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Prediction of Crop Diseases

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***Abstract*—** Agriculture is a significant yet low-paying occupation in India. Machine learning has the ability to transform agriculture by altering the revenue scenario through crop selection. The goal of this study is to estimate agricultural yield using various machine learning techniques. The outcomes of various solutions are compared using mean absolute error. The predictions of machine learning algorithms will help farmers decide which crop to produce to optimize yield.

Keywords- *CNN,RNN,ReLU,*

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1. INTRODUCTION

The world's biggest rural need is high creation; consequently, most nations utilize current procedures to support crop yields. Cutting edge innovation ought to increment yields. Different factors like ecological burdens (bothers, infections, dry spell pressure, nourishing shortfalls, and weeds) and irrigations influence plants at any stage. Hence, in horticulture, both amount and quality decrease. Crop disease is the main justification behind quality and amount misfortunes in cultivating such misfortunes adversely influence the benefit and creation expenses of partners in cultivating. [1] Expectedly, plant pathologists and farmers use their eyes to see illnesses and form choices relying on their insight that are in many cases not exact and on occasion one-sided as in the previous time a great deal of sorts of sicknesses is by all accounts comparable [2]. This plan made ready for the unnecessary use of pesticides that brought about high wage costs [3].

Therefore, a precise infection indicator linked to an authentic dataset is required to assist farmers, especially in the case of untrained and young farmers [4]. Headways in PC vision assist with the utilization of ML or DL plans. Besides, there is a prerequisite for a previous sickness. Acknowledgment framework for safeguarding the yield over the long run [5].As a result, CNN is extensively used to identify agricultural diseases, with acceptable results. However, the crop disease photos collected from lands were characterized by a high level of unpredictability, which has an important effect on the improvement of crop disease detection via image accuracy [6].The "Plant Village dataset" a widely used dataset for identifying leaf diseases is used to identify these illnesses[7].CNN trained the big datasets. Super- resolution methods must be used to improve crop disease identification from photos[8].

As a result, CNN is extensively used to identify agricultural diseases, with acceptable results. However, the crop disease photos collected from lands were characterized by a high level of unpredictability, which has an important effect on the improvement of crop disease detection via image accuracy [6]. There is a detrimental effect on agricultural output due to the prevalence of crop diseases, and increase food insecurity [9]. Spots or scars on the leaves, stems, flowers, or fruits are common symptoms of crop diseases. The leaves of crops are often the first to show signs of disease, making them an excellent starting point for diagnosis [10].The physiology of the plants is affected, and the crop is severely damaged because of the disease. In addition, there are several ways in which agricultural crops might spread to new hosts. Roots, fruits, leaves, flowers, and stems are all potential sites of symptoms for a wide range of diseases. Negative effects of crop diseases include diminished fruit quality and size, as well as abnormalities in the appearance of the leaves, flowers, and stem.

2. RELATED WORK

Agriculture is essential to the survival of all nations. The severity of crop disease or a variety of environmental factors has an influence on agricultural productivity. As a result of the ignorance, crop productivity decreases, and the contaminated produce is also detrimental to human life. Three distinct "Convolution Neural Network" (CNN)-based architectures were create for the purpose of diagnosing large multi-crop diseases using images taken with cell phones. This methodology reduces classification complexity even with the big multi-crop dataset [11].The relevant data in the proposed model enhanced accuracy and eliminated misclassification. The suggested model lacks "incremental learning strategies" for detecting crop diseases. A new set of pre-trained models, Alex Net and VGG16 net, has been presented to classify tomato crop illnesses [12]. Alex Net‟s mini-batch size has no relationship with classification accuracy; however, VGG16net'saccuracy falls with increasing mini batch size.

Alex Net supported the proposed model for maximum accuracy with the least amount of processing time while taking into account computational load. Described a modern technique for detecting and categorizing paddy illnesses based on neural networks and fuzzy logic. This has been demonstrated to be beneficial in preventing and treating crop illnesses before they become serious [13].Successful crop management, which the proposed model integrates, has ensured crop health and increased agricultural yields. However, contextual constraints such as "lighting, background difficulties, and sometimes noises "have made this proposed paradigm challenging to implement.

Recommended a DCNN-oriented framework: The experiment was performed using corn leaf images. The adopted CNN‟s were trained to identify 4diverse classes (1healthier and 3diseaseclasses). Furthermore, the simulated results established the enhancement of the proposed scheme concerning accuracy [14].It was suggested to use a multimodal strategy to identify agricultural diseases more intelligently. Accuracy in illness detection is a difficult problem since it directly affects future prevention measures and medicine spraying [15].Applied cloud-based "Faster R- CNN to detect pest insects. To help farmers, a repository of suggested pesticides was connected to agricultural pests. This method struggled with computational time [16].

Shows Deep learning-based BR-CNNs are autonomous image-oriented crop leaf disease diagnostic and severity assessment systems that can identify different crop species and identify illnesses .A hybrid approach for identifying agricultural leaf diseases has been developed [1] using the integration of auto encoders and CNNs. A dataset of 900 images was used to get the results. Three crops and five different crop diseases were examined by researchers. To identify crop disease from leaf photos, the proposed network has been trained [17].Different convolution filtration techniques, including 22 and 33, were used in the proposed study proposed a new crop disease prediction [18]. A novel approach for predicting crop diseases was established. These studies found that disaster management actions could be adopted in advance to reduce probable disasters based on expected results. Deep learning and computer vision crop disease diagnostics can improve crop quality and productivity. Variations in crop production or quality can severely affect the economy .Therefore, it is important to identify crop diseases early on before they severely damage crop yield.

A novel method called smart farming has been developed to take advantage of high-ended applications of modern farming by collecting a variety of data from live streams, social media, sensors, robotics, and other sources. When using smart farming approaches to detect crop diseases, the processing of the data obtained from many sources under a multilevel database becomes increasingly difficult.

When applying machine learning to real-worldapplications, the needs for adopting supervised or unsupervised methods are strengthened. The major goal is to use the modified deep learning architecture to construct a unique crop disease detection model. The publicly available benchmark sources are used to acquire the images from the "New Plant Dataset" with different agricultural diseases, which are then, pre- processed utilizing filtering and contrast-enhancing algorithms. Image enhancement is preceded by abnormality segmentation using the cutting- edge technique. In the subsequent step, edge features and texture features are extracted that have been segmented based on abnormalities. The performance determined using a variety of traditional techniques that guarantee the proposed model's accurate diagnosis of crop diseases.

One of the factors that make it challenging to harvest crops is crop disease, which reduces the rate of productivity and induces big losses in the agriculture- based economy[1].Therefore, agricultural diseases recognize at early stage is important for their treatment ,that boost s agricultural productivity and reduces the need for pesticides. Crop disease affects the majority of crops, and significantly lowers agricultural production and quality [19].However, intensive chemical use in farmland leads to the creation of chemical residues, which contribute to environmental contamination.

Since people's standard of living has improved, therefore has their expectation for a high-quality harvest. So, the difficult issue is to identify the crop disease as quickly as possible and begin treatment. There have been multiple investigations into the issue of crop diseases, but all of them have taken one of two broad approaches [20]. The first is known as the "conventional physical method," which makes use of spectral detection to spot various leaf ailments and insect infestations [21]. Then extra point of view focuses oncomputer vision. Technologies applied to crop images in order to diagnose diseases by contrasting images of healthy and affected crops [22].The majority of crops significantly lowers agricultural production and quality [23].However, intensive chemical use in farmland leads to the creation of chemical residues, which contribute to environmental contamination. Since people's standard of living has improved, therefore has their expectation for a high-quality harvest. So, the difficult issue is to identify the crop disease as quickly as possible and begin treatment.

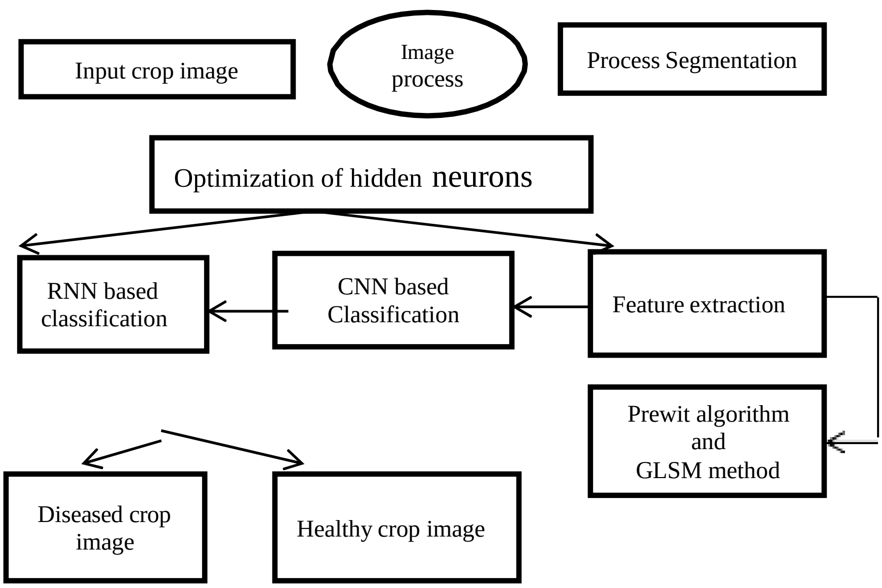
The work contribution is as follows:

To create a crop disease prediction model using the created VGG19 and implement the recommended for precisely detecting crop illnesses to boost agricultural yield by recognizing and preventing crop diseases earlier than usual.

1) To apply segmentation using the proposed a crop disease prediction model to increase entropy and decrease variance for accurate segmentation. Accurate segmentation improves classification and identification.

2) The proposed crop disease prediction algorithm requires an VGG19 classifier to be created to achieve the highest accuracy in crop disease recognition and to detect leaf diseases through the proposed models.

3) Introduce the VGG19 algorithm, a modified technique for enhancing crop image classification and segmentation, increased overall performance of the proposed crop disease prediction model



The suggested model employs a range of input crop photos from the "New Plant Diseases Dataset" to identify crop diseases. Median filtering helped to keep the edges' characteristics while reducing the amount ofrandom noise. In a similar manner, contrast enhancement boosts pixel intensities and yields extremely high-quality images that are superior to the originals. The preprocessed images are segmented. This segmentation method enhances convergence by adapting to new models. By increasing entropy and optimizing crop picture cluster centers, this enhances abnormality segmentation. Images with segments are used to extract features.

Applied to freshly produced features are forwarded to CNN, which picks the best features before identifying and classifying them. By applying the proposed optimize the corresponding hidden neurons, the proposed model performs better. It is possible to obtain either healthy images or recognize outcomes that are diseased. The input images are shown to indicate or signify how many input crop images there are in total.

Pre-Processing of Images

The pre-processing stage of the suggested crop disease prediction model begins with gathered input photos for improving the quality. To accomplish this, the images can be pre-processed with methods includes median filtering and contrast enhancement in order to remove any unexpected distortions or noise.

Median filtering: Median filtering is applied to the input images with objective of maintaining edge characteristics even while removing the noise [24].

Contrast Enhancement:: The images are processed for contrast enhancement using median filtering for minimizing the distortions and improve the images. picture content information may be obtained by adjusting picture intensity and histogram equalization. Intensity modification improves images by changing their intensity values. To maximize the details in the crop images, the contrast pixel intensities should be fixed to their highest level [25].While processing the input images, CNN benefits more from the local receptive field.

Pooling layer: The convolutional layer provides the most crucial properties. A complete receptive field's random, mean, and maximum values are calculated by pooling.

$$fnr = \frac{f_n}{f^n + t^p} \quad (3.37)$$

Activation layer: It preserves a linear relationship between the input and output layers. Some activation processes use nonlinear ReLUs (Rectified Linear Units), such as CNN.

Fully connected layer: It is a completely connected network with the outer layer and usesthe data gained from activation the pooling layer procedures. The output layer then gives the relevant characteristics that were extracted using the SoftMax approach. The total 12 features are calculated.

The following measurements are to evaluate the efficacy of proposed model

i) **SPE *spt* is rate at which negativity are discoveredas shown in equation 3.31**

$$spt = \frac{t^n}{t^n + f^p} \quad (3.31)$$

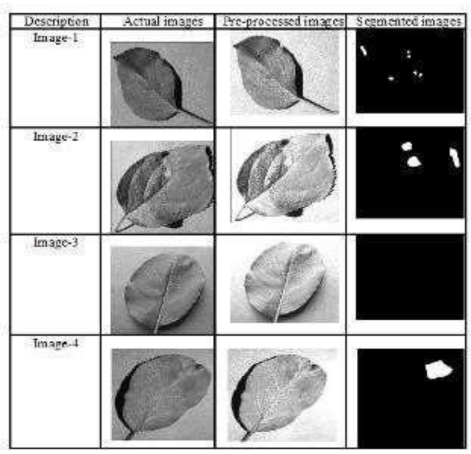
viii) Precision *prn* is described as the percentage of appropriate examples amongst some ofthe instances that were retrieved, in Eq. (3.38).

$$prn = \frac{t^p}{f^p + f^p} \quad (3.38)$$

ii) **NPV *nv* defined as in Eq. (3.32).**

$$\frac{t^n}{+ f^p} \quad (3.32)$$

<u>Proposed model's actual and abnormality segmented Images of the Leaves</u>



iii) **F1-score $F1$ calculated by Eq. (3.33).**

$$F1 = \frac{2 \text{ K } t^p}{2t^p + f^p + f} \quad (3.33)$$

iv) FDR fdr equation (3.34) depicts the rate of testingerrors while performing numerous comparisons

$$fdr = \frac{f^p}{f^p + t^p}$$

(3.34)

v) SEN sen Eq. (3.35) accurately determines theproportion of positives.

$$sen = \frac{t^p}{t^p + f^n} \quad (3.35)$$

vi) FPR fpr is defined as Eq. (3.36).

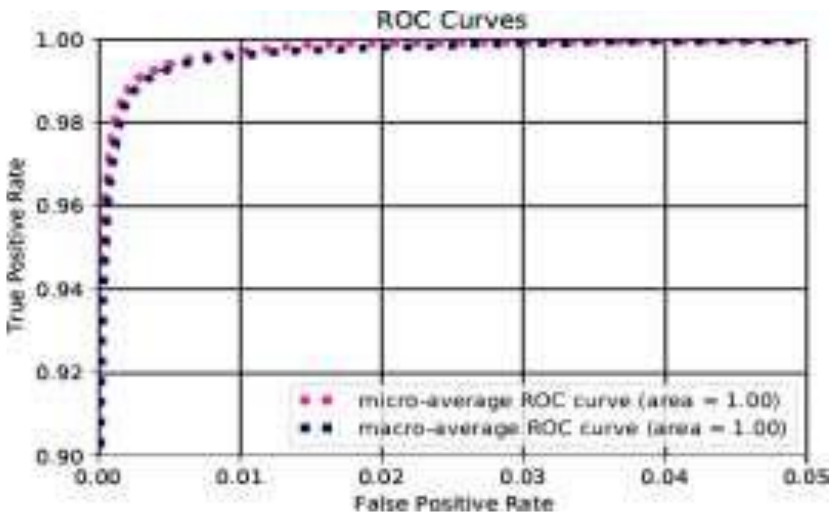
$$fpr = \frac{f^p}{f^p + t^n} \quad (3.36)$$

vii) FNR fnr is the rate at which false- positive results occur when employing the formulas Eq. (3.37).

Perf or ma nce Analysis on Dataset based on VGG19

The performance of the suggested model using various heuristic-based methods and learning percentages is shown in Fig. 3.3.The proposed method gives 0.03%, higher F1-score than respectively.

The Performance matrix of Crop Disease Recognition Predictation Model:



Crop Disease		Precision (%)	Recall (%)	F1-score (%)
Apple Scab		0.9007	0.9925	0.9444
Apple Black Rot		0.9703	0.9849	0.9776
Apple Ceder rust		0.9941	0.9711	0.9825
Apple Healthy		0.9780	0.9685	0.9732
Blueberry Healthy		0.9536	0.9867	0.9699
Cherry Healthy		1.0000	0.9887	0.9943
Cherry powder mildew		0.9795	0.9970	0.9882
Corn_(maize)Cercospora_leaf_spot		0.9344	0.9344	0.9344
Corn (maize) common rust		0.9973	0.9892	0.9932
Corn (maize)Healthy		0.9973	1.0000	0.9987
Corn (maize) northern leaf blight		0.9554	0.9531	0.9543
Grape Black rot		0.9803	0.9859	0.9831
Grape esca (Black measles)		0.9877	0.9877	0.9877
Grape Healthy		0.9971	0.9942	0.9956
Grape_Leaf_blight_(Isariopsis_Leaf_Spot)		1.0000	0.9855	0.9927
Peach Healthy		0.9948	0.9922	0.9935
Pepper bell healthy		0.9837	0.9810	0.9824
Potato Early Blight		0.9945	0.9891	0.9918
Potato Healthy		0.9911	0.9380	0.9638
Potato Late Blight		0.9586	0.9789	0.9686
Raspberry Heathy		0.9802	99.00	00.9851
Squash powdery mildew		0.9552	0.9884	0.9715
Soybean Heathy		0.9684	0.9735	0.9710
Strawberry Healthy		0.9968	0.9485	0.9720
Strawberry Leaf Scorch		0.9951	0.9738	0.9844
Tomato Early Blight		0.9879	1.0000	0.9939
Tomato Healthy		0.9481	1.0000	0.9734
Tomato Late Blight		0.9893	0.9920	0.9907
Tomato Leaf Mould		0.9851	0.9649	0.9749
Tomato Septoria Leaf spot		0.9171	0.9352	0.9261
Tomato Spider mites Two spotted spider mite		0.9690	0.9921	0.9804
Tomato Target spot		0.9800	0.9026	0.9397
Orange Haunglongbing_(Citrus_greening)		0.9432	0.9555	0.9493
Peach Bacterial spot		0.9785	0.8788	0.9260
Tomato Bacterial spot		0.8947	0.9947	0.9421
Pepper bell Bacterial spot		0.9329	0.8439	0.8862
Tomato mosaic virus		0.9819	0.9921	0.9870
Tomato_Yellow_Leaf_Curl_Virus		0.9975	0.9828	0.9901

Result:

There are 38 recognized forms of crop illnesses in the experimental dataset created from the Kaggle new-plant-diseases-dataset. In compared to training and testing ratios of 90:10 and 70:30, the experiment's dataset with an 80:20 training to testing ratio yields the greatest results.

Based on classification performance reported on the prepared dataset and determined to be thebest in comparison to other designs including VGG, ResNet, and ResNetV2 that are trained on ImageNet, the VGG19 architecture was chosen for the crop disease prediction system. The benefit of training these designs is that they acquire optimum accuracy and converge more quickly.

Despite this, it is discovered that all designs had approximately same categorization accuracy from the beginning. From the second epoch on, the VGG19 outperforms other designs. The VGG19 architecture is proven to have testing accuracy of 97.24%. The best accuracy that the VGG19 architecture can attain is 97.24%. The greatest accuracy recorded by other designs, including VGG16, ResNet, and ResNetV2, is 95.2%, followed by 96.1% and96.2%.

Conclusion:

In this research paper, I put the suggested Crop prediction system to use by implementing a fresh model.

By including a meta-heuristic-based enhanced deep learning classification model, we haveimproved the crop disease classification model utilizing the hybrid deep learning model.

Improving the performance of the above two models introduced new crop disease classifications based on the optimization techniques which improved the performance of the VGG-19 classification model.

We focused on pre-processing crop photos using several strategies that are more advantageous for classification, such as abnormality segmentation, feature extraction,and classifiers that are utilized to categorize illnesses. Three datasets are examined in order to meet the goals.

There are 87,000 photos of both healthy and ill leaves in one dataset taken from Kaggle.All of the high- quality photos are utilised to identify traits and categorise illnesses.

Performed the comparative analysis between the proposed model and existing deep learning classifiers (NN, DNN, CNN, LSTM, and RNN), and found that the proposed model is better than the others.

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