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Image Based Potato Leaf Disease DetectionUsing CNN-LSTM model

Gargi Sharma[1], Gourav Shrivastava[2]

[1]Research Scholar, [2]Assistant Professor
Sanjeev Agrawal Global Educational University, Bhopal

***Abstract*— In recent years, the agricultural industry has faced significant challenges in food production due to the prevalence of crop disease. Potato is one of the most well-known crop cultivates in India and diseases such as early blight and late blight, significantly impact the quality and yield of potatoes, and manual interpretation of these leaf disease is time consuming and labour intensive. To address the issue, this paper proposes a novel approach for potato leaf disease detection by combining CNN and LSTM algorithms. In the proposed algorithm CNN is used to extract different features from leaf images and then with the help of LSTM classifier, the result was perceived. The objective of the model is to develop an accurate and efficient model that can identify diseases affecting potato crops and the proposed model has achieved an accuracy of 98.5% on the potato dataset.**

***Index Terms*—Deep learning, CNN, LSTM, leaf Disease**

I. INTRODUCTION

Plant diseases in agriculture have a negative impact on food output.[1]. For nearly 58% of the population in India, Agriculture is the most important source of revenue.

[2] In FY20, agriculture, forestry, and fisheries contributed Rs.19.84crore lakh (US$ 276.37 billion) to GDP. Agriculture and associated industries account for 18.8% of total GVA, according to preliminary national income estimates for FY22 (at current prices). India's consumer spending is predicted to grow by 6.6% in 2021, following a pandemic-related decrease. Agriculture and related sectors grew by 3.6% at constant prices in FY21. Pests, crop diseases, and post-harvest losses account for 40–50% of all agricultural yields in the poor world. Even within the USA, that proportion ranges from 20- 25%." Analyzing Image could aid in the discovery of an object on the farm. Furthermore, we can find weeds on the field using picture object categorization, which will promote crop growth. For financial and quantitative field evaluation, determine agricultural commodities strategy plans for import- export policies and trebling farmer earnings., early and ac- curate crop yield estimation is crucial [3]. The food market is prepared for significant expansion in India, with India's contribution to the global food trade expanding annually, thanks to its enormous value-adding potential, notably in the food processing business. The Indian grocery and food market is the sixth-largest in the world, with retail accounting for70%of total sales. Food processing is one of India's largest industries, accounting for 32% of the country's overall food industry and ranking fifth in production, consumption, export, and anticipated growth. [4] The potato is the world's most significant food crop. The potato has long been regarded as a 'poor man's friend. Potatoes have been grown throughout the country for more than300 years. Potato is now one of the most well-known crops in the country for vegetable production. Potatoes are a cost-effective food that adds low-cost energy to the human diet. Potatoes are high in starch, vitamins, particularly C and B1, and minerals. [5] After rice, wheat, and maize, the potato (Solanum tuberosumL.) has risen to become India's fourth most significant food crop. Potato isa must-have in any Indian vegetable basket. Because potato has a high dry matter, edible energy, and proteincontent, it isa nutritionally superior vegetable and a staple food not only in our country but worldwide. It has now become a staple of breakfast, lunch, and supper menus worldwide. Because it is a short-term crop, it produces more dry matter, edible energy, and protein in a shorter period than cereals such as rice and wheat. As a result, potatoes may prove to be a helpful instrument in achieving national nutritional security. Potato is anintegral part of our economy, and some harmful diseases affect potato diseases like Early Blight, Late Blight, Common scurf, and Black scarf. [6] Insects and plant diseases wreak havoc on the economy, society, and environment. Plant diseases must be diagnosed it in advance in order to avoid such losses. To detect plant diseases, these businesses have traditionally relied on specialists such as agricultural engineers or botanists, resulting in significant overhead costs, time loss, and inefficiency. Recent developments in object identification have made it feasible to detect diseases and pests in a very effective manner, both quickly and without the need for expertise. [7] India's production is estimated to be 53.7 million tons. Detail state-wise chart of potatoproduction in India in fig1.

II. LITERATURE SURVEY

[7] The author employs leaf images and a 2-stage deep CNN model for plant disease detection and citrus disease categorization. The proposed approach consists of two key stages: first, suggesting the probable target diseased region using a region proposal network and second, categorizing the most likely target region to the appropriate disease class using a classifier. The model has accuracy of 94.37% and an average precision value of 95.8%.

[8] This research systematically provides a method for systematically classifying plant disease symptoms using con- volitional neural networks. When paired with the suggested training configuration, the memory efficiency of these net- works enables the quick creation of industrial applications by lowering training times. The inappropriate distribution of samples among classes, often known as the class imbalance problem, is a fundamental issue that may be resolved us-ing a straightforward statistical technique. Transfer learning is a well-known method for training small datasets that transfers

previously-learned weights from a more extensive dataset. However, negative transfer learning is a prevalent issue during transfer learning. Therefore, a step-by-step strategy to transfer learning is given, facilitating rapid convergence while minimising overfitting and limiting negative transfer learning during knowledge transfer between domains. The system is trained and tested using two plant disease datasets, namely Plant Village (a publicly available dataset) and the pepper disease dataset supplied by the National Institute of Horticultural and Herbal Science, Republic of Korea. The pepper dataset is complex since it comprises photos of several plant sections, including leaf, pulp, and stem. The suggested approach outperformed prior efforts on the Plant Village dataset and obtained accuracy 99.9 % on Pepper dataset and accuracy of 99.69% on the Plant Village dataset.

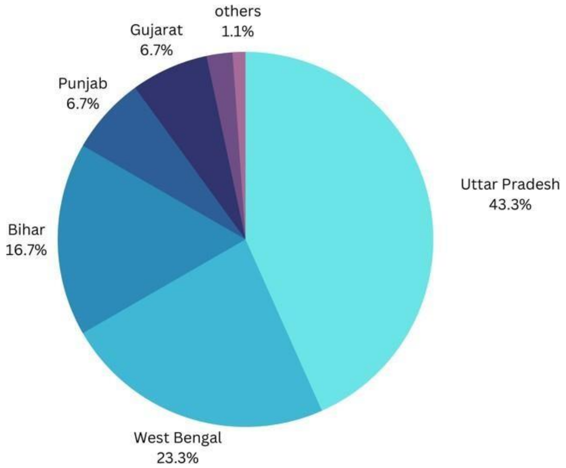

Fig. 1. Potato Production in India

[9]. In this paper, a restructured residual dense network was proposed to identify tomato leaf diseases. This hybrid deep learning model combines the benefits of deep residual and dense networks, reducing the number of training process parameters to improve calculation accuracy and enhance the flow of information and gradients. The original RDN model was first employed for super image resolution. Thus, it is necessary to reconstruct the network architecture for classification tasks by modifying the input image characteristics and hyper parameters. Experimental findings demonstrate that this model can obtain a 95% average identification accuracy onthe Tomato test dataset from the AI Challenger 2018 datasets, proving its good performance. In addition, the redesigned residual dense network model may make considerable gains in crop leaf recognition over most current state-of-the-art modelswhile using less computation to attain excellent performance. [10]. This study proposes a convolutional neural networks (CNNs) model using an integrated method. The suggested CNN model aims to distinguish healthy fruits and leaves fromthose with common citrus illnesses such as black spot, canker,scab, greening, and Melanose. By merging several layers, the proposed CNN model obtains complementing discriminativecharacteristics. On the Citrus and PlantVillage datasets, theCNN model was compared to several contemporary deep learning algorithms. In a range of measuring parameters, the CNN Model surpasses its competitors, as determined by experimental data. The CNN Model has a test accuracy of 94.55%, making it a powerful decision support tool for farmers' citrus fruit/leaf disease classification.

[11] The author uses a Custom CenterNet framework with a DenseNet-77 base network, and they have developed a robust plant disease classification system. The described procedure consists of three phases. First, annotations are created to identify the region of interest in the initial phase. Second, denseNet-77 is proposed to extract deep vital points in an enhanced CenterNet. Lastly, the one-stage detector CenterNet is utilised to identify and classify various plant illnesses. To do the performance study, they utilised the PlantVillage Kaggle database, which is the standard dataset for plant illnesses and challenges involving intensity fluctuations, colour changes, and leaf shape and size discrepancies. These analyses demonstrate that the given method is more effective and trustworthy than other contemporary methodologies for identifying and classifying plant diseases.

[12] In this paper, "Convents" were utilized for the detection and categorization of plant diseases. They obtained a PlantViallge dataset from the Kaggle platform. It features photos of 15 distinct plant leaf classes from three different plants: potato, pepper, and tomato. We separated the dataset into three datasets and applied Convnets to each of the three datasets. they attained an accuracy of 98.3%, 98.5%, and 95% for detecting potato plant disease, pepper plant disease, and tomato plant disease, respectively. The experimental findings indicate that the model has a high detection and classification rate for plant leaf diseases.

[13]. The Author discusses the challenge of plant disease and pest detection and compares it to conventional plant diseaseand pest detection techniques. This report summarises the research conducted in recent years on detecting plant diseases and pests using deep learning from three perspectives: classification network, detection network, and segmentation network, along with the merits and disadvantages of each technique. Existing research' efficacy is evaluated with the introduction of shared data sets. This article explores potentialobstacles in practical implementations of severe learning-basedplant disease and pest detection. In addition, potential remediesand research ideas for the issues are suggested, and numerous proposals are made. This research finishes with a study and forecast of the future evolution of machine learning-baseddetection of severe plant diseases and pests.

[14] The author intends to detect early illness on plant leaves with microscopic disease blobs using Artificial Neural Network, that can be recognised with higher resolution photos. After a pre-processing phase employing a contrast enhancement technique, all contaminated blobs in the whole dataset are segmented. They employed a hybrid metaheuristic-based wrapper-based feature selection method A Numerous measurement-based features that represent the blobs are identified, and they are then selected depending on how they affectthe performance of the model. The selected features are inputsto Artificial neural network. The author compares the results using CNN model The ANN's results outperform CNNs with a more straightforward network structure (89.41% vs. 78.64%, 79.92%, and 84.88%, respectively). It demonstrates this technique may be applied to low- end

devices such as cellphones, which would greatly benefit farmers.

[15] The author discusses a Tomato illness detection usinga deep learning method. To identify and categorize tomato disease A CNN based model is used. This model consists of 3 convolution layers, three max-pooling layers, and two fully linked layers. The results of this shows that the proposed model outperforms the pre-trained models VGG16, InceptionV3, and MobileNet. The suggested model has an average classification accuracy of 91.2% for the nine illnesses and one healthy class, ranging from 76% to 100% depending on the class.

[16] Researchers created a dataset of 5,406 HLB-infected citrus leaf images using Huanglongbing infected leaf photo which is collected from crowd AI and PlantVillage. The severity of citrus HLB was then taught to be detected by six well- known model types, which determined which model types are most suited to detect HLB severity under the same training settings. The Inception v3 model with epochs=60 achieves better accuracy than other models for severity identification, with an accuracy of 74.38% based on experimental results, thanks to its excellent computational efficiency and minimal parameters. In addition, they used DCGANs (Deep Convolutional Generative Adversarial Networks) to expand the initial training dataset by a factor of two in order to test whether GANs-based data augmentation may enhance model learning performance. A new dataset of 14,056 leaf images, made upof the original training shots as well as the improved ones, was used to train the Inception v3 model. As a result, they achieved an accuracy of 92.60%, which is almost 20% higher than that of the Inception v3 model trained with the original training dataset. This finding suggests that the GANs-based data augmentation is extremely successful for increasing the model learning performance.

[17] To improve the recognition model accuracy and pinpoint the position of diseased leaves, this work provides an improved Faster RCNN to distinguish between healthy tomato leaves and four illnesses, including powdery mildew, blight, leaf mould fungus, and ToMV. First, in order to extract more detailed disease characteristics from images, we use a residual depth network to replace VGG16. The k-means clustering method is then used to group the bounding boxes. Based on the results of the clustering, we strengthen the anchoring. The improved anchor frame gets close to the bounding box of the actual data set. Our final experiment uses three different feature extraction network types in a k-means analysis. Accordingto test results, the updated approach for identifying agricultural leaf diseases has a recognition accuracy that is 2.71 percentage points higher and a detection time that is quicker than the original Faster RCNN.

[18] In order to identify plant diseases and pests, this paper developed Multi-model LSTM-based Pre-trained Convolution Neural Networks (MLP-CNNs) as an ensemble majority classifier. The proposed method used multiple CNN models at first to extract deep features, and then SVM and LSTM classifiers to classify the features. The performance of the deep models was assessed using both the individual and concatenated CNN model outputs. The evaluation findings demonstrate that when compared to the separate models, the concatenated models gave better outcomes. Additionally, the LSTM classifier produced results that were superior to those of the SVM classifier. MLP-CNNs and an LSTM classifier produced a score of 99.2% accuracy, which was the highest possible.

[19] This study offers an improved convolutional neural network deep learning approach for real-time illness detection in apple leaves (CNNs). The apple leaf disease dataset (ALDD), which comprises of intricate photographs taken in the field and laboratory settings, is first put together in this work employing techniques for data augmentation and image annotation. We offer a unique deep-CNN-based model for identifying apple leaf diseases using the GoogLeNet Inception structure with Rainbow concatenation. The proposed model is trained to identify these five common apple leaf diseases using 26,377 images of diseased apple leaves outside the hold-out testing dataset. According to the testing results, the INAR-SSD model detects objects with an accuracy of 78.80% mAP on ALDD at a fast detection rate of 23.13 FPS. The findings show that the novel INAR-SSD model offers a high-performance approach for early prediction of disease in apple leaf, which can recognise these diseases in real-time with more precision and detection speed than earlier systems.

[20] This study presents a technique for identifying mildew illness in pearl millet-based on transfer learning and feature extraction. In precision agriculture, deep learning promotes a practical and engaging data analysis. The project's projected benefit is to aid stakeholders (scholars and ranchers) by providing information and knowledge through the use of the reasoning process. With an accuracy of 95.00%, precision of 90.50%, recall of 94.50%, and fl score of 91.75%, the trial's results are encouraging.

[22] In this paper, the author talks about Changes in the environment and a lack of crop immunity that have contributed to a significant increase in agricultural diseases in recent years. This results in widespread crop destruction, a decline in cultivation, and ultimately a financial loss for farmers. The detection and treatment of the disease have become formidable obstacle due to the fast expansion of disease types and the farmer's inadequate understanding. Similarities in leaftexture and appearance facilitate the identification of disease types. Therefore, computer vision combined with deep learningsolves this issue. This research offers a deep learning-based model developed using a publicly available dataset of photographs of healthy and damaged crop leaves. The algorithm achieves this goal by categorising leaf pictures into sick categories.

[23] In this paper the author aims to forecast the incidence of pests and illnesses in cotton using an LSTM network. First, the pest and disease incidence problem were defined as a time series forecast. Then, LSTM was utilised to tackle the issue. LSTM is a unique recurrent neural network (RNN) that employs a gate mechanism to avoid the vanishing or inflating gradient. Finally, it has demonstrated excellent performance in addressing time series problems and can handle the long-term dependence problem, as indicated in several publications. The experimental findings demonstrated that LSTM worked well predicting the prevalence of pests and illnesses in cotton fields, with an AUC of 97%.

III. METHODOLOGY

Introduction to Algorithm used: 3.1.1Convolutional Neural Network.

CNNs are neural networks which are feed forward used to evaluate visual images utilising grid-like data processing. [30] It is also referred to as a ConvNet. A convolutional neural net-workis utilised to recognize and categories visual objects. [31] Convolutional Neural Networks (CNNs) are similar to conventional ANNs because they consist of neurons optimizing themselves through learning. Each neuron will continue receiving input and executing an operation (such as a scalar product followed by a non-linear function) - the fundamental building blocks of innumerable ANNs. The complete network will continue to represent a single perceptual score function (theweight) from input raw picture vectors to output class score. Thelast layer will contain loss functions connected with the classes, and the standard techniques developed for conventionalANNs will still be applicable

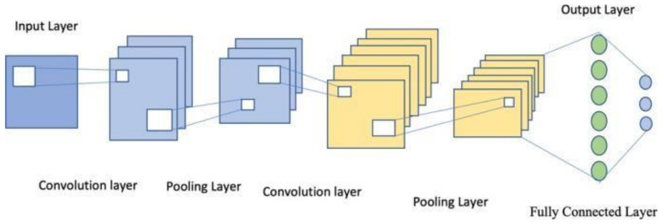

Fig. 2. CNN Architecture

Architecture of CNN

Although CNN is a particular type of multilayer perceptron, deep learning architecture may learn complex properties that a simple neural network cannot. CNNs have proven to perform exceptionally well in a variety of applications, including image classification, object recognition, and medical image analysis. The purpose of CNNs is to transport local information from high-layer inputs to lower layers, which have more complex features, for further processing. A CNN uses convolutional layers, pooling and being fully integrated (FC). In fig. 1, a typical CNN design is shown with these layers. The kernels in the convolutional layer are used to calculate a tensor feature mapping. [32]. To ensure that the output volume's dimensions are integers, these kernels stride the entire input. The input volume's dimensions are decreased once the convolutional layer is used to carry out the striding method. In order to preserve an input volume's dimensions with low-level features, zero padding is required. As for how the convolutional layer works:

I(i+m,j+n)K(m,n) = F(i,j)=(I*K)(i,j) (1). typical configuration of a neural network

I is the input matrix, K is a 2D filter with dimension m n, and F is the output, which is a 2D feature map. The operationof the convolutional layer is represented by I*K. The rectified linear unit (ReLU) layer makes feature maps more nonlinear. ReLU determines activation by disregarding the input threshold. Mathematically, it reads as follows:

max (0, x) = f(x) (2)

By down sampling a specific input dimension, the pooling layer lowers the number of parameters. The most popular strategy, for instance, is max pooling, which generates the largest value possible in an input region. Based on the characteristics obtained from the convolutional and pooling layers, the FC layer functions as a classifier.

Long Short-Term Memory

Long Short-Term Memory networks, commonly referred to as "LSTMs," are a specific type of RNN that can learn long-term dependencies. LSTMs are purposefully designed to circumvent the problem of long-term reliance. In overcoming the disappearing and exploding gradient problem, STM recommends memory chunks rather than conventional RNN units [33]. To store long terms an added cell state is used, which is the primary distinction between RNNs and CNNs. An LSTM network is capable of remembering and connecting past knowledge to present data [34].

LSTM Architecture

Step1: The initial hidden state and the fresh input data are given to a neural network. This network generates a vector with each member between 0 and 1. (by using activation function sigmoid). [31] The network (inside the forget gate) is then train to output near 0 when an input component is regarded irrelevant and near 1 when it is deemed relevant. For example, consider this vector's elements as filters or sieves that allow more data to flow through as their values increase by 1. The values are now transferred upward and multiplied point- by-point with the initial cell state. This pointwise multiplication suggests that cell state components judged unneeded by the forget gate network and it will be multiplied by a value close to 0, and as a result, exert less influence on succeeding stages. The initial concealed state and the current data point in the sequence define whether parts of long-term memory shouldbe ignored (given lower value) at this time.

Step2: In this step, the new memory network and input gate are implemented. This step is to identify what new information should be added to the network's long-term memory (cellstate) based on the network's prior concealed state and new input data. The new memory network is a tanh-activated neural network that has trained to mix the prior hidden state with fresh input data to produce a 'new memory update vector' Given the context of the previous hidden state, this vector effectively contains information from the new input data. This vector tells us, given the new data, how much to update each component of the network's long-term memory (cell state). Note that a tanh is used here since its values lie in the range [1] and can therefore be negative. Negative values are required if we desire to lessen the effect of a component on the state of the cell. Furthermore, there is a significant issue in step 1 above, where we generate the new memory vector: it does not assess if the new input data is deserving of being remembered. The input gate's function is to provide this. The input gate, which acts as a filter to choose which elements of the "new memory vector" should be kept, is a sigmoid-activated network. This network will produce a vector of values in the range [0,1] because of the sigmoid activation, which enables it to do pointwise multiplication and act as a filter. An output around0 suggests that we shouldn't update that portion of the cell's state, similar to forget gate.

Step3: Final step is the Output gate, which decides the new hidden state Final state can be concluded as

Pointwise application of the tanh function towards the current cell state results in the squashed cell state.

Input the prior hidden state and current input data into the sigmoid-activated neural network to obtain the filter vector.

Utilize pointwise multiplication to employ this filter vectoron the compressed cell state.

Output is the new hidden state.

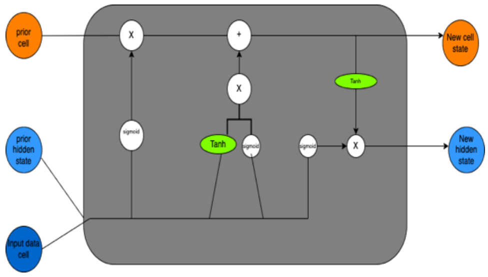

Fig. 3. LSTM Architecture

Fig. 4. 1)leaf affected by Light Blight (2): leaf affected by Early Blight (3): leaf unaffected (Healthy)

Proposed Algorithm- HybridCNN-LSTM

Step1-Data Collection-

Data is collected from Kaggle. It is a resource that provides Plant Village Dataset for research purposes. We have used potato photos to solve a classification problem with three classes shown in fig4

TABLE I. Train-Test Split Data

Label	Category	Number	Training Sample	Test Sample
1.	Early Blight	1000	787	213
2.	Late Blight	1000	791	209
3.	Healthy	152	122	30
Total		2152	1700	452

Step-2 Data Preprocessing

Loaded the train, validation and test dataset using image_dataset_from_directory function of keras pre-processing with image size of 256 X 256 with a batch size of 32.

Cached, shuffle and prefetch the train, validation and test dataset.Perform data augmentation (random flip and random rotation) on train dataset.

Step3-Proposed Model

Build the model with input shape (32,256,256,3 (batch_s,image shape (width and height and chan- nelsBuilded a sequential model with following layers 3.Firstly, Resize and rescale layer which will resize and rescale the input layer of the model

Convolution layer featuring 32 filter with 3*3 filter with relu activation function

Max pooling layer with 2*2 kernel

With five convolution layers with 64 filter with 3*3 filter with relu activation function and five Max Pooling layer with 2*2 kernel

Flatten layer

Reshape layer that will reshape the output of flatten layerinto (256,1

LSTM (Long short-term memory layer with 128 units

Flatten layer

Dense layer with output size 256

Added a dropout layer

Dense layer with softmax as activation function

Compile the model with adam optimizer,SparseCategoricalCrossentropy loss function Trained the model with batch size 32 using train andvalidationdataset.

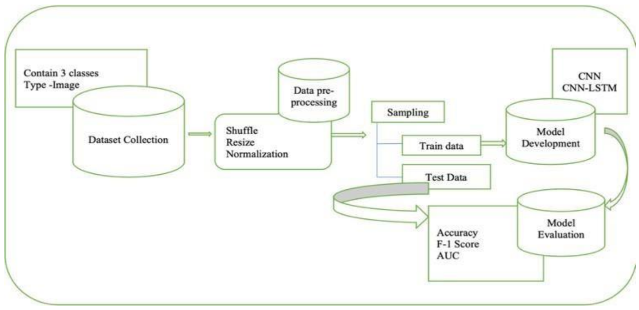

Fig. 5. Proposed Model

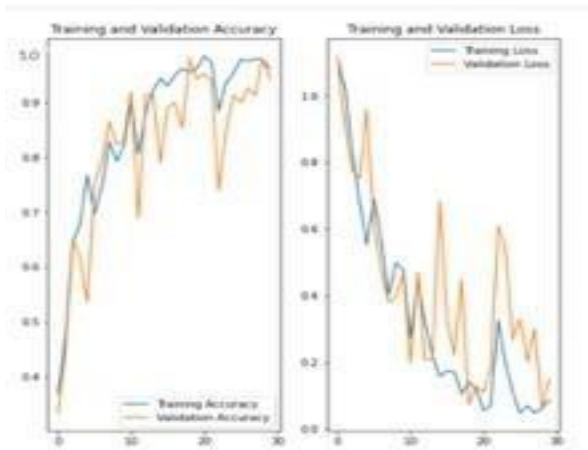

Fig. 6. Model Accuracy

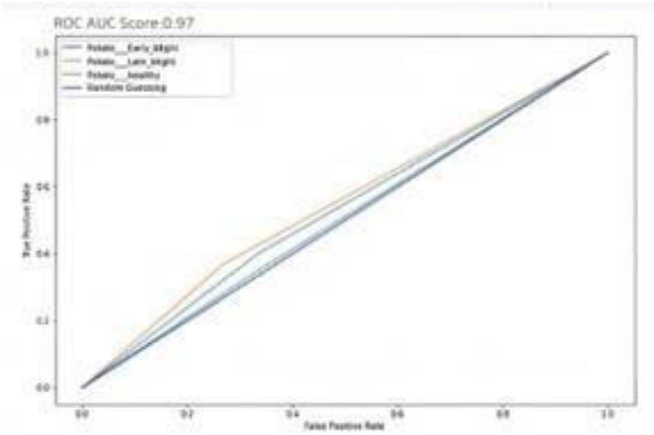

Fig. 7. ROC Score

IV. RESULT AND SCREENSHOTS

The overall accuracy of the model is 98.5%. Evaluated the model on the test dataset and found test accuracy of 98.5% and Plotted the train and validation accuracy and the losses Calculated the precision, recall and f1 score using sklearn metrics Finally calculated the AUC (area under curve and plotted the ROC curve as shown infig 6 and 7.

V. CONCLUSİON

Food plants are vulnerable to many issues that endanger their health in interior scapes, production areas, gardens, and landscapes. These issues may have minor cosmetic effects on the plant or more severe ones that result in plant mortality, crop loss through decreased yield and quality, and plant deformity. Hence it is necessary to identify these issues at an early stage. Agriculture has advanced in terms of technology. Agriculture's complicated difficulties will be resolved with the aid of technology. Modern technology, a word widely used in agriculture, combines agriculture with technology. The paper uses a hybrid CNN-LSTM-based approach to predict two diseases, late blight and early blight, along with healthy potato leaf. The model has achieved 98.5%accuracy, which is best compared to different approaches on the same dataset. This work will be very effective in identifying the disease in potato leaves, which will increase the production of potatoes. The proposed model has certain limitations. Firstly, the dataset is small. Secondly, it only focuses on two diseases.

Future scope: Researchers can work with a larger dataset Can work on other diseases such as Common scab, Blackscur.

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