scale, high-level semantic feature maps. The extracted feature maps are then used by a Region Proposal Network for generating Regions of Interest (ROIs) on an image. In the RPN, a small network slides on the output feature map of the backbone, and each sliding window is mapped to a lower-dimensional feature vector. This feature vector is the input to two parallel fully-connected layers, one of which is responsible for outputting the locations of the region proposals while the other one judges if there is a target object in the region box or not. For k number of region proposals, these regression and classification layers are realized though a 1×1 convolution filter resulting in 4k and 2k output values for the regression and classification layer, respectively. These k region proposals are parameterized relative to reference boxes known as anchors.

According to the size and position of the region proposals, these ROIs are then assigned to different scales in the pyramid of the features. In essence, these ROIs are clipped from the feature maps and are passed into an ROI Align layer. Using ROI Align, a small feature vector of a fixed size (7×7) was extracted from each ROI and sent into the heads of the network. The first head predicts the classification result of the boxes while the second one provides the regression output which gives the coordinates of the region proposals. These results were realized by passing the fixed-length vector into two parallel fully-connected layers. The third and the final branch of the network predicts segmentation masks of the detected objects. These masks were acquired by an FCN-based architecture using an ROI pool size of 14×14 instead of 7×7. It is later up-sampled to a size of 28×28 for generating the final predicted masks.

Implementation details: The initial experiments were performed without augmenting the dataset. For comprehensive evaluation, we performed experiments on two backbones, the ResNet50 and ResNet101. Both of the backbones were initialized with pre-trained MS-COCO ResNet101 weights. Since ResNet50 has fewer layers than ResNet101, for ResNet50 we only took weights of the corresponding layers from the pre-trained ResNet101 weights. We chose Stochastic Gradient Descent (SGD) as the optimizer with the learning rate set to 0.0001, a momentum of 0.9 and a weight decay of 0.0001. Batch size was set to 2 and the training was conducted on a NVidia GeForce GTX 1650. For the settings related to image size, we selected a value of 512 and 960 as the minimum and maximum image dimensions, respectively. Here, the maximum dimension value ensures that the longer side of an image does not exceed it. We resized and padded an input image with zeros to obtain a square final image of the aforementioned size. The number of validation steps and iterations in each epoch were set at 200 and 725, respectively. For both the experiments, all of the network layers were fine-tuned.

ResNet50 outperforms, ResNet101 despite having a lesser depth and a weaker feature representation capability. We can conclude that it is due to ResNet101 slightly overfitting the training dataset. That is the reason as backbone we have selected resNet50 framework. After testing and validation, mask rcnn model gives the accuracy of 98% which can be improved by training our model with large dataset.

Sr.no	Name of research paper and year	Authors	Algorithm used	Accuracy
1	Plants diseases prediction framework: A image-based system using deep learning. -2022	Madhu Kirola., Kapil Joshi, Sumit Chaudhary, Neha Singh, Harishchander A., Ashulekha Gupta.	Convolutional neural network(CNN)	90%
2	Literature review of disease detection in tomato leaf using deep learning techniques. -2021.	Hepzibah David, Hemalatha G, K. Ramalakshmi, R. Venkatesan.	Hybrid CNN-RNN	87%
3	TLNet: A deep CNN model for 25rediction of tomato leaf diseases. -2021.	Md. Afif Al Mamun, Dewan Ziaul Karim, Subroto Nag Pinku, Tasfia Anika Bushra.	Convolutional neural network(CNN)	91.77%
4	Deep learning-based object detection improvement for tomato disease. -2020.	Yang Zhang, Chenglong Song, Dongwen Zhang	Faster RCNN	75%
5	ToLeD: tomato leaf disease detection using CNN -2019.	Mohit Agrawal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, Suneet Gupta	Faster RCNN-resNet	85%
6	A survey on different plant disease detection using machine learning techniques. -2020.	Sk Hassan, Khwairakpam A., Michal Jasinski, Zbigniew L., Elzbieta jasinska, Tomas Novak, Arnab Kumar.	Convolutional neural network(CNN)	89%
7	Tomato diseases	Qimei Wang,	Faster RCNN	90.87%

	recognition based on faster RCNN. -2019.	Feng Qi.		
8	Tomato disease detection and classification by deep learning. 2020.	Huiqun Hong, Jinfa Lin, Fenghua Huang.	Deep learning with resNet50	87.10%
9	Food preservation techniques and nanotechnology for increased shelf life of fruits, vegetables, beverages and spices: a review. -2019	Adithya Sridhar, Muthamilselvi P., Ponnusamy S. K., Ashish Kapoor.	IOT and deep learning	70%
10	**"TomatoHub"- Analysis of tomato disease detection using Mask RCNN. -2024.**	**Gunjan Chimote Sakshi Waghmare, Trupti Ikhar, Kunal Kirimkar, Shivam Gupta.**	**Mask RCNN**	**98%**

Table no. 3: Comparison with research papers.

As per the above comparison table it is clear that disease detection with Mask-RCNN gives more accuracy as compared to other deep learning or machine learning model.

4. TESTING AND RESULTS:

Thoroughly testing of application is needed to ensure that it can accurately detect and segment tomato disease in real-time. Testing under various conditions is needed to ensure robust performance. We have 2000 images for testing. For each class we have performed testing. Some examples are as follows.

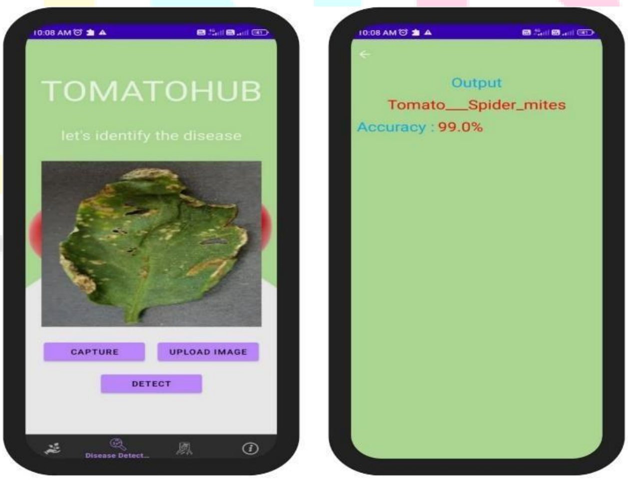

Fig no.5 testing of tomato spider mites.

In the above image the upload image is of spider mites disease. Output of the detection is same with the accuracy of 99.0%.

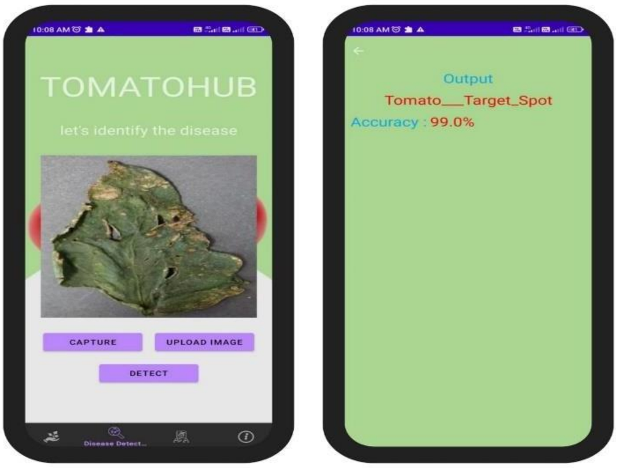

Fig no. 6 testing of tomato target spot.

In the above image the upload image is of target spot disease. Output of the detection is same with the accuracy of 99.0%.

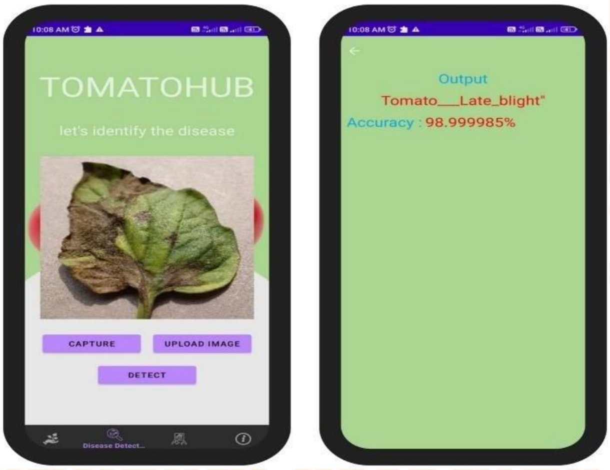

Fig no.7 Testing of tomato late blight disease.

In the above image the upload image is of late blight disease. Output of the detection is same with the accuracy of 98.999985%.

Fig no. 8 Testing of healthy tomato

In the above image the upload image is of healthy tomato. Output of the detection is same with the accuracy of 99.0%.

As we can see our app detect tomato disease with accuracy. This accuracy is 98%. To increase the accuracy up to 100% we need to train our mask RCNN model with lakhs of images.

5. CONCLUSION:

"TomatoHub" emerges as a beacon of innovation and collaboration in the realm of agricultural technology, poised to reshape the landscape of tomato cultivation and contribute significantly to global food security. By seamlessly integrating advanced technologies such as Internet of Things (IoT), machine learning, and deep learning into its framework, TomatoHub transcends traditional boundaries, offering cultivators an unprecedented level of precision, insight, and control over their agricultural practices. Through its comprehensive approach encompassing cultivation insights, disease detection methodologies, and post-harvest preservation techniques, TomatoHub addresses the multifaceted challenges faced by tomato growers with unparalleled sophistication.

By empowering cultivators with knowledge, tools, and resources necessary for success, TomatoHub not only enhances agricultural productivity and economic stability but also fosters a deeper connection between humans, technology, and the natural world. Looking ahead, the future of TomatoHub is characterized by endless possibilities for expansion, refinement, and impact. As it evolves in tandem with emerging trends and technological advancements, TomatoHub holds the potential to transcend its current capabilities, becoming a global platform for agricultural innovation and collaboration.

By embracing user feedback, engaging with agricultural research institutions, and fostering a vibrant community of cultivators, TomatoHub can continue to evolve dynamically, adapting to the evolving needs and challenges of the agricultural sector. Ultimately, TomatoHub represents more than just a technological solution; it embodies a vision of harmonious coexistence between humans and nature, where sustainable agriculture flourishes, and communities thrive. As we navigate the complexities of the modern agricultural landscape, TomatoHub serves as a guiding light, illuminating a path towards a future where food is not just abundant but also nourishing, resilient, and sustainable for generations to come.

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