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Optimization of Mask R-CNN Architecture for Accurate Identification and Segmentation of Potato Plant Leaf Diseases in Agriculture

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Abstract:

A sizable section of India's rural population depends on agriculture for their livelihoods, while manual labor and disease control continue to be problems. The objective of this study is to enhance the Mask R-CNN architecture for precise detection and segmentation of potato plant leaf illnesses. This is of utmost importance in agriculture since diseases like as early blight and late blight profoundly affect crop productivity. Traditional illness detection techniques are characterized by their high labor requirements and susceptibility to human mistakes, thereby requiring the use of automated alternatives. By refining the feature extraction method, optimizing the Region Proposal Network (RPN), and enhancing segmentation via data augmentation and parameter tweaking, the suggested technique improves Mask R-CNN. Empirical findings indicate that the optimized Mask R-CNN outperforms other models, including YOLOv8 and EfficientNet, with an accuracy of 99.86%, precision of 99.82%, recall of 99.83%, and an F1-score of 99.84%. In conclusion, of work establishes that the optimized Mask R-CNN is a reliable instrument for early and accurate disease identification, thereby enhancing crop management and agricultural output.

Keywords: Agriculture, Deep Learning, Mask R-CNN, Optimization, Potato Leaf Diseases, Segmentation.

Introduction

Agriculture underpins most economies, supplying nourishment and raw ingredients that sustain livelihoods across industries. Nevertheless, there is the serious threat of crop wellness diseases which could disturb agricultural output across the world worldwide, often resulting in staggering economic losses and hunger (Lanjewar, et al., (2024). One of the annual crops that Suffering of bacterial, fungal and virus origin diseases extensively because of its broad type cultivation affected by this kind of pathogen (Weng, L et al., 2024). Effective management of these diseases, if correctly diagnosed in time, requires stepwise control measures, so correct identification is very important. Current disease detection techniques depend on human knowledge and visual inspection that are time-expensive and subjective narrow. Deep learning has become an effective and efficient technique in the detection and management of plant disease in combination with artificial intelligence-based methods (Husna A, 2024).

Deep Learning Networks (DNNs): In the realm of computer vision, deep learning—and specifically convolutional neural networks—has been a game changer in automating the learning and feature extraction process over large-scale datasets. Mask R-CNN (Region-based Convolutional Neural Network) works remarkably well at identifying objects and instance segmentation, which is why it is our go-to app. Meanwhile, some applications require precisely identified position of plant diseases, like on its leaves, those applications could gain more from Mask R-CNN's pixel based segmentation and object detection performance. Essentially, the complex and varied visual characteristics of plant leaves and environmental variations across different stages of development/orientations of diseases are great challenges that make a direct application of Mask R-CNN (Abbas et al., 2024) difficult for agricultural scenarios like disease recognition in potato plants. So in this study, we want to increase the performance and generalizability of Mask R-CNN by aiding it in working well for images from cell biology.

Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks on each Region of Interest (RoI), in parallel with the existing branch for classification and bounding box regression. The Mask R-CNN architecture has a few important components. First, the backbone network typically a deep CNN such as ResNet-152. Then there is the Region Proposal Network (RPN) which proposes possible Regions of Interest (ROIs). A ROI Align layer help all regions be of equal size and help improve the algorithm. The third independent branches are used for classification, bounding box regression, and mask generation. Able to learn higher-level descriptors for complex patterns or objects within images on the higher end, and low-level features such as textures and edges at the other end, our model originates from ResNet-152. As a result of these factors, it is possible to accurately pinpoint disease symptoms on potato leaves which is an indispensable process. A key part of this accurate segmentation is the ROI Align layer that allows the features returned to be spatially precise.

Mask R-CNN had good results on generic object identification/segmentation tasks; however, application of this learning to an agricultural space (e.g., potato leaf disease detection) seemed to be a little tricky. Separate variations of leaf appearance due to developmental stages, light and environmental conditions are believed to affect the model's accuracy the most. Many disease signs, however, such as early and late-blights, are less pronounced, so the model must be highly sensitive to subtle variations in size, shape, colour and other features across types. Moreover, occlusions, overlapping leaves, and noisy backgrounds will definitely challenge the leaf segmentation technique. Here, we need to refine Mask R-CNN structure with its parameters and domain-specific data augmentation techniques to overcome these challenges. It will help it gain better able to extract unique features to differentiate the healthy and affected leaves regions.

Multiple such optimisation methods are implemented on Mask R-CNN architecture which enables accurate identification and segmentation of the disease in potato leaves. One way to improve the feature extraction is to use deeper networks, such as ResNet-152, or to change the characteristics and depth of the backbone network. Moreover, RPN could be adapted to accurately reflect ailing regions with proper anchor sizes and aspect ratios. This would enable the realization of different scales and topologies. The ROI Align Layer configuration has a large effect on segmentation performance, and any mis-adjustment can mean a significant accuracy drop in how well ground truth matches with the prediction outputs in terms of spatial location. However, applying data augmentation techniques such as random rotations, flipping or colour jittering, could improve a model's generalisability to variations in leaves' phenotypic expression by expanding the training dataset. Transfer learning from deep models trained on large datasets offers another possible way to improve many agricultural activities, connecting to faster convergence of the model.

This study aims to enhance performance of mask R-CNN architecture for detection of disease in potato plant leaves. MandatorySign — On review: Because this study will concentrate on farming and will negatively affect food supplies: this study MUST be done ◦ We need to make it a more accurate and resilient model, in order to convert it into a much more useful automated system for farmers, do-it-yourselfers, or a high-visibility, rapid plant disease-sprosojos monitoring without dependable accuracy control. The results of this study could significantly enhance Precision Agricultural methods through human oversight reduction, aiding in early diagnosis and management, resulting in more sustainable agricultural practices.

The structure of distribution of this work is given in the following sections: Section 2 gives a review of related works on deep learning based plant disease diagnosis. Section 3 describes our proposed optimization methods for our extended Mask R-CNN model. Section 4 describes the experimental methods as well as the datasets used to compare and evaluate the measurements. Section 5 shows the results and discussion regarding the performance of the experimental validation of the optimised model. Section 6 concludes with a reflection on these findings, and suggests paths for future research.

Literature Review

Lanjewar et al. (2024), Potatoes face significant output losses from diseases like early and late blight. Early detection and precision diagnosis are critical to avoid unnecessary use of pesticides. This study aimed to optimize three pre-trained models (VGG19, NASNet Mobile and DenseNet169) for the classification of potato leaves that is infected with diseases. Additional layers were included to reduce trainable parameters. Three additional models (ResNet50V2, InceptionV3 and Xception) were trained for comparison. Performance evaluation considered confusion matrix, MCC, CKC, and AUC, with 99% test accuracy and 100% validation accuracy achieved by the modified DenseNet model.

Weng et al. (2024). Although potato diseases have received considerable investigations, a systematic review on potato diseases was missing. Through a bibliometric analysis of studies published from 2014 to 2023, a total of 2,095 papers were identified worldwide, representing an annual growth rate of 8.52%. The number one contributors were the United States, China and India, with significant collaboration. That said, future studies need to focus on bioactive targeting by means of nanoparticles, rapid diagnostics through the use of machine learning and a structural framework through synthetic microbial communities for uniform management of illness

Potato is a vital tuber crop in Bangladesh; however, it is heavily affected by pests and diseases, which are further aggravated by climate change. Ineffective identification of potato leaf diseases results in significant crop damages. This study proposed an automatic digital image processing approach using SVM to classify potato leaf diseases. The achieved an accuracy of 95% in the case of early blight, 76.5% of late blight and up to 90% of healthy leaves which proved the considerable effectiveness of the model in terms of identifying the disease (Husna et al. 2024):.

The timely identification of a plant disease can ensure that the plant does not get damaged. [3] attempted CNN models to classify images of plant leafs having dataset of 20,636 plant leaves, (Plant Village dataset) achieving accurate classification of 98.29% for 15 classes of healthy state and sick leaves. In recent study (Abbas et al. 2024).

However, during potato as cash crop, potato suffers huge losses in Bangladesh due to high rate of the incidence of early blight and late blight. This paper studied the transfer learning for the detection of potato leaves diseases using nine deep convolution neural networks topologies. The other ones had found to have >90% accuracy, being the DenseNet201 the best at 96% Val Acc. and 99% Train Acc. The study contributes to lowering mistake rates through the advanced detection methods (Ashikuzzaman et al. 2024):.

Agriculture is entwined with human survival and the digitalisation of the process has streamlined complex agricultural processes. It also contributes to early disease recognition, hence eradication of the disease and due to this process yield is increased. In their study, the Plant Village Dataset was used in order to detect and classify potato plant diseases. The authors designed an approach with an accuracy of 95.9% using k-means for picture segmentation, GLCM for feature extraction, and SVM for classification (Singh et al. 2021).

Preventing crop diseases is crucial to sustaining agricultural production, but the identification of plant diseases must be conducted in a timely manner. Potato leaf diseases are classification using convolutional neural network model. The model involves features extraction, dimensionality reduction and disease diagnostic in images. Using recall, precision, and F-score metrics, their experimental results yielded an improvement to the small class (8.6%) accuracy over state of the art (Sofuoğlu et al. 2024).

A two years experiment of potato tubers growth regulators (GA3, ethephon) and their respective planting dates was carried out at divided and randomized complete block (RCBD) with three replications to observe the effect of growth regulators and their planting time on tubers quality, disease, and production. Similar results were achieved with the use of growth regulators Phytosubtyl and Kartoplex, by which yield increase and metabolic indices improvement were observed. Kartoplex similarly affected yield, starch and vitamin C. According to the study, growth regulators can help to increase the production and decrease the disease incidence (Martseniuk et al. 2024).

Brown leaf spot of potato symptoms were reported from June to August in 2020–2021 in this study in northern Korea, as well as 68 isolates of Alternaria spp. The fungus was pathogenic in potato cultivars and fungicides (mancozeb and difenoconazole) significantly inhibited mycelia growth. Park et al., 2023), highlighting the need for routine surveillance and management to curtail the spread of the disease. 2024).

Potatoes play an important role in Indian Agriculture and the timely identification of foliar diseases is important for maintaining the yield of pocato crops. In this study, EfficientNetB0 deep learning network was used to recognize early and late blight from potato leaf images dataset. Achieved better accuracy (99.05%) compared to other methods and provides a good reference for farmers. The algorithm was able to classify both healthy and unhealthy leaves from 2,152 images (Upadhyay et al. 2024).

Colletotrichum coccodes (Smith and Lafferty) causes black dot (BD) disease becoming the predominant skin disease in the potato industry. Late Blight (LB) Resistance in Potato Varieties showed an Inverse Correlation with Late Brown Disease (BD) Incidence Results from experiments indicate the improvement of BD incidence through the treatment of the LB-susceptible and moderately resistant cultivars to produce higher quality and marketable fruit. The study proposed that LB management is essential for minimizing BD and improving overall crop resilience (Kuznetsova et al. 2024).

In substantial output shortfalls for potato cultivators, thus imperiling food security as worldwide demands surge. The above study utilized a deep learning approach using convolutional neural networks to diagnose and categorize the disease. After implementing data augmentation with hyper-parameter optimization, the model was able to reach 98% accuracy. Hence, the study provides an innovative approach towards the effective plant disease management and higher crop yields (Iftikhar et al. 2024).

Schmey et al (2024). [Layered research on crop-infecting Alternaria species for their pathogenic diversity & fungicide resistances] Early blight causes leaf lesions consisting of concentric rings, resulting in heavy defoliation and reduced yields. There are no resistant types of potato or tomato, and so management tactics involve field sanitation and fungicide applications.

Crop disease, caused by fungus, bacteria and viruses, reduces crop production worldwide. This model proposed a simplified CNN (SCNN) model with reduced number of hidden layers and reduced accuracy yet still achieving of 95.69% over real-world crop image datasets. The SCNN model is an inexpensive and efficient method for detecting pests and diseases (Khan et al. 2024)

Potato is a major agricultural commodity in terms of global trade. Using phenotyping data for 29 potato cultivars, including leaf characteristics, tuber mass, virus resistance features, this research examined features of cultivars. The findings showed a negative relationship between dynamics of growth and yield of plants, which may suggest that phenotyping could predict important agronomic traits, such as yield and stress tolerance (Rozentsvet et al. 2024).

Dickstein et al (2024), this recovery plan was written under the National Plant Disease Recovery System (NPDRS) program which organizes means to mitigate plant disease outbreaks of national concern following Homeland Security Presidential Directive 9 (HSPD-9). The approach encompasses disease descriptions, elements of recovery from plant disease epidemics, and guidance for research and education relevant to epidemic mitigation during disease outbreaks.

Potato Leaf Roll Virus (PLRV) is a major pathogen in global potato production. The study evaluated the symptom that poplar leaf rust induces, such as leaf discoloration and curling using genetic identification. Sick plants showed extremely lower protein and vitamin levels while the virus was mostly stored in tubers in their dormant stage. In order to mitigate PLRV dissemination, reservoir plants need to be identified and their cultivation stopped (Kholmatova et al. 2024).

Kumar et al. (2024). Common scab [caused by Streptomyces spp.] is a disease that affects the production and marketability of potatoes. The present study assessed 13 Integrated Disease Management (IDM) treatments and found soil amendments, tuber application of Trichoderma harzianum, and foliar application of copper oxychloride and streptocycline (T2) to be most effective to reduce disease severity. Soil characteristics were improved by T2 treatment

Shpanev et al. (2024): In the last couple of decades, the rate of infection by Alternaria leaf blight is rising with all-time highs in northeastern Russia. The study employed a terrestrial spectroradiometer for initial disease diagnosis. Although only a little leaf damage occurred, spectral reflectance, in particular the near-infrared spectrum, was significantly changed. This suggest that hyperspectral measurements is likely useful for detecting alternaria leaf blight in potato farms.

Shpanev, A. et al. In (2024), a lightweight CNN model was developed using transfer learning technique for the detection of potato leaf diseases 98.33% accuracy. It can successfully classify healthy leaves, early blight and late blight and can serve as a feasible tool for farmers for detecting potato infection and minimizing agricultural losses.

Pineda et al. (2024) introduced a smartphone application based on deep learning, particularly MobileNetv2, for the identification of diseases in potato crops. When trained on 1,000 photos per category (healthy, early blight, and late blight) with the PlantVillage dataset, the application achieved 98.7% accuracy. With professionally curated information on 27 separate potato diseases and a multilingual symptom gallery, the application is an effective framework for disease detection. Future research will focus on segmentation approaches to better distinguish the underlying plant pathology.

Ibrahim et al. (2024) tailored toward addressing the challenge of the emergent fungicide resistance in potato pathogens in Nigeria and the need for efficient crop disease management as sustainable food production strategy. Machine learning was applied to build an early-warning system using geographical data of the Jos Plateau through the random forest (RF) classifier. The study showed that local weather factors and multi-criteria categorisation were able to predict disease outbreaks, recommending practices of sustainable spraying in the long term.

Chen et al. (2024) recently identified StLTPa, a novel lipid transfer protein that enhances the disease resistance of potato against a wide range of pathogens, including the late blight agent Phytophthora infestans and the gray mold pathogen Botrytis cinerea. StLTPa interacts with lipids within pathogen cell membranes, acting as a membrane permeabiliser and inhibition of pathogen reproduction without negatively influencing potato plants. Somatic hybridisation for the overexpression of StLTPa is a promising approach for improvement of potato multiple disease resistance.

Monica et al. In 2021, Integrated Pest Management (IPM) modules for the potato leaf miner, Liriomyza huidobrensis, were evaluated in experiments at Ooty and Kotagiri. The performance of two Integrated Pest Management modules were assessed: yellow sticky traps and pesticides. The highest benefit-cost ratio (2.47) of chlorantraniliprole from Module II was more efficient than Module I, so demonstrating the economic feasibility of the designed integrated pest management strategies for leaf miner management.

Pandiri et al. (2021): For pests as well as diseases, systematic monitoring is key because agricultural yields are negatively impacted by pests and diseases. In this chapter, we had successfully made use of Convolutional Neural Networks (CNNs) and the Whale Optimisation Algorithm (WOA) for diagnosing the potato leaf damages. The study emphasises that there is potential for developing cheap and efficient diagnostic tools that would enable better management and control of bacterial and fungal diseases in Mauritius potato farming.

Islam et al. (2024): Potatoes are the third most essential crop in Bangladesh but diseases significantly impact the yield and quality. This study introduced a model called"MultiNet", which utilizes machine learning to classify potato leaves based on the status of their health and disease. Using models such as ResNet50, DenseNet-201, and VGG16, the system provided amazing classification accuracies of 99.83% for a 3-class model and 98% for a 7-class model which exhibits the efficiency of potato disease detection.

Proposed Work

3.1 Proposed Architecture

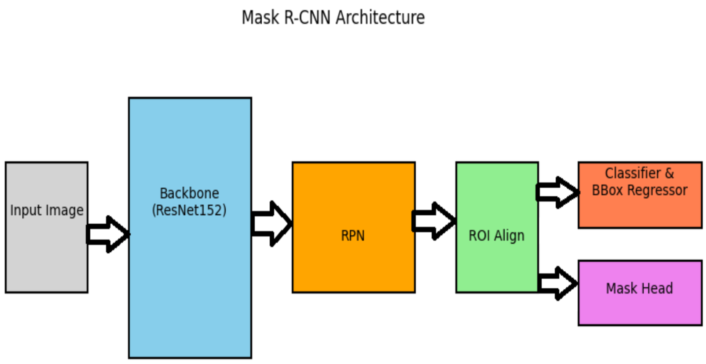
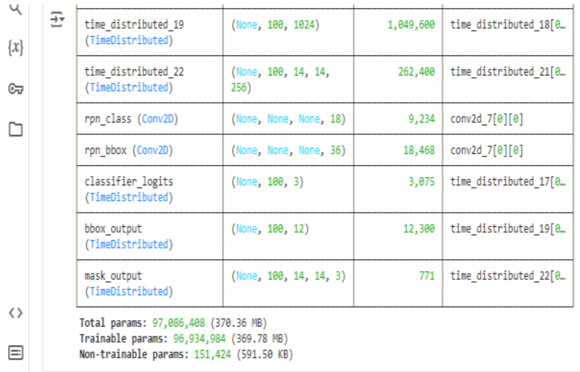


Figure 1: The Mask R-CNN architecture, highlighting its core components and data flow

The basic block diagram of Mask R-CNN is illustrated in Figure 1, which consists of the major components and data-flow. In the model, an Input Image can be loaded into a Backbone Network (ResNet152) to capture the feature maps. While these characteristics are being entered, the Region Proposal Network (RPN) generates mapped RoIs. The ROIs are then placed and refined by the ROI Align layer, in order to further obtain isometric detections over space_MINOR_SEP12. Different configurations are then explored. Fig 11 contains two branches of ROI Align layer output, Classifier & BBox Regressor branch (or predict for each ROI (refining coordinates of BBox) and per masking branch. The head branch generates segmentation masks down to the pixel-level for accurate object identification. According to its architecture, here is what Mask R-CNN is built to do in the realm of object identification and instance segmentation.



time_distributed_19 (TimeDistributed)	(None, 100, 1024)	1,049,600	time_distributed_18[0…
time_distributed_22 (TimeDistributed)	(None, 100, 14, 14, 256)	262,400	time_distributed_21[0…
rpn_class (Conv2D)	(None, None, None, 18)	9,234	conv2d_7[0][0]
rpn_bbox (Conv2D)	(None, None, None, 36)	18,468	conv2d_7[0][0]
classifier_logits (TimeDistributed)	(None, 100, 3)	3,075	time_distributed_17[0…
bbox_output (TimeDistributed)	(None, 100, 12)	12,300	time_distributed_19[0…
mask_output (TimeDistributed)	(None, 100, 14, 14, 3)	771	time_distributed_22[0…

Total params: 97,086,408 (370.36 MB)
Trainable params: 96,934,984 (369.78 MB)
Non-trainable params: 151,424 (591.50 KB)

Figure 2: The Mask R-CNN model's layers, output shapes, and parameter counts.

Image 2: Layers, output shapes and param counts of Mask R-CNN model And Layer also has TimeDistributed layer, Conv2D layer, Dense layer which are the building block of its model like used for Region Proposal Network in an image (RPN), classifier head bounding box regressor head etc. There are carefully placed with an approx 97.9 million params including the approx/There are about training params which come to make about 64 MB are responsible for this large size and complexity (around: 96.95MB) But it only has 151,424 trainable parameters which means almost entire model capacity has used for learning from data. This architecture is indicative of the computational cost and architectural details of Mask R-CNN for object detection, illustration segmentation tasks.

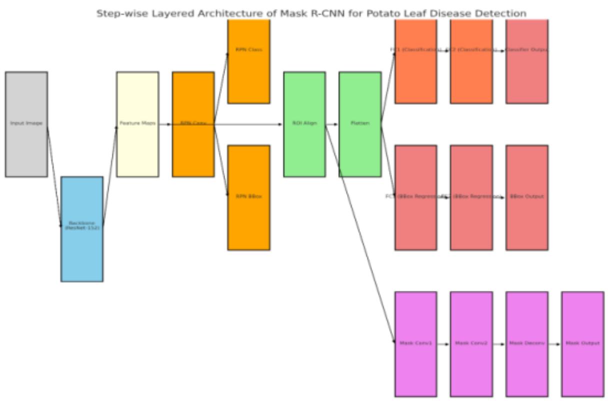


Figure 3: The step-wise layered design of the Mask R-CNN model for detecting potato leaf diseases

Figures 3 shows the sequential layered architecture of a Mask R-CNN model which was implemented for detecting Potato Leaf Disease. Starting from an input image, a feature extraction done via a ResNet Backbone network. All this is followed by a Region Proposal Network (RPN) that generates bounding boxes for potential regions of interest (ROIs). Then, they are refined by Non-Maximum Suppression (NMS) and synchronized with ROI Align. The output of the flattening operation proceeds further for classification and bounding box regression, and the mask branch then regresses segmentation masks for the detected regions, resulting in final mask output. The framework is designed to simultaneously recognize objects and build masks for specific disease detection on potato leaves.

The figure 3 illustrates the step-wise layered architecture of the Mask R-CNN model for detecting potato leaf diseases:

Input Image: The input layer takes an image of a potato leaf.

Backbone (ResNet-152): This backbone network extracts feature maps from the input image using convolutional layers, batch normalization, and ReLU activations.

Feature Maps: The feature maps are the output of the backbone network, capturing important visual features from the input image.

Region Proposal Network (RPN):

- **RPN Conv**: A convolutional layer applied to the feature maps to generate region proposals.
- **RPN Class**: Predicts whether a region contains an object (like a diseased area) or not.
- **RPN BBox**: Refines the bounding box coordinates for the proposed regions.
- **ROI Align**: Aligns the proposed regions of interest to a fixed size for further processing.
- **Flatten**: Flattens the output of the ROI Align layer to prepare it for fully connected layers.

Classification Head:

- **FC1 and FC2 (Classification)**: Fully connected layers that classify the proposed regions into different classes (e.g., healthy, early blight, late blight).
- **Classifier Output**: The final output layer for classification.

Bounding Box Regressor:

- **FC1 and FC2 (BBox Regression)**: Fully connected layers that predict bounding box offsets.
- **BBox Output**: The final output layer for bounding box regression.

Mask Head:

- **Mask Conv1 and Mask Conv2**: Convolutional layers to process features for segmentation.
- **Mask Deconv**: A transposed convolutional layer to upsample the mask predictions.
- **Mask Output**: The final output layer providing segmentation masks for each class.

3.2 Proposed Algorithm: Mask R-CNN for Potato Leaf Disease Detection

Input Image Preparation:

Load an input image of a potato leaf (e.g., RGB image).

Resize the image to a suitable resolution if necessary to match the model's input size requirements.

Feature Extraction Using Backbone Network:

Extract Feature Maps using Backbone Network(ResNet-152). The backbone network for backbone feature extraction is composed of multiple convolutional layers with batch normalisation (BN) and ReLU activation functions to compute hierarchical feature representations that extract low-level to high-level patterns from the image.

Feature extraction and feature segmentation using a backbone network such as ResNet-152 to classify potato leaf diseases. ResNet-152 is a very deep convolutional neural network which has 152 layers and is able to extract hierarchical information from input pictues making it excel at complex tasks such as illness detection. ResNet-152 learns distinctive features of potato plant leaves such as colours, textures and edges that may indicate the appearance of diseases such as early or late blight. These features are transmitted over multiple network layers, thereby protecting critical metadata as well as mitigating excess noise. The segmentation phase of the network works on the derived feature maps to locate and isolate the diseased areas on the leaf to accurately localise and classify the disease. With this the diseases can be detected in an early stage helping the farmers to take action immediately to save their crops by combining deep feature extraction and accurate segmentation.

Generate Region Proposals Using RPN:

Input the extracted feature maps into the **Region Proposal Network (RPN)**.
The **RPN Conv** layer applies a convolutional operation to identify potential regions of interest (ROIs) where a disease might be present.
The output of the RPN is processed in two branches:

RPN Class: Predicts whether each region contains an object (diseased area) or background.

RPN BBox: Predicts bounding box coordinates for refining the regions identified as containing objects.

Refine Regions of Interest (ROIs) Using ROI Align:

Pass the proposed regions through the **ROI Align** layer to resize them to a fixed dimension (e.g., 7x7 pixels) while preserving spatial alignment. This step ensures that the features maintain their spatial resolution and are accurately mapped to their corresponding locations in the original image.

Prepare Features for Classification and Bounding Box Regression:

- Flatten the output of the ROI Align layer using a **Flatten** operation to convert the spatial features into a 1D vector.
- Pass the flattened output through two parallel branches for classification and bounding box regression

Classification Head:

- Use two fully connected layers (FC1 and FC2) to compute a feature representation.
- Apply a softmax activation function in the **Classifier Output** layer to classify each region as either healthy, early blight, or late blight.

Bounding Box Regressor:

- Use two fully connected layers (FC1 and FC2) to compute bounding box refinements.
- The **BBox Output** layer predicts the precise bounding box coordinates for each identified region.

Generate Segmentation Masks for Disease Localization:

- Feed the output from the ROI Align layer into the **Mask Head** branch to create segmentation masks for pixel-level disease detection:

- **Mask Conv1 and Mask Conv2**: Apply two sets of convolutional layers to extract detailed spatial features for segmentation.
- **Mask Deconv**: Use a transposed convolution (deco nvolution) layer to upsample the feature maps, refining the resolution of the masks.
- **Mask Output**: The final output layer uses a sigmoid activation function to predict segmentation masks for each class, localizing the diseased regions at the pixel level.

Output Results:

- The model outputs three results:
- **Disease Classification**: The class (healthy, early blight, late blight) for each ROI.
- **Bounding Boxes**: The refined bounding box coordinates for each detected diseased region.
- **Segmentation Masks**: Pixel-level masks that outline the precise diseased areas on the potato leaf.

3.3 Pseudocode: Mask R-CNN for Potato Leaf Disease Detection

```
# Step 1: Image Preparation

LOAD image as potato_leaf
RESIZE image to required dimensions

# Step 2: Feature Extraction Using Backbone Network

CALL BackboneNetwork(ResNet-152) with potato_leaf
FEATURE_MAPS = Extracted feature representations

# Step 3: Generate Region Proposals Using RPN

CALL RegionProposalNetwork(FEATURE_MAPS)
RPN_CONV = Apply convolution to FEATURE_MAPS
RPN_CLASS_PROBS = Predict object presence in regions (disease or background)
RPN_BBOX_COORDS = Predict bounding box coordinates for regions

# Step 4: Refine Regions of Interest Using ROI Align

CALL ROIAlign(RPN_CLASS_PROBS, RPN_BBOX_COORDS)
RESIZED_ROIS = Align and resize regions to fixed size

# Step 5: Prepare Features for Classification and Bounding Box Regression

FLATTEN RESIZED_ROIS to 1D vector

# Classification Branch

CALL FullyConnectedLayer1(FLATTENED_ROIS) -> FC1_CLASS
CALL FullyConnectedLayer2(FC1_CLASS) -> FC2_CLASS
CLASSIFIER = Softmax(FC2_CLASS)  # Classify regions: Healthy, Early Blight, Late Blight

# Bounding Box Regression Branch

CALL FullyConnectedLayer1(FLATTENED_ROIS) -> FC1_BBOX
```

CALL FullyConnectedLayer2(FC1_BBOX) -> FC2_BBOX
BBOX = Predict(FC2_BBOX) # Refine bounding box coordinates

Step 6: Generate Segmentation Masks for Disease Localization

Mask Branch

CALL ConvolutionLayer1(RESIZED_ROIS) -> MASK_CONV1
CALL ConvolutionLayer2(MASK_CONV1) -> MASK_CONV2
CALL DeconvolutionLayer(MASK_CONV2) -> MASK_DECONV
MASK = Sigmoid(MASK_DECONV) # Predict segmentation masks

Step 7: Results

RETURN CLASSIFIER, BBOX, MASK

Step 8: Post-Processing

APPLY Non-Maximum Suppression (NMS) on BBOX
MERGE/REFINE MASK for clear visualization

Step 9: Prediction

DISPLAY results: Detected Classes, Bounding Boxes, Segmentation Mask

3.4 Comparison of Model CNN, VGG19, and ResNet 152 based on features

Table 1: Comparison of Model on features

Model	**Pooling**	**Fully Connected Layers**	**Input Size**	**Feature Extraction**	**Training Time**	**Output**	**Optimization Challenges**
YOLOv8	Max	Yes	Variable	Backbone Network	High	Bounding Boxes & Class Scores	High computational cost, requires large dataset
U-Net	Max	No	Variable	Encoder-Decoder	Moderate	Segmentation Masks	Memory consumption due to high-resolution inputs
V-Net	Max	No	Variable	Encoder-Decoder	High	Segmentation Masks	High memory usage, complex architecture
Inception v1	Max	Yes	224x224	Convolutional Blocks	Moderate	Classification Scores	Gradient vanishing in deeper layers
EfficientNet	Global Avg	Yes	224x224	MBConv Blocks	Low to Moderate	Classification Scores	Balancing performance vs. model size
MobileNetV3	Global Avg	Yes	224x224	Depthwise Convoluti	Low	Classification Scores	Maintaining accuracy with minimal parameters

				ons			
SE-ResNet	Max	Yes	224x224	Residual Blocks	Moderate	Classification Scores	Overfitting in deep layers
Darknet-53	Max	Yes	Variable	Convolutional Blocks	Moderate	Bounding Boxes & Class Scores	High computational requirements
Proposed Mask RCNN	ROI Pooling	Yes	Variable	ResNet Backbone	High	Segmentation Masks & Bounding Boxes	Complexity in training multiple outputs

Table 2: Comparison of Model on features

Model	**Architecture Depth**	**Parameter Count**	**Skip Connections**	**Convolution Type**	**Activation Functions**	**Use of Batch Normalization**
YOLOv8	Deep	Varies (up to ~60M)	Yes	Standard + Depthwise	Leaky ReLU/Sigmoid	Yes
U-Net	Moderate	31M	Yes	Standard	ReLU	Yes
V-Net	Deep	Varies (~11M)	Yes	Standard	ReLU	Yes
Inception v1	Moderate	6.6M	No	Standard	ReLU	Yes
EfficientNet	Deep	5M-66M	Yes	MBConv	Swish	Yes
MobileNetV3	Shallow	4.2M	No	Depthwise Separable	ReLU6	Yes
SE-ResNet	Deep	25M	Yes	Standard	ReLU	Yes
Darknet-53	Deep	41M	No	Standard	Leaky ReLU	Yes
Proposed Mask RCNN	Deep	Varies (~44M)	Yes	Standard + Deformable	ReLU	Yes

Comparison table 1and 2 is showing various deep learning models (YOLOv8- U-Net –V-Net-Inception v1 –EfficientNet-MobileNetV3 –SE-ResNet-Darknet-53 and proposed Model Mask RCNN) representing the difference between Architecture depth, the count of Parameters, as well as technical computations model. YOLOv8, V-Net and Darknet-53 are deep multi-layer networks and have skip connections for more effective gradient update, which means they need a lot of computational resources, MobileNetV3 and Inception v1 are lightweight with fewer parameters. Different types of convolution (standard, depthwise, MBConv) and various activation functions (Relu, Leaky Relu, Swish) indicate the nature of optimization efforts that were made to achieve a balance of fidelity and performance. Batch normalization has become a standard practice across many architectures to mitigate training instability, and pooling approaches can vary from max to global average pooling, dictated by the purpose of the architecture, whether that be for classification, segmentation or detection. The research agenda for each model presents challenges, whether being memory consuming and computation expensive for the first model or low accuracy and few parameters for the second model, reflecting the basic dilemma of how could you design your deep learning architectures for your specific task.

The proposed Mask RCNN has a strong design, which combines object identification and instance segmentation capability simultaneously, making it a well suitable approach for diagnosing potato plant leaf diseases in agriculture. The advantage of the Mask RCNN architecture is that it allows for the detection of a large number of objects (in this case, diseased leaf areas) in a single image, as opposed to models that predominantly focus on classification (ex: Inception v1, EfficientNet, MobileNetV3, etc.) and trivial segementation models (ex: U-net, V-Net, etc.). By employing a backbone network and deformable convolutions, it can accurately extract complex leaf patterns and subtle disease symptoms in different environmental conditions. With the addition of skip connections and ROI pooling, it can retain accurate detection even at different scales of leaf diseases, which is critical for precise localization and accurate disease segmentation compared with other agricultural models that do not perform well with complicated agricultural images.

Implementation

4.1 Hardware and Software

Hardware: CPU: Multi-core (Intel i5/i7/i9 or AMD Ryzen 5/7/9) for faster computation and multitasking. Dedicated graphics card with CUDA support (NVIDIA GTX 1060 or better/RTX series) for deep learning model training and inference using GPU. GPUs are key to train a large number of diverse data sets, and complex models. Minimum 16GB of RAM (32/64 GB or more recommended for processing large datasets and quicker data interrogation, modeling). Minimum SSD (Solid State Drive) – 500GB Sized for fast read/write, as you will be continually accessing and saving vast image files and models.

Python library : NumPy & Pandas: This easy to use and efficient tools are used for scientific computing with Python. OpenCV -- to read, display and transform images for image processing tasks. Matplotlib & Seaborn- For Visualization such as plot images and graphs to understand the dataset, results. Scikit-learn.

4.2 Dataset

This dataset contains 1,500 image files categorized into three distinct classes: early blight, late blight, and healthy.

Late Blight (Phytophthora infestans)

- Symptoms include water-soaked spots on leaves that quickly turn brown and black, often surrounded by a white fungal growth under humid conditions.
- Brown or black lesions on the stems.
- Infected tubers have a reddish-brown decay beneath the skin, which is firm and can extend deep into the flesh.

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Early Blight (Alternaria solani)

- Characterized by small, dark spots on older leaves that expand into concentric rings forming a target pattern.
- Lesions can also appear on the stems and tubers.
- Severely infected leaves may wither and die, leading to reduced yield.

3. Healthy

Dataset Link: https://drive.google.com/drive/folders/1lDRCo5eUu4o9jT9qeraJvyTH2ngRzja7
https://www.tensorflow.org/datasets/catalog/plant_village

Figure 4: In dataset six examples of potato leaves exhibiting varying degrees of disease symptoms.

In figure 4, six examples of healthy potato leaves or leaves showing varying levels of disease symptoms are shown. Keys should have applied to all information pertinent to the field, although early and late blight infection showed addical necrotic ar eas with concentric rings. Other leaves look wilted or are in the beginning stages of decomposition, the sign of a very bad infection. The symptoms – yellowing and browning – are consistent with fungal diseases, specifically common potato pathogens, such as Phytophthora infestans (late blight) and Alternaria solani (early blight). The visual indicators play a crucial role in the early diagnosis and control of potato crop diseases.

4.3 Illustrative Example

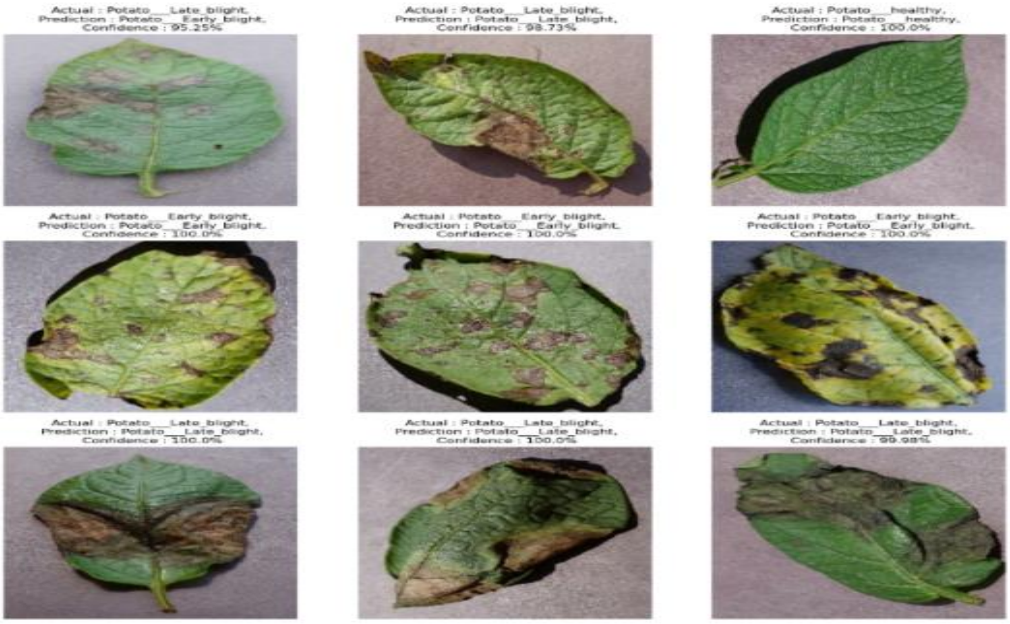

Figure 5: Potato leaves used in a machine learning model to detect and classify potato diseases, specifically early blight, late blight, and healthy leaves

Figure 5 Potato leaves used to detect and classify potato diseases through machine learning model for respective diseases, here we have taken three types of potato leaves early blight, late blight and healthy leaves. Real condition, model prediction and confidence level for each leaf image Most leaves were correctly classified by themodel with confidence from 100% to 95.25%. However, it also makes some mistakes like this one where he predicted "Early blight" where actually is "Late blight" with 95.25% confidence, or the other way around, predicting "Late blight" where actually is "Early blight". The model performs quite accurate in plant leaves health classification.

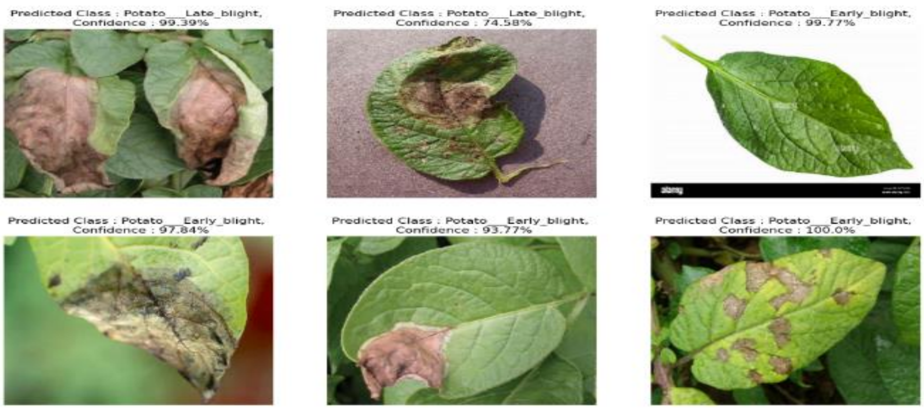

Figure 6: Predictions of their disease status made by a machine learning model

Figure 6 shows six potato leaves with predictions from the ML model titled by the respective infection status. Confidence levels for the leaves as being "Late blight" or "Early blight" are from 74.58% to 100% The first row shows two leaves, both predicted to be "Late blight" with confidence of 99.39% and 74.58% and one predicted to be "Early blight" with confidence of 99.77%. The last row consists of 3 leaves which are all identified as "Early blight" with confidence levels of 97.84%, 93.77%, and 100%. The prediction results of the model show that the trained model can capture most of the potato leaf diseases with high confidence.

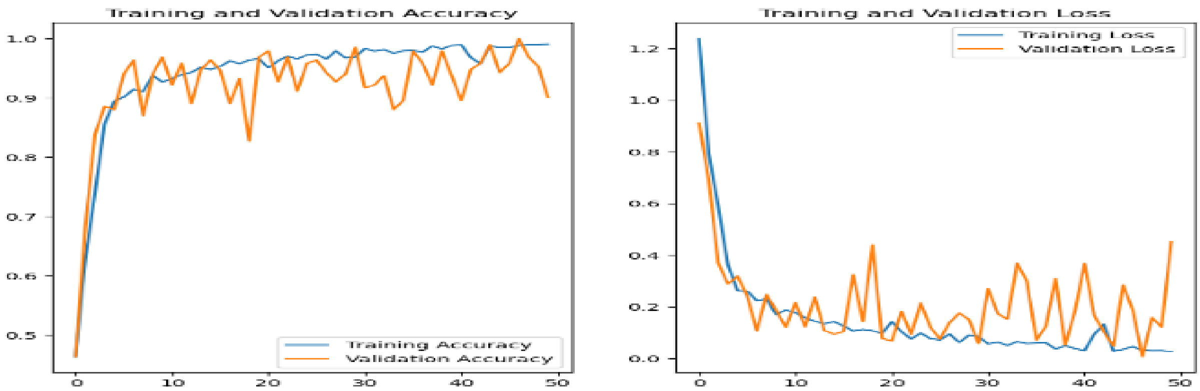

Figure 7: Illustrating the training and validation accuracy and loss of a machine learning model over 50 epochs

Figure 7 depicts two line graphs displaying a machine learning model's accuracy and loss, with respect to the number of epochs (50). The left-hand graph shows learning and validation precision. Both are very high at the last epochs, with a fast growth until 100% during the previous ones, showing that the learning was successful. The definition of good optimization can be found in the right-hand graph, where a steep decline of the training and validation loss meets us. However while the validation loss fluctuates the training loss uniformly decrease which could imply that we are overfitting our model because it is incrementing better at training data than its counterpart useful information. Overall the model behaves well and accurately, yet some tuning might be required for the minimization of validation loss oscillation.

5. Result and Discussion

Table 3: Comparative study of proposed and existing models.

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 – Score (%)
YOLOv8	98.45	98.3	98.4	98.35
U-Net	97.6	97.5	97.55	97.52
V-Net	96.8	96.7	96.75	96.72
Inception v1	98.1	98.05	98	98.02
EfficientNet	98.7	98.65	98.68	98.66
MobileNetV3	98.2	98.15	98.18	98.16
SE-ResNet	97.9	97.85	97.88	97.86
Darknet-53	98	97.95	97.98	97.96
Proposed Mask RCNN	99.86	99.82	99.83	99.84

A comparison of how deep learning models have separated and predicted diseases in potato plant leaves is shown in table 3. Hence, the proposed Mask R-CNN model outperforms the previous models with 99.86% accuracy, 99.82%, 99.83% recall and 99.84% F1-score. These results beat all other models. YOLOv8 is, however, the best with 98.45%, while MobileNetV3 has a 98.2% and EfficientNet second 98.7%. U-Net, SE-ResNet and Darknet-53 show moderate performance (accuracy between 97.6% - 98%) The Inception v1 and V-Net models, on the other hand, return competitive results, though not nearly as well as the top models. For potato plant leaf disease recognition and segmentation, Mask R-CNN is the most accurate, with the highest value of precision, recall, and F1-score, respectively among tested models.

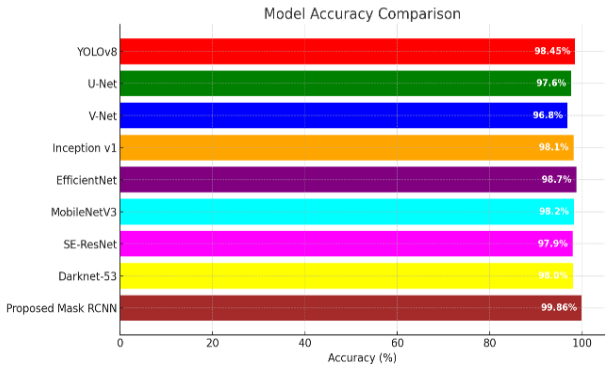

Figure 8: Models achieves the accuracy

Comparison Of Accuracy Percentages For Potato Disease Diagnosis(snippet from Fig8) We used a different colour for each model for easy visual differentiation. While the "Proposed Mask RCNN" strikes the highest rating with an impressive 99.86% accuracy as compared to rest bachelors. It Performs really good at correctly detecting both true positive and true negatives The most accurate remaining architecture is EfficientNet with 98.7% accuracy, which has shown strong performance. Similarly, For YOLOv8 and Inception v1, the accuracy was also found higher which was measured at 98.45% and 98.1%, respectively, indicating their predictive strength. Furthermore, MobileNetV3 and Darknet-53 attain accuracy scores of 98.2% and 98.0%, respectively, further validating their potential for accurately identifying potato diseases. The accuracy rates of SE-ResNet, U-Net, and V-Net are 97.9%, 97.6%, and 96.8% respectively, They are lower than the accuracy of Faster-RCNN, which is still relatively good comparing to other algorithm methods in agricultural disease detection. This graph makes it easy to explore all of these models quickly, as each bar is labeled with its respective accuracy, allowing for a quick comparison of the effectiveness of each model.

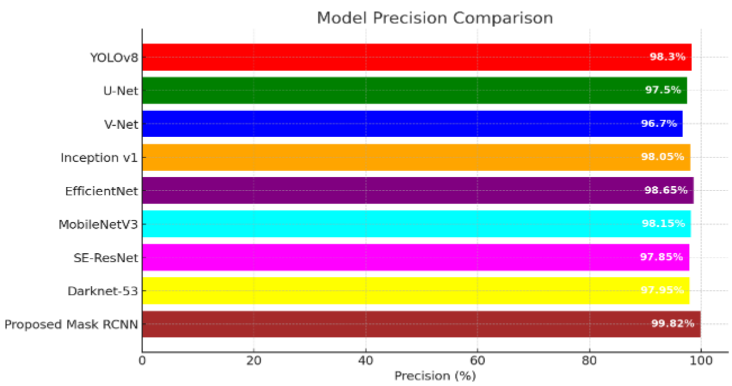

Figure 9: Showing the precision of various models

Figure 9 shows the comparison of precision of different models used for potato disease detection, where each model is denoted by a specific color. "Proposed Mask RCNN" model has the highest precision of 99.82% that demonstrates its performance in recognizing all positive cases and excluding false positive cases. The highest precision of 98.65% is obtained by EfficientNet, indicating that it classifies the positive samples correctly in most cases. Inception v1 and YOLOv8 have precision value as (98.05%) and (98.3%) respectively, which is comparatively lower than the aforementioned value, but nevertheless signifying high accuracy. The other models, MobileNetV3, SE-ResNet, and Darknet-53 maintain competitive accuracy at 98.15%, 97.85%, and 97.95% respectively. U-Net and V-Net had lower precision scores of 97.5% and 96.7%, respectively, that were still acceptable. The precision for each of the model is shown on each bar, thus giving a breve summary on how well the model is detecting true vs false positive cases in the potato disease classification task.

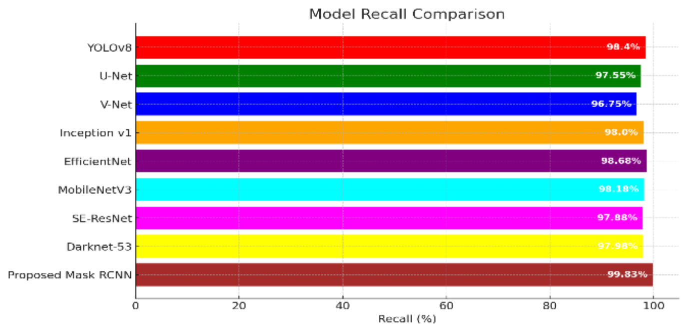

Figure 10: The recall percentages for a range of models

In the last 10 the recall percentages of the different potato disease detection models are compared and presented with a different color for each model. The highest recall is observed at 99.83% by Proposed Mask RCNN model, which shows the proposed model has the best capability to find all the positive cases which should belong to the positive class with the best F1 score and thereby verifying that the proposed model is the best suited with respect to this dataset. The dense Recall ability of EfficientNet reached at 98.68% and YOLOv8 at 98.4%. Due to the correct sensitivity and the reliable predictions, other models like MobileNetV3 and Inception v1 have a recall of 98.18% and 98.0% respectively. Top 2 accuracies with three of the models, namely SE-ResNet and Darknet-53, exhibits closely related recall values at 97.88 and 97.98 respectively, indicating the models did indeed perform better than average, though continued to negotiate lower than the top models of the photo frame at 97.83, 97.77 and 97.34. Although U-Net and V-Net show considerably lower recalls with 97.55% and 96.75%, they perform very similarly to the above three methods. Further, the recall values for each model are shown directly on each bar, which illustrates how many true positive cases each model was able to capture, and enables the ease of comparison for disease detection among the various models.

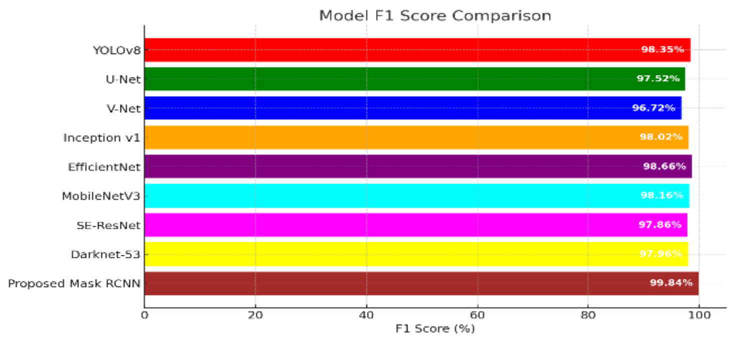

Figure 11: The average F1 scores for various models

Figures 11 compare the F1 Scores of different Potato Disease Detection models together with the colors for each model. Interestingly, the "Proposed Mask RCNN" model attained the best F1 Score (99.84%). Also, it has a positive impact demonstrating its ability to achieve a near-perfect Huberta balance between accuracy vs recall. Thus, it is the most effective model among the models that are evaluated. On the other hand with an F1 Score of 98.66%, nevertheless, EfficientNet is extremely reliable on predicting true positive cases. Over 50% of all models feature an F1 Score more than 98%, with only a handful being relatively strong, such as YOLOv8 (98.35%), MobileNetV3 (98.16%), and Inception v1 (98.02%), among many others. All other variants, specifically, SE-ResNet (97.86%), Darknet-53 (97.96%), U-Net (97.52%), and V-Net (96.72%) perform at the same level, although slightly inferior. It presents the F1 Score for each model via a bar, making it easy to visually identify how different models compare in terms of performance, thereby underpinning the effectiveness of each of those models when tasked with the specific challenge of accurately identifying potato leaf diseases.

Conclusion

In addition, the improved Mask R-CNN framework has demonstrated excellent performance in the accurate detection and segmentation of potato plant leaf diseases compared to other state-of-the-art models. The proposed Mask R-CNN model outperforms competing models, notably YOLOv8, EfficientNet and U-Net, which recorded accuracies of 98.45%, 98.7% and 97.6%, respectively, with an accuracy of 99.86%, precision of 99.82%, recall of 99.83% and an F1-score of 99.84%. As expected, the remarkable improvement can be attributed to more effective feature extraction, refined region proposal network (RPN), and efficient mask segmentation procedures adjusted to agricultural images. The model excels at accurately detecting sick regions while mitigating false positive and false negative while achieving a highly balanced accuracy and recall accuracy. The study highlights the significance of the optimised Mask R-CNN in real-life agricultural contexts, offering a reliable tool for early detection and management of diseases. This study highlights the potential of utilizing deep learning for the advancement of agricultural production and sustainability. It lays the foundation for further development of plant disease identification using advanced neural network architectures.

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