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A Comprehensive Analysis of Classification of Potato Leaf Disease Detection using Machine Learning

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Abstract — India is the world's second-largest producer of potatoes, demonstrating the country's importance in the agricultural sector. In order to develop a sustainable agricultural system, it is essential to perform relevant research, especially in light of the recent advances in farming technology and the application of artificial intelligence in the detection of plant diseases. Early blight and Late blight have a substantial effect on potato yield and quality, and detecting these leaf diseases by hand can be laborious and time consuming. Due to the complexity involved, computerized and precise identification of these problems during the germination phase can help increase potato crop yield. Various models have been put up in the past to identify various plant diseases. The model offered in this study makes use of pre-trained models, such as Painter's embedding method, to generate results that are more accurate and to extract the required properties from the dataset. After running the results through various classifiers, it became clear that Support Vector Machine (SVM) - Polynomial Kernel was the clear winner, with an accuracy of 99.48% throughout the whole test dataset.

Key words — Potato Leaf Diseases, Image based Machine Learning, Image Embedding Techniques, SVM

I. Introduction

One of the most significant non-cereals, high producing horticultural food crops in the world, the potato is indigenous to Peru and Bolivia in the Andes (South America), and it appears that Portuguese traders brought it to India from Europe in the early 17th century. At first, it became a significant cool season crop in the plains and hills. Producing over 28.9% of the country's total crop output, it is the most adaptable crop, and is now cultivated in almost all of Indian states under diverse agricultural climates. Potatoes are the planet's fourth-biggest agricultural food product, following corn, wheat, and rice in importance. In terms of annual potato production, India comes in at number two with 48.5 million Tonnes produced [1]. The Agricultural and Processed Food Products Export Development Authority (APEDA) reports that over 30.33 percent of the country's entire potato output comes from the state of Uttar Pradesh. Cotton and worsted are sized using potato starch (farina) in the textile business. In potatoes, there is an abundance of potassium, fiber, and vitamins (especially C & B6). It aids in the treatment of diseases like high blood pressure, heart disease, and cancer by lowering blood cholesterol levels. Diseases that have impacted plants on a global scale have had an adverse effect on the agricultural industry. Microorganisms, genetic abnormalities, and infectious agents like bacteria, fungus, and viruses are the main causes of these conditions. Late blight and early blight are fungal infections, but soft rot and common scab are bacterial diseases that affect potato leaves [2]. As a result, we are driven to develop an automated method for detecting and diagnosing these pathogens in order to increase crop production, farmer profit, and overall economic output at the national level. Popular image processing methods such as linear binary pattern (LBP) [3] and K-means clustering [4] have been recommended by several computer vision and image processing experts as a means of detecting these leaf abnormalities. Because of their superiority in function mapping, deep learning models make for excellent feature generators. In this study, we present a deep learning model for disease detection in potato leaves by utilizing a large number of classifiers.

The study has been divided as follows: Section I serves as an introduction, Section II offers related literature to the potato leaf diseases, Section III gives a description of the data set, Section IV shows the platform used, Section V depicts the proposed approach, section

VI provides the results and discussion, and section VII shows as the study's conclusion.

II. Related Works

Numerous researchers have presented a wide variety of ways for diagnosing illnesses of the potato leaf in their studies, demonstrating the diversity with which plant diseases can be detected. This section provides an inventory of such strategies. Badar *et al.* [5] segmented potato leaf image samples based on their various characteristics, such as color, texture, area etc. using K Means Clustering [13] then applied the back propagation neural network technique to the leaf image to discover the disease with 92% classification accuracy. The contrast, correlation, energy, homogeneity, mean, standard deviation, and variance of a picture were all extracted using the image segmentation approach developed by Kumari *et al.* [4]. Diseases on the leaves of cotton and tomato plants are discovered and classified using a neural network as a classifier. They achieved 92.5 percent accuracy in their classifications using this method. To classify illnesses, Islam *et al.* [3] used multiclass SVM on a segmented image from the potato leaf class of the Plant Village dataset [1] and were 95% accurate when classifying data. Grape leaf fungal infections were identified and classified using an image segmentation technique by Li *et al.* [5]. In this research, colour, texture, and shape features were extracted from images using K Means clustering. The retrieved features are subsequently put to use in an SVM-based disease identification process. Chen *et al.* [6] employ the CNN models Leaf Net [18] and DSIFT [19] to extract visual features. The tea leaf images are classified with support vector machine (SVM) and multi-layer perceptron (MLP) classifiers using a bag of visual words (BOVW) model. For the purposes of both image classification and identification [16, 17], recent improvements in the Faster R-CNN [20] method have been applied. The concept of transfer learning was applied by A. Ramcharan *et al.* [15] to images of cassava disease.

III. Dataset

The Plant Village Dataset [1] is an open-source collection that is available for scholarly use. Apple, blueberry, pepper, tomato and potato are just some of the fruits and vegetables included in the almost 55,000 images of healthy and diseased leaves included in the dataset. There are colored and grayscale images of each folder of fruits and vegetables. There are numerous leaf diseases that can affect any crop, and these diseases are typically separated out into their own categories. Two types of leaf images, one with a background and one without, are included in dataset [1]. In Fig.1 you can see an example of each type of illness that can affect potato leaves. The number of photos in a given class varies from 152 to 1000 and is not constant. Only potato photographs were used to solve our classification issue, which consists of three classes: early blight, late blight, and healthy leaf images. Table 1 displays information about the dataset, such as the quantity of training and testing samples.

Table 1: The train-test-split data

Label	Category	Total Samples	Training Samples	Testing Samples
1	Healthy	152	122	30
2	Early Blight	1000	787	213
3	Late Blight	1000	791	209
	Total	2152	1700	452

Fig.1. Sample Image of Potato Leaf diseases (a) Healthy (b) Early Blight (c) Late Blight

IV. Platform Utilized

The research work is done in the computer system having the specifications: Intel (R) Core (TM) i5-5200U CPU @ 2.20GHz with Windows 10Pro 64-bit, version 21H2. An orange data mining programme with an image analytics plugin is used to complete the feature extraction and classification operation. Orange is a free, publicly available Python package used for data analysis and visualization. The user can construct a data analysis process by dragging and dropping widgets into a canvas interface. Users can experiment with visualization in an interactive manner by making use of the foundational functionalities such as data table presentation, feature selection, constructing predictors, visualizing data pieces, etc.

V. Proposed Approach

A. Feature extraction using VGG16

K. Simonyan and A. Zisserman's VGG16 is a CNN-based method [6]. ImageNet, a dataset of over 15 million superior-resolution photos that have been labelled and fall into 22000 categories, was used to train this model. This model was developed for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), in which 1.3 million photos were utilized for training, 50000 for validation, and 100000 for testing. In VGG16 [6], the only preprocessing carried out is the simple subtraction of each pixel's mean RGB value. By exchanging all of the large kernel-sized filters over a 2×2 window with a 2-stride size with a set of smaller 3×3 kernel-sized pooling, the VGG16 [7] model achieved better classification accuracy than AlexNet. Finally, the model incorporates a SoftMax layer. All of the model's hidden layers have been given non-linearity with the use of the ReLu function [7] and successively stacked filters. The 1-1 filters were also incorporated into the model to make use of the linear transformation. The padding of 1 pixel is done in order to preserve the spatial resolution. Only 5 convolutional layers carry out spatial pooling. GoogleNet, the challenge winner, had an error rate of 6.7% in the top 5 validation and test errors, while VGG16's error rate was 6.8%.

B. Architecture of CNN

There are two main parts to a CNN's architecture. A convolutional tool is used in the feature extraction process, which isolates and catalogues the various parts of a picture for analysis. There are numerous convolutional and pooling layers in the network used for feature extraction. A fully-connected layer uses the convolutional output into account when deciding which category, the image belongs to. This methodology for extracting CNN features from datasets aims to do it with as few features as possible. It generates new features by merging together preexisting features into a single, more robust feature. There are many tiers of CNN, as shown in the Fig.2.

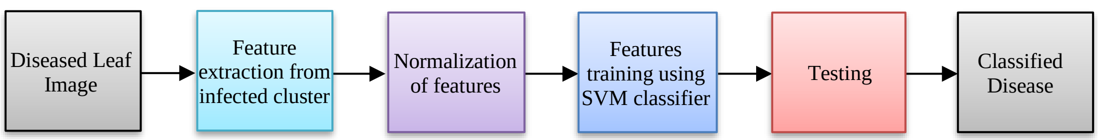


Fig. 2. Block diagram of the proposed work

C. Model

The medical, agricultural, and other sectors have all found widespread use for deep convolutional neural network applications. To get the most useful information out of the dataset, we employed a pre-trained model called Painters. In this manner, we make use of our prior knowledge rather than starting from scratch. Many pre-trained models are available, including VGG16, VGG19 [7] and InceptionV3 [11]. Pre-trained models allow us to retrieve features from the photos. Classifiers like SVM [8], Logistic Regression [9], Neural Network [10] and KNN [12], and now use these features as input. We discovered that SVM Polynomial kernel provided the most up-to-date answer after analyzing the outcomes from all the aforementioned ways

D. Classification

Since SVM can be used for classification as well as regression, it is termed as the most used supervised learning method. The most intriguing aspect of SVM is that it can operate on non-linear datasets as well. To do this, we employ a kernel method that makes it simpler to categorize the points. The formula of the Polynomial Kernel is:

$$f(X_1, X_2) = (X_1^T . X_2 + 1)^d \quad (1)$$

Here, d denotes the polynomial's degree. Given X_1 and X_2 as features and Y as the target variable, we get,

$$X_1^T . X_2 = [X_1 \ X_2] . [X_1 \ X_2] = \begin{bmatrix} X_1^2 & X_1 X_2 \\ X_1 X_2 & X_2^2 \end{bmatrix} \quad (2)$$

So, we basically need to find X_1^2, X_2^2 and $X_1 X_2$ and now we can see that two dimensions got converted into 5 dimensions.

VI. Results and Discussion

A. Performance Evaluation

Performance evaluation is crucial to machine learning, and classifier algorithms can be evaluated using a variety of performance metrics. This section compares various Machine Learning (ML) algorithms for identifying images of Potato Leaf Disease in terms of

Area under the Curve (AUC), Classification Accuracy (CA), F1 Score, Precision, and Recall.

1) The efficacy of a solution to a multi-class classification problem is verified by examining the area under the receiver operating characteristics curve in short mentioned as AUC. It is one of the most important evaluation metrics for assessing how well a classification model is performing. Greater AUC shows that the model can distinguish between positive and negative classifications more effectively [25].
2) Classification Accuracy (CA) is a crucial parameter that gauges a classifier's overall performance, and defined as:

$$\text{CA} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

3) A hybrid metric called the F1 score, which is provided as:

$$\text{F1 Score} = \frac{2TP}{2TP + FP + FN} \tag{4}$$

4) The term "precision" refers to the process of measuring the accuracy of optimistic forecasts:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

5) Given the coverage of the actual positive samples, recall is a statistic that is expressed as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

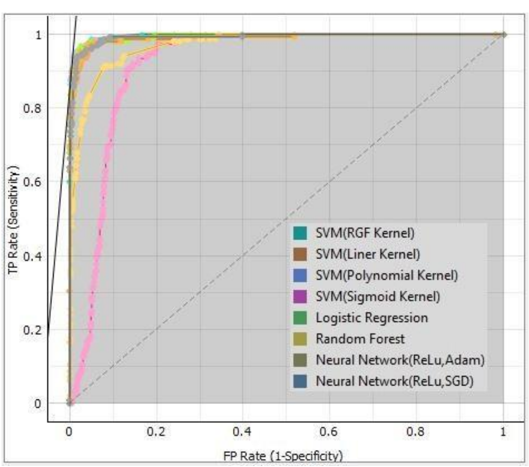
Table 2: Performance Evaluation of Learning models for various Image embedding Techniques

Embedding Technique	Learning Model	AUC	CA	F1 Score	Precision	Recall
SqueezeNet	SVM (Sigmoid Kernel)	0.854535	0.641264	0.635173	0.697128	0.641264
	SVM (Polynomial Kernel)	0.996983	0.969796	0.96965	0.969666	0.969796
	SVM (Linear Kernel)	0.994746	0.959108	0.959022	0.958967	0.959108
	SVM (RBF Kernel)	0.996271	0.962825	0.962587	0.962893	0.962825
	Random Forest	0.965037	0.880576	0.876434	0.881236	0.880576
	Neural Network (Adam)	0.996811	0.968788	0.96982	0.969847	0.969796
	Neural Network (SGD)	0.996942	0.967472	0.967346	0.967282	0.967472
	Logistic Regression	0.996741	0.969331	0.969189	0.969122	0.969331
VGG 16	SVM (Sigmoid Kernel)	0.959318	0.896375	0.897452	0.900266	0.896375
	SVM (Polynomial Kernel)	0.996472	0.969331	0.969163	0.969245	0.969331
	SVM (Linear Kernel)	0.996539	0.967937	0.967809	0.967785	0.967937
	SVM (RBF Kernel)	0.992127	0.952138	0.951575	0.953901	0.952138
	Random Forest	0.975279	0.906134	0.902535	0.906014	0.906134
	Neural Network (Adam)	0.994594	0.966078	0.966164	0.966301	0.966078
	Neural Network (SGD)	0.99478	0.966543	0.966453	0.966642	0.966543
	Logistic Regression	0.998183	0.974907	0.974741	0.974761	0.974907
Inception V3	SVM (Sigmoid Kernel)	0.949229	0.874535	0.874574	0.876794	0.874535
	SVM (Polynomial Kernel)	0.998003	0.969796	0.969424	0.969359	0.969796
	SVM (Linear Kernel)	0.997968	0.974442	0.974345	0.974272	0.974442
	SVM (RBF Kernel)	0.996832	0.968401	0.967551	0.968116	0.968401
	Random Forest	0.965804	0.88987	0.883568	0.890141	0.88987
	Neural Network (Adam)	0.997447	0.969331	0.969068	0.968958	0.969331
	Neural Network (SGD)	0.996466	0.965149	0.964951	0.964907	0.965149
	Logistic Regression	0.997925	0.975372	0.975215	0.975142	0.975372
Painters	SVM (Sigmoid Kernel)	0.993656	0.960967	0.960901	0.961942	0.960967
	SVM (Polynomial Kernel)	0.999923	**0.994888**	0.994869	0.994901	0.994888
	SVM (Linear Kernel)	0.999895	0.992565	0.992566	0.992582	0.992565
	SVM (RBF Kernel)	0.999831	0.987918	0.987799	0.988143	0.987918
	Random Forest	0.992185	0.953996	0.953182	0.954678	0.953996
	Neural Network (Adam)	0.999706	0.990242	0.990237	0.990255	0.990242

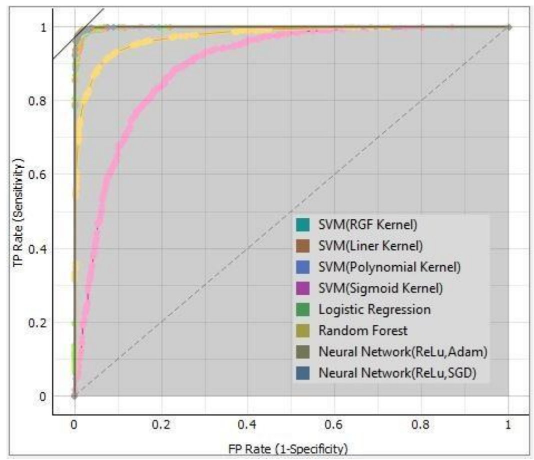
	Neural Network (SGD)	0.999658	0.988848	0.988844	0.988927	0.988848
	Logistic Regression	0.999843	0.99303	0.993022	0.993043	0.99303
Deeploc	SVM (Sigmoid Kernel)	0.700113	0.460502	0.404263	0.519436	0.460502
	SVM (Polynomial Kernel)	0.687551	0.590613	0.553984	0.672285	0.590613
	SVM (Linear Kernel)	0.744255	0.583643	0.581404	0.589699	0.583643
	SVM (RBF Kernel)	0.851248	0.736989	0.737125	0.747042	0.736989
	Random Forest	0.930092	0.835967	0.832935	0.833101	0.835967
	Neural Network (Adam)	0.970595	0.896375	0.89602	0.895774	0.896375
	Neural Network (SGD)	0.966122	0.88987	0.888396	0.888601	0.88987
	Logistic Regression	0.978638	0.91171	0.911418	0.911216	0.91171

B. SqueezeNet

SqueezeNet, an alternative to AlexNet for image identification, utilizes 50 times less parameters and achieves the same accuracy as AlexNet. We constructed the SqueezeNet using the weights from the author's original model. As an embedding, we employ activations from the pre-SoftMax (flatten10) layer. The suggested model makes use of 2152 photos of potato leaves, including 1000 early blight, 1000 late blight, and 152 photos of healthy leaves from a plant village dataset. There are a total of 1700 photos (70% of the total) in the dataset's training section, and 452 images (30%) in its test section. SVM, Random Forest, neural network, and SVM are all different classifiers. SVM (Polynomial Kernel), among them, offers the most cutting-edge solution with a classification accuracy of 99.48%. Performance metrics including AUC, CA, Precision, and Recall are used to assess the effectiveness of the model. The values evaluated between various ML algorithms for various picture embedding approaches are shown in Table.1. The most important statistic to assess is classification accuracy (CA), which shows the actual number of accurate predictions.



(a)



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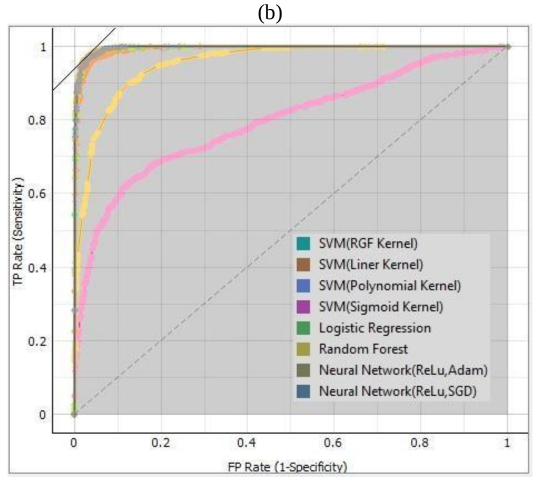


(c)

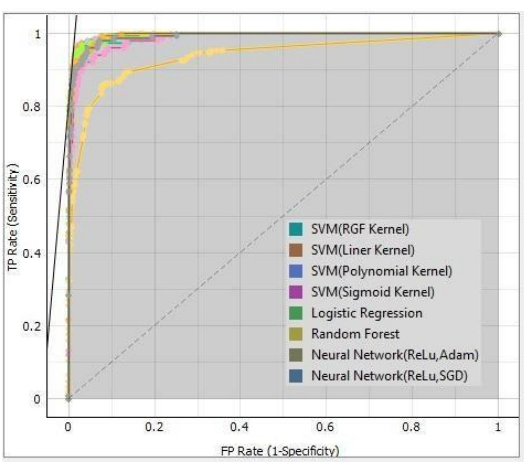
Fig.3. ROC plot of Potato leaf diseases using SqueezeNet (a) Healthy (b) Early Blight (c) Late Blight

SVM-sigmoid, SVM-polynomial kernel, SVM-linear kernel, SVM-RBF kernel, Random Forest, NN (Adam), NN (SGD), and Logistic Regression had respective CA values of 64.12%, 96.97%, 95.91%, 96.28%, 88.05%, 96.87%, 96.74%, and 96.93% when used with the SqueezeNet image embedding technique. With a score of 96.97%, the SVM-polynomial machine learning algorithm was found to perform better. The NN (Adam) algorithm comes next, and then the NN (SGD) algorithm. With the SVM-sigmoid model, the lowest accuracy percentage may be seen in this situation.

The relative CA values for the AUC of the SVM-sigmoid, SVM-polynomial kernel, SVM-linear kernel, Random Forest, NN (Adam), NN (SGD), and Logistic Regression models are 85.45%, 99.69%, 99.47%, 99.62%, 96.5%, 99.68%, 99.69%, and 99.67%. Since the AUC shows how well a classification model performs, the SVM-polynomial model once more outperforms all of its competitors, with a top value of 99.69%SVM-polynomial values for precision and recall are likewise relatively high at 96.96% and 96.97%, respectively. Figure 3 shows the ROC curves for the potato leaf diseases using SqueezeNet.

C. Inception V3

InceptionV3 is the name of Google's deep neural network for picture identification. It is trained using the ImageNet data set. For the embedding, we use the activations of the model's penultimate layer, which represents images as vectors. The 2152 photos of leaves employed in this proposed model were generated from a plant village dataset consisting of 1000 images of early blight, 1000 images of late blight, and 152 images of healthy potato leaves. Classification Accuracy (CA) values for the SVM-sigmoid, SVM-polynomial kernel, SVM-linear kernel, SVM-RBF kernel, Random Forest, NN (Adam), NN (SGD), and Logistic Regression are 87.74%, 96.97%, 97.44%, 96.84%, 88.98%, 96.93%, 96.51%, and 97.53%, respectively. Out of all the methods, the Logistic Regression machine learning algorithm has the best efficiency and accuracy outcomes, with a value of 97.53%.



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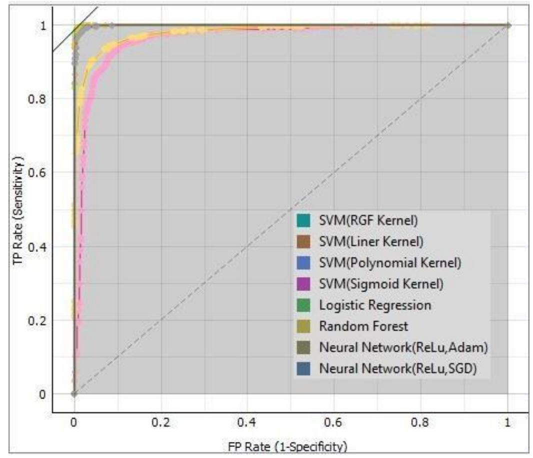

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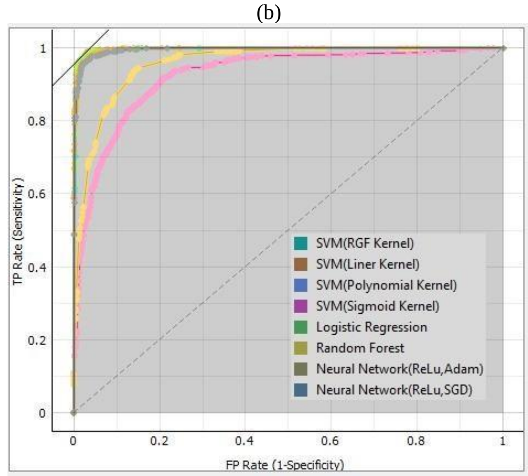
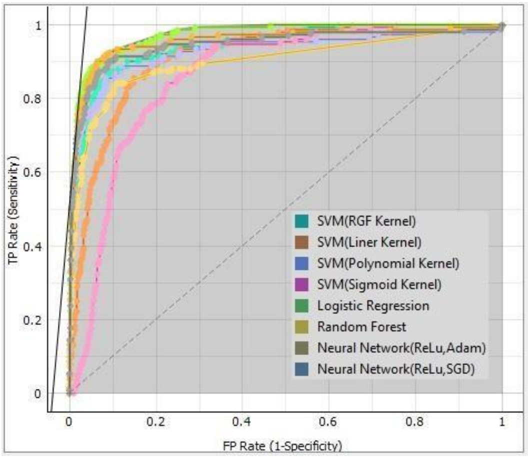


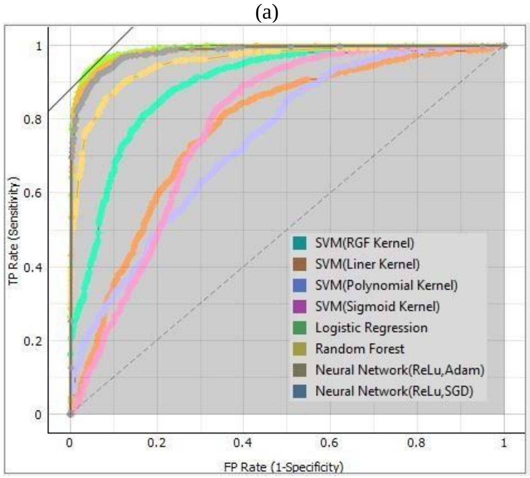
(c)

Fig.4. ROC plot of Potato leaf diseases using Inception V3
(a) Healthy (b) Early Blight (c) Late Blight

The SVM linear algorithm is the next, and then the SVM polynomial algorithm. With the SVM-sigmoid model, the lowest accuracy percentage may be seen in this situation. The relative AUC values for the SVM-sigmoid, SVM-polynomial, SVM-linear, Random Forest, NN (Adam), NN (SGD), and Logistic Regression models are 94.92%, 99.8%, 99.79%, 99.68%, 96.58%, 99.74%, 99.64%, and 99.79%.



(a)



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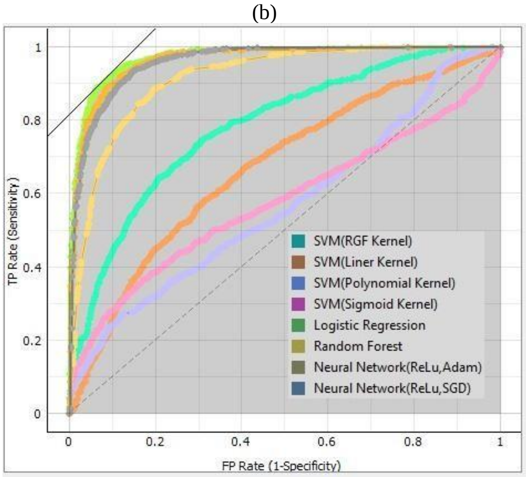


(c)

Fig.5. ROC plot of Potato leaf diseases using Deeploc
(a) Healthy (b) Early Blight (c) Late Blight

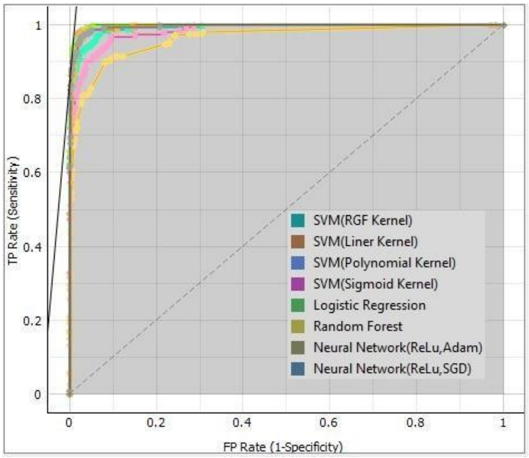
Since the AUC shows how well a classification model performs, the SVM-polynomial model once more outperforms all of its competitors, with a top value of 99.8%. With values of 96.93% and 96.97%, respectively, Precision and Recall scores for SVM-polynomial are likewise relatively high. Figure 4 shows the ROC curves for the potato leaf diseases using Inception V3.

D. Deeploc

Using 21,882 single-cell pictures that had been manually sorted into one of 15 localization compartments, the convolutional network Deeploc was trained. The embedding's are fc/2's penultimate layer activations. The learning models SVM-sigmoid, SVM-polynomial, SVM-linear, SVM-RBF, Random Forest, NN (Adam), NN (SGD), and Logistic Regression have respective classification accuracy (CA) values of 46.05%, 59.06%, 58.36%, 73.69%, 83.59%, 89.63%, 88.98%, and 91.17%. Out of all the methods, the NN (Adam) machine learning algorithm has the best efficiency and accuracy outcomes, with a value of 89.63%. The NN (SGD) is the next, and then comes logistic regression. With the SVM-sigmoid model, the lowest accuracy percentage may be seen in this situation. The relative AUCs for the SVM-sigmoid, SVM-polynomial, SVM-linear, SVM-RBF, Random Forest, NN (Adam), NN (SGD), and Logistic Regression models are 70%, 68.75%, 85.12%, 93%, 97%, 96.61%, and 97.86%. Since the AUC shows how well a classification model performs, logistic regression fared well, scoring 97.86%. With values of 91.12% and 91.17%, respectively, precision and recall for logistic regression are likewise relatively good. Figure 5 shows the ROC curves for the potato leaf diseases using Deeploc.

E. VGG-16

Deep neural networks called VGG16 and VGG19 were proposed for picture recognition by the Visual Geometry Group at the University of Oxford. On the ImageNet data set, they are trained. We employ a community implementation of original weighted networks. Classification Accuracy (CA) ratings for the learning models SVM-sigmoid, SVM-polynomial, SVM-linear, SVM-RBF, Random Forest, NN (Adam), NN (SGD), and Logistic Regression are 89.63%, 96.79%, 95.21%, 90.61%, 96.6%, and 97.49%, respectively. Out of all the methodologies, it has been shown that the Logistic Regression produces the best accurate and efficient outcomes, with a value of 97.49%. The SVM-linear kernel and SVM-polynomial are the following two. With the SVM-sigmoid model, the lowest accuracy percentage may be seen in this situation. The relative AUC values for the SVM-sigmoid, SVM-polynomial, SVM-linear, SVM-RBF, Random Forest, NN (Adam), NN (SGD), and Logistic Regression models are 95.93%, 99.64%, 99.65%, 99.21%, 97.52%, 99.45%, 99.47%, and 99.81%.



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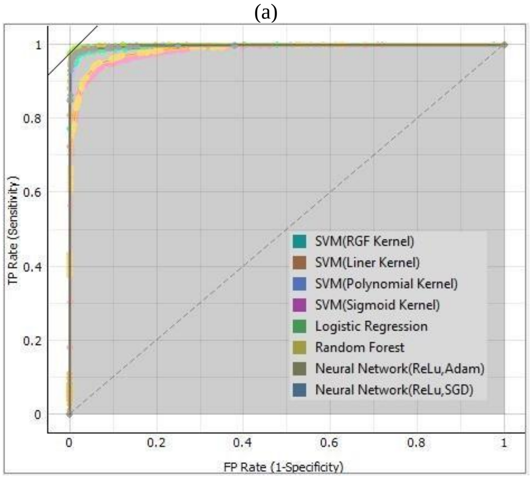

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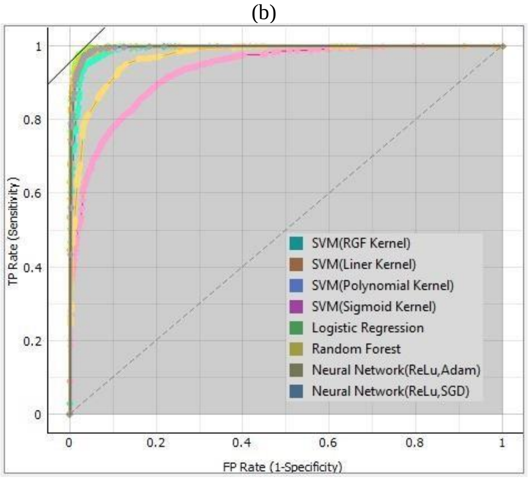
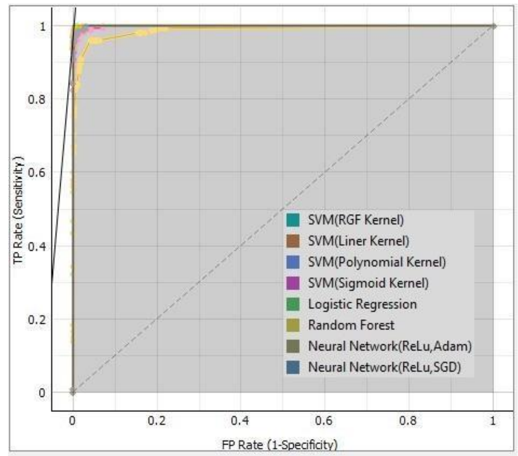


(c)

Fig.6. ROC plot of Potato leaf diseases using VGG-16
(a) Healthy (b) Early Blight (c) Late Blight

Since the AUC shows how well the classification model performs, logistic regression did well with a 99.81% accuracy rate. With values of 97.74% and 97.49%, respectively, precision and recall values for logistic regression are somewhat lower. Figure 6 shows the ROC curves for the illnesses of potato leaves.



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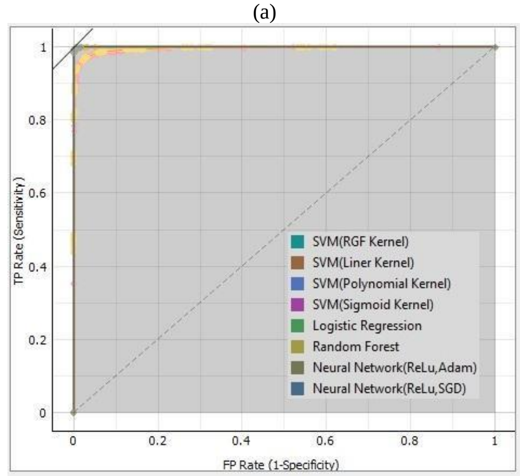
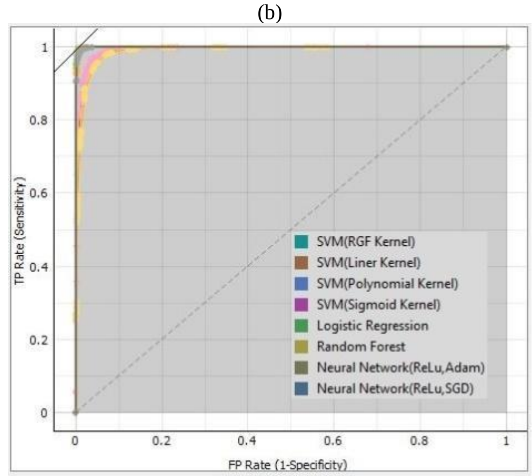


(b)



(c)

Fig.7. ROC plot of Potato leaf diseases using Painters
(a) Healthy (b) Early Blight (c) Late Blight

F. Painters

Kaggle's Painter by Numbers champion, the Painters embedder, learned from 79,433 images of paintings by 1,584 artists. An embedding is calculated based on the activations of the hidden layer of the network. For the classification accuracy (CA) for Painters image embedding technique, the learning models SVM-sigmoid, SVM-polynomial kernel, SVM-linear kernel, SVM-RBF kernel, Random Forest, NN (Adam), NN (SGD), and Logistic Regression have respective CA values of 96.09%, 99.48%, 99.25%, 98.79%, 95.39%, 99.02%, 98.88%, and 99.3%.. Out of all the methodologies, it has been found that the SVM-polynomial kernel machine learning algorithm produces the best accurate and efficient results, with a value of 99.48%. Logistic regression is the next, followed by SVM-Linear kernel. With the SVM-sigmoid model, the lowest accuracy percentage may be seen in this situation. Random Forest, NN (Adam), NN (SGD), SVM-sigmoid, SVM-polynomial, SVM-linear, SVM-RBF, and Logistic Regression all have respective AUC values of 99.36%, 99.99%, 99.98%, 99.21%, 99.97%, 99.96%, and 99.98%. Since the AUC illustrates the performance of the classification model again SVM-Polynomial kernel performed best. Precision and Recall values are comparatively same value for SVM-polynomial kernel having the values of 99.49% and 99.48% respectively. The ROC curves for the potato leaf diseases using Painters are depicted in Fig.7.

VII. Conclusion

In this work, an investigation is developed on eight kinds of machine learning classifiers for identifying the potato leaf diseases. The concept of transfer learning, as well as the creation of an automated system is developed for detecting and classifying diseases in their early and late blights with their healthy stages. When compared to other classifiers SVM-kernel gave a solution in achieving the CA of 99.48% for the dataset, with an increase of 1.9% and 2.7% compared to the earlier researchers in [2] and [3] respectively. Our method assists farmers in boosting crop yields and spotting diseases at their early stages since a disease in a plant must be found sooner for higher productivity and crop quality. It would be really helpful if this system could be installed on smartphones so that farmers could take a photo of a diseased or healthy leaf and upload it to the server because disease detection requires a lot of skill. The type of illness will be identified and categorized by the server automatically.

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