A SURVEY ON MACHINE LEARNING-BASED DETECTION OF POTATO PLANT DISEASE

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ABSTRACT

Agriculture is the backbone of our nation. A significant portion of the Indian economy, accounting for 17% of the nation's GDP, is employed in agriculture, where 58% of the population works. One of the most extensively consumed crops, potatoes are affected by a wide range of illnesses. There are obvious diseases present in the leaf area of this plant. Farmers now have less work to do since deep learning models have produced technologies that boost agricultural output rates and lower plant disease infestation. The diseases of potato plants, including Early Blight (EB) and Late Blight (LB), are covered in detail in this paper, with an emphasis on the many machine learning models used to treat these problems. The results of this investigation confirm that Convolutional Neural Networks (CNN) are more accurate in identifying diseases than any other alternative methods for detection.

Keyword: - *Convolution Neural Network, Potato plant, machine learning, Disease detection*

1. INTRODUCTION

Agriculture is the oldest form and traditional occupation followed by most of the people all around the world. With about 22% of the world's potato crop coming from China, the country leads the globe in potato production. Though agriculture is primarily concentrated in China's north and south, potatoes are the only crop that can be cultivated anywhere in the nation. India has twenty-three states where potatoes are grown. However, Himachal Pradesh, Punjab, Uttar Pradesh, Madhya Pradesh, Gujarat, Maharashtra, Karnataka, West Bengal, Bihar, and Assam are important states that cultivate potatoes. Uttar Pradesh is the top producer with 15,892.00 tons produced yearly.

A potato is a healthy carbohydrate source. However, a number of illnesses that attack potato plants these days have severely hindered potato production. Diseases and disorders are a variety of variables that impact plants and their products[1]. The diseases brought on by fungi, bacteria, or algae are known as biotic factors; on the other hand, rainfall, moisture, and temperature are known to produce problems. In addition to nutritional scarcity [2]. The harmful oomycete, or water mold, Phytophthora infestans is a fungus-like microbe that causes late blight, also referred to as potato blight, on tomatoes and potatoes. "Potato blight" is another common name for Alternaria solani-caused early blight.

Where Alternaria solani fungus forms the recognizable "bullseye" patterned leaf spots. cause stem lesions and tuber blight in potatoes. Therefore, it's critical to detect these illnesses early on so that preventative actions can be performed to preserve the plantation. Farmers or other local specialists visually evaluate the disease as the conventional method of identifying and diagnosing plant leaf diseases. Unfortunately, lengthy processing periods, a lack of specialists on farms, and usually subpar results make this approach unfeasible. There is an urgent need for an automated leaf disease detection system to solve this situation. [1].

In order to detect plant diseases, this research investigates a variety of deep learning and machine learning methods, such as CNNs, DBNs, image processing, and feature extraction. It examines the benefits and drawbacks of each, taking into account elements like image quality and data accessibility. The study shows that the speed and accuracy of plant disease detection are greatly increased by using these methods. The report also contrasts the accuracy of several machine learning methods.

2. REVIEW OF LITERATURE

2.1 Comparison Of different machine leaning models in terms of accuracy

This section presents a number of papers that specifically look at and contrast the performance and accuracy of various machine learning models.

Table-1: Comparison of different machine learning models [1]

SL No.	Machine learning models	Accuracy	References
1	ANN	85-91%	[2]
2	NN	93%	[3]
3	BPNN	92%	[4]
4	Naive Bayes	88.67%	[5]
5	KNN	94.00%	[5]
6	SVM	96.83%	[5]
7	SSD & RCNN	94.60%	[6]
8	CNN	99.09%	[7]

Out of all the models compared in the above table CNN gives the highest accuracy of 99.09%. Below is the graphical representation (Figure 1) of performance of different machine learning models as compared in above Table 1.

- An artificial neural network (ANN) is a paradigm for information processing that is modelled after the way biological nervous systems, such as the brain, process information. The many errors that will occur during the simulation have a greater chance of being reduced as more data is appropriately supplied. This is due to the fuzzy method's inability to take advantage of the ANN approach's training feature. The ANN technique uses the instruction and the portable scanner to deliver 85 to 91% accurate disease detection, depending on the quality of the images provided[2].

- It is possible to model various classifiers, such as Decision Trees and Neural Networks, to develop an effective feature extraction technique for the machine learning classification of plant diseases.
The results can then be compared using the recommended method, like Naïve Bayes, SVM, and CNN [5].

- The image segmentation process employed the K-means methodology, feature extraction was accomplished through the concept of Gray Level Co-occurrence Matrix, and classification was conducted using the multi-class support vector machine approach[8]. This proposed methodology was able to achieve accuracy of 95.9%.

- The ultimate result of CV, which combines pattern recognition and image processing is picture understanding. The process entails transforming an image into a digital format and applying multiple adjustments such as sharpening, color correction, and smoothing to improve the image quality [12].

- A unique architecture with a convolutional network is the basis of a specialized deep learning model that has been created to identify plant diseases from photos of various leaves. SSD functions like a single-shot detector. SSD increases coverage on location, scale, and aspect ratios and yields more predictions with lower quality images. As a result, the model can operate quickly in real time. [9].

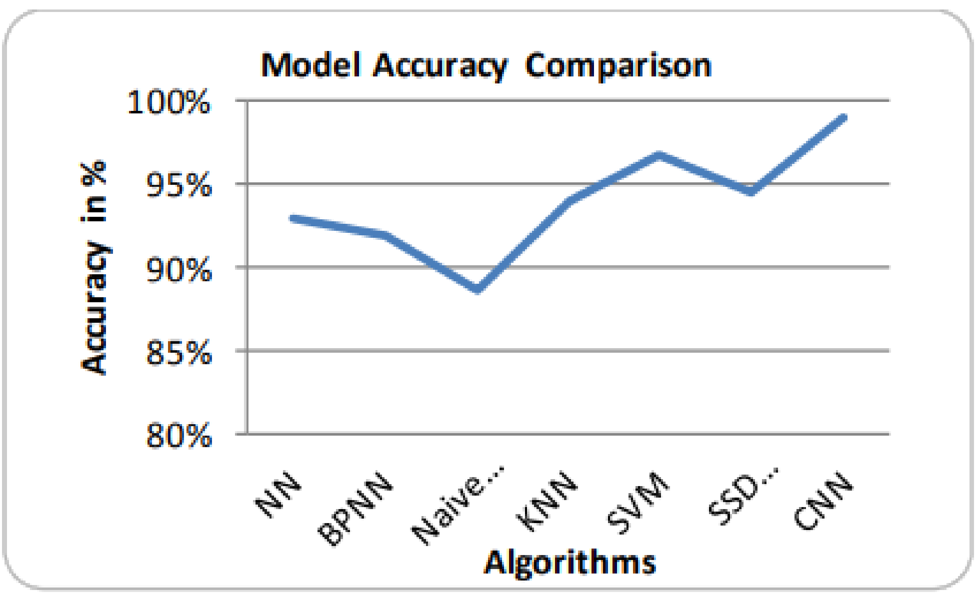

Fig-1: Model accuracy comparision

- Convolutional neural networks (R-CNN) are created by combining rectangular region suggestions with convolutional neural network features. R-CNN is a two-stage detection algorithm. The first step in the process is to identify a portion of an image's regions that might contain an object. The second step involves classifying the object in each region. This improves the efficiency of the classification process [9].

2.2 Comparison of different CNN architecture

- This study describes a CNN that achieves an 18.2% top-5 error rate. An error rate of 16.4% is obtained by averaging the predictions of five comparable CNNs. To categorize the full ImageNet, Fall 2011 release, one CNN was trained with an additional sixth convolutional layer above the final pooling layer and "fine-tuning" it on ILSVRC-2012 yields an error rate of 16 percent. With the five CNNs stated above, averaging their predictions from the pre-trained release of Fall 2011 results in an error rate of 15.3% [14].
- For large-scale picture categorization, they tested very deep convolutional networks (up to 19 weight layers) in this work. It was shown that representation depth improves classification accuracy and that a typical ConvNet architecture with significantly more depth can reach state-of-the-art performance on the ImageNet challenge dataset [15].
- The architecture of the network places a high priority on computational efficiency and practicality, allowing inference to be carried out on individual devices with different processing capacities, especially those with small memory footprints. It was expected that much more expensive non-Inception-type networks with similar depth and width might yield results of similar quality in both detection and classification. Additionally, this paper provides recommendations for future research on automating the construction of sparser and more complex structures and on extending the insights of the Inception architecture to other domains.
- This paper investigates convolutional networks within the Inception architecture framework and presents several design concepts for their scalable enhancement. This advice may result in elevated performance vision networks that are less computationally expensive than more straightforward, monolithic their best-quality iteration of Inception-v2 architectures achieves top-1, top-5, and 21.2% errors for a single crop. assessment of the ILSVR 2012 classification, establishing a new standard cutting edge [17]
- Inception-v4, a pure Inception variation with no residual connections, performs comparably to Inception-ResNet-v2 in terms of recognition. They investigated how the Inception architecture's training speed can be significantly increased by adding residual connections. Due to its increased model size alone, their latest models, with and without residual connections, exhibit superior performance compared to their earlier networks. Remarkably, they achieve this while keeping a lower total number of parameters and computational cost in comparison to alternative methods [18].
- Three main observations are made. First, residual learning flips the situation: the 34-layer ResNet outperforms the 18-layer ResNet (by 2.8%). Furthermore, the 34-layer ResNet demonstrates significantly reduced training error that can be applied to the verification information.

This suggests that the issue of degradation is well handled in this context, and we are able to get gains in accuracy with greater depth. Second, because the training error is successfully decreased, the 34-layer ResNet reduces the top-1 error by 3.5% in comparison to its plain equivalent. Finally, they mentioned that the 18-layer residual/plain nets are comparatively precise; yet, the 18-layer ResNet converges more quickly. If the internet is "not" too deep" (18 layers), the SGD solution in use today is still able to solve the plain net with good solutions. Here, the ResNet facilitates optimization by offering quicker early-stage convergence [19] can be used to calculate the aforementioned measurements [20].

Table-2: Comparison of different CNN architectures[9]

SL No.	Architecture	Highlights	References
1.	AlexNet	While AlexNet and LeNet-5 are similar, AlexNet has stacked convolutional layers, is deeper, and has more filters in each layer.	[10]
2.	VGGNet	Improving the model's accuracy involves increasing its depth through the utilization of small 3 × 3 convolutional filters in each layer. This strategic design choice played a significant role in securing the second-place position in the ILSVRC-2014 challenge.	[11]
3.	GoogLeNet	Enhancing the architecture involves making it both deeper and wider, incorporating various receptive field sizes, and utilizing multiple small convolutions. .	[12]
4.	Inception v3	It boosts the performance of a network by leveraging Batch Normalization for accelerated training. The efficacy of initializing building blocks is maximized through deeper dives.	[13]
5.	Inception v4	In practical terms, the extensive number of layers in Inception-v4 results in a notable decrease in speed.	[14]
6.	ResNet	An innovative design incorporating "skip connections" and extensive batch normalization.	[15]

2.3 Comparison of Accuracy, Recall, F1-score, Precision

Prior surveys have demonstrated that Convolution Neural Networks (CNN) outperformed other machine learning models in terms of outputs Table 1. Other machine learning models include DenseNet201, ResNet50, InceptionV3, and VGG16. Four types of factual measurements are used to evaluate this survey: recall, accuracy, precision, and F1-score. The confusion matrix, which is displayed in Table 3, can be used to calculate the aforementioned measurements [20].

Table-3: Confusion Matrix [16]

TP (True Positive)	FN (False Negative)
FP (False Positive)	TN (True Negative)

Accuracy: The ratio of patients who were successfully classified to all patients indicates the model's accuracy.

$$(TP + TN) / (TP + FN + FP + TN)$$

Precision: The precision of the model is indicated by the ratio of patients with the condition that are correctly classified to the overall number of patients predicted.

$$TP / (TP + FP)$$

Recall: A model's recall metric is the percentage of disease patients who have received a correct diagnosis out of all disease patients.

TP / (TP + FN)

F1-score: Score is a measure that strikes a balance between recall and precision; it is also called as the F Measure.

(2 * Precision * Recall) / (Precision + Recall)

Table 4: Comparison of different machine learning architectures in terms of Accuracy, Recall, F1-Score and Precision [17].

Table-4: Comparison of different machine learning architectures in terms of Accuracy, Recall, F1-Score and Precision [17]

Architectures	**Training Accuracy**	**Validation Accuracy**	**F1-Score**	**Recall**	**Precision**
VGG-16	0.8339	0.8189	0.8188	0.8194	0.8182
Inception ResNet V2	0.9551	0.9091	0.9089	0.9105	0.9075
ResNet-50	0.9873	0.9423	0.9354	0.9358	0.9351
Inception V4	0.9586	0.9489	0.9438	0.9466	0.9410
Improved GoogleNet	0.9829	0.9521	0.9533	0.9539	0.9528
AlexNet	0.9689	0.9578	0.9566	0.9570	0.9563
DenseNet-121	0.9826	0.9580	0.9575	0.9569	0.9581
MobileNet	0.9764	0.9632	0.9618	0.9612	0.9624

- Then, Inception-v4, ResNet-50, and Inception ResNet-v2 architectures have acquired an excellent F1-score, followed by the MobileNet, DenseNet, and AlexNet designs. Due to its fewer parameters, which greatly shortened its computing time, the MobileNet model is somewhat more desirable. The convolutional layers, both depthwise and pointwise, contributed to improving the classification outcome. Consequently, future studies based on the MobileNet design may suggest a CNN model. In addition, this model used fewer epochs than DenseNet and AlexNet models to reach its final accuracy and loss. Furthermore, 58–59 epochs were needed for the DL models, including Inception-v4, Inception ResNet-v2, OverFeat, and VGG-16, to converge training/validation plots, which considerably lengthened the training period.
- By using the idea of the Inception module from the original GoogLeNet model, the enhanced GoogLeNet architecture attained the greatest performance among all the modified versions of CNN architectures in terms of validation accuracy/loss and F1-score. Additionally, it took longer to complete one epoch of training than other modified or enhanced versions of the DL models examined in this article, but it obtained the ultimate accuracy and loss value in 53 epochs, which is the least amount of time.
- An acceptable F1-score that was near to each other was attained by the two MobileNet models, dubbed Modified and Reduced MobileNet models. These altered DL architectures featured six times fewer parameters than the original MobileNet model, which shortened their training time per epoch, and they included depthwise separable convolutional layers, which contributed to a good classification result.
- Additionally, a hybrid version of AlexNet that combined VGG architectures with other architectures has also been studied. It performed well in terms of F1-score and validation accuracy, but it required a significant

amount of time to complete each epoch of training due to its large number of parameters. The model's high performance can be attributed to the incorporation of concepts from the AlexNet and VGG models, including normalization and filter depth selection.

The below Figure 2 shows sample leaves of potato namely (a): leaf affected by Light Blight (b): leaf affected by Early Blight (c): leaf unaffected (Healthy).

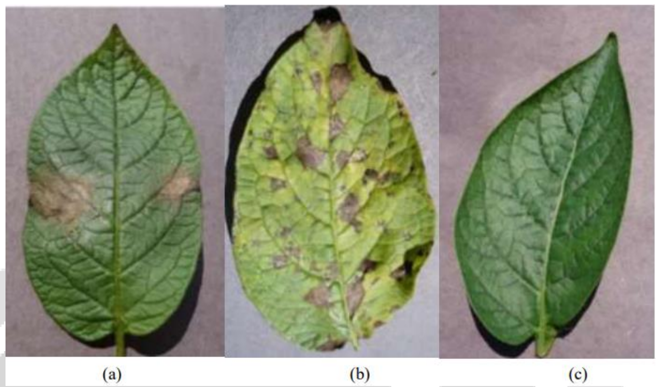

Figure-2: Three sample leaves of potato

Now, the below graph (Figure3) shows the graphical representation of Evaluation Metrics of Proposed Methodology Across the Various Categories.

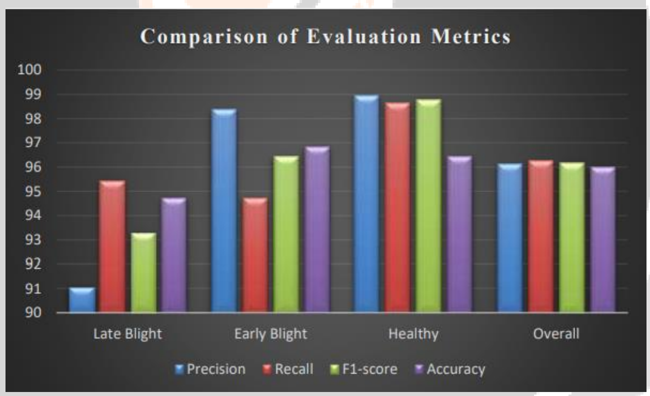

Figure-3: Evaluation Metrics of Proposed Methodology Across the Various Categories [19]

The standard dataset under consideration was freely accessible and comprised two subsets: the training dataset, including 210 images, and the testing dataset, comprising 90 images. A number of evaluation criteria, including accuracy, precision, recall, and F1-score, were used to assess the suggested framework. The suggested model's overall accuracy was about 95.99%, approximately 96.12% for precision, about 96.25% for recall, and approximately 96.16% for the F1-score. The correctness of the suggested framework is 95.99%. However, this precision has to be raised. Convolutional neural networks, in particular, are artificial neural networks that can be used to further extend the current work. These days, a lot of image-related research is conducted using CNN approaches in an effort to achieve more accurate and dependable results. Convolutional layers, fully connected layers, batch normalizations, and activation functions are all important concepts in CNN architectures that help improve accuracy.

3. CONCLUSIONS

After talking about and comparing a number of machine learning models, including ANN, NN, BPNN, Naive Bayes, KNN, SVM, SSD & RCNN, and CNN, we were able to determine which one had the highest accuracy, coming in at 99.09%. Next, we contrasted the highlights of several research papers with the CNN architectures, including VGG-16, Inception ResNet V2, ResNet-50, Inception V4, Improved GoogleNet, AlexNet, DenseNet-121, and MobileNet. Finally, we examined the Evaluation metrics of the suggested methodology in a number of categories, including healthy, early blight, and light blight. In order to further improve this domain, future research should focus on improving the model's accuracy and utilizing multiple datasets to detect potato plant diseases through machine learning models.

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