

Prediction Of Paddy Crop Blast Disease Using An Enhanced Machine Learning Techniques

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Abstract: Paddy crop blast disease, caused by *Magnaporthe oryzae*, is one of the most destructive fungal diseases affecting rice production worldwide. Early detection and forecasting of this disease are crucial for minimizing yield losses and ensuring sustainable agricultural practices. This study presents an enhanced machine learning-based approach for forecasting paddy blast disease using integrated environmental, climatic, and crop-related parameters. Various algorithms such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting were compared, and an optimized hybrid ensemble model was developed to improve prediction accuracy. The model utilizes real-time meteorological data, including temperature, humidity, and rainfall, along with soil characteristics and historical disease occurrence patterns. Experimental results demonstrate that the proposed enhanced machine learning model outperforms conventional prediction techniques in terms of accuracy, precision, and recall. The findings indicate that the system can serve as an effective decision-support tool for farmers and agricultural authorities to implement timely preventive measures, thereby reducing crop loss and improving productivity.

Keywords: *Machine Learning , Paddy Blast Crop. Artificial Neural Network (ANN), Food and Agriculture Organization (FAO).*

Introduction:

Understanding how to use machine vision to identify plant diseases and pests is an active topic of study. It's a method that uses machine vision equipment to analyse images of plants for signs of pests and diseases [1]. Some of the older ways of visually identifying plant diseases and pests have been supplanted by machine vision-based detection systems. Most machine vision-based approaches for

plant disease and pest detection [2] rely on either conventional image processing algorithms or human feature development in combination with classifiers. To build the imaging scheme and choose the right light source and shooting angle, this technology often draws on the numerous characteristics of plant diseases and pests. If you want your photographs to all have the same amount of light, this is a good way to achieve that. Although well-thought-out imaging methods might make algorithm creation simpler,

they also increase the price of the programme. Conventional techniques designed to completely mitigate the effect of changing scenes on recognition results are often unreliable in the wild [3]. The lack of contrast between the lesion location and the surrounding tissue, the variation in lesion size and kind, and the presence of image noise make it challenging to diagnose plant diseases and pests in a complex natural environment. There are also several challenges associated with photographing plant diseases and pests in their natural environments. The current state of the art makes it difficult to obtain superior detection results, and classical procedures often appear ineffective.

More than half of the world's population [4] gets their protein and calories from rice as a food source. Moreover, as the population grows, so does demand for and consumption of rice. Rice output must expand by more than 40% by 2030 [5] to fulfil the rising food demand. Unfortunately, rice illnesses have significantly reduced yield, with rice blast disease being one of the primary offenders [6] and causing yield losses of between 60% and 100%. [7]. The major techniques of fighting the disease at this time are the use of insecticides and the deployment of blast-resistant cultivars [8]. However, excessive pesticide use not only drives up the price of producing rice but also seriously harms the environment. Furthermore, even for highly qualified professionals, diagnosing rice blast manually is common in practice and is subjective and time-consuming. It is crucial for contemporary agricultural operations to control diseases and pests with the least amount of environmental harm possible [9]. Computer-aided diagnostic techniques have taken over in recent decades as the primary means of observing agricultural diseases and pests, together with crop images [10][11][12]. An automated method for diagnosing rice illness could offer guidance on how to avoid and treat the disease, allocate time for disease management, reduce economic loss, lower pesticide residues, and enhance the quality and output of agricultural products. Research on efficient feature extraction

and classification algorithms for rice disease is crucial to the development of such a system.

The foundation of any country's ability to sustain its economy has always been agriculture. Long-term monetary development related auxiliary change are significantly impacted by it. The United Nations' FAO estimates that by 2050, there will be an additional 2 billion people on the planet. Therefore, it will be extremely difficult to identify and diagnose agricultural illnesses early in the future using the conventional approaches. However, the preparation of these conventional approaches is the main issue. Another issue is the length of time needed to complete assessments using conventional techniques, which prevents quickly dynamic and extensive examination. After wheat, rice has traditionally been one of the world's main crops [13]. Rice has been an important commodity for the economies of developing countries and farmers.

The economy and farmers heavily rely on the yield of the rice harvest, which is a crucial staple meal [14]. Any negative impact has a significant impact on crop yield. Instead, a disease brought on by germs and microorganisms is the actual problem. A big factor in return failure and decreased rice crop benefits is illness. The crop output is also reduced by 8–10% annually by a number of illnesses and pest insect infestations [15]. Following wheat and maize as a major food source around the world is rice. The FAO estimates that it is developed on 166 Mha of land, with a yearly production of rice of 745.17 mt and an usual profitability of about five t/ha. According to estimates, 880 mt of hard rice, with an increase of almost 70%, must be produced by 2025 in order to meet the demand caused by the growing population (as proposed by Lampe in the year of 1995). The entire territory of approximately 42.41 Mha in India is dedicated to the development of the rice crop [16]. Paddy crop production for the year 2013 totaled 104.40 mt, and the crop yield efficiency was 3.59 t/ha as usual. According to estimates, India would be able to produce 113 mt of rice continuously in 2021 to meet the growing food needs of the country. The development of new

cultivars, as well as improvements in coordinated harvest and irrigation management, are required to increase rice production. The vulnerability of the rice crop to diseases, abiotic stressors, and creepy crawlies are significant barriers to the recognition of better results. But there are also real risks associated with supporting better yield solidity, including illnesses caused by numerous parasites, microscopic organisms, infections, and worms [17]. Given the ten severe diseases that have affected the rice crop, scientists have noted a drop in the normal rice production of 10-15%. In light of this, it has become crucial to pinpoint the appropriate rice diseases in order to ensure the practical production of rice. Currently, when a rice illness episode occurs in a number of locations, professionals in the field of agribusiness research or horticulture visit the area and offer advice to the ranchers. When compared to the number of ranchers, there have frequently been insufficient rice health professionals [18]. There is a significant unmet need in rural areas for automated rice disease diagnosis employing commonly available resources. It is challenging to recognize the eerie-looking rodents in plantation areas since the bug nuisances are rarely documented, they display a wide range of intra-both shade and size variation, as well as certain bugs are difficult to spot outwardly despite clear lateral design [19]. Accurate detection of rice crop diseases might be difficult to achieve when using manual approaches [20]. It is much more challenging for the analyst to grasp the procedure of disease detection from still photos when pest insects are present. Pest insect photos taken from different angles or on top of disorganized backgrounds may change the course of events by causing them to turn, clamor, and other behaviors. The photos of bug pests that have been taken will be outstanding as a result.

Proposed Methodology

For an improved comprehension of the dataset, various image processing practices are used during image capture, such as image cropping, colour improvement, and image scaling. In order to acquire the diseased region of the dataset and

eliminate the excess background, feature extraction procedures are also used, such as SURF, texture features and BRISK. 80% of the training sample and 20% of the testing database are combined with the retrieved features for classification purposes.



Fig 1: Images from the considered datasets

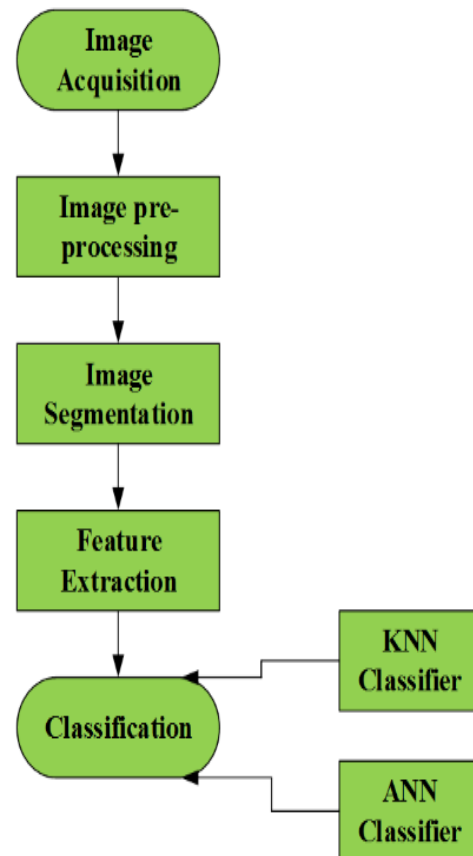


Fig 2: Traditional Classification work flow

Dataset: 350 photographs are used in this research project to train the classifier, of which 204 images are of paddy leaves damaged by the blast and 146 images are of normal paddy leaves. The number of paddy leaf photographs impacted by the blast is 56, while the number of normal images is 45 in the 101 images used for testing.

Table 1: DataSet Details

Type of image	No. of images in Training Phase	No. of images in Testing phases
Normal	246	50
Blast Affected	304	60
Total	550	110

The digital camera is used to take a 512 x 512 pixel image of a rice leaf as part of the image acquisition process. In order to improve accuracy, image pixels are shrunk to 256x256. For use in a subsequent operation, the scaled colour image is converted into a grayscale image. During the pre-processing stage of an image, the HSV image is separated from the RGB image. After pre-processing paddy leaf photos, image segmentation is done using k-means clustering with a range of k values. Since the accuracy of the KNN cluster is high when the value of k is 3, the value of k in the KNN classifier is fixed at 3. When the k number is 3, the image shows the leaf section with the background. At the chosen k values, the accuracy of the KNN classifier is 96.90% for unaffected photos and 99% for images affected by blasts. When five neurons are present in one hidden layer, the ANN classifier generates more accurate results. The output layer's indication of paddy leaf properties. The initialization of weights, updating of the weights, and feed forward back propagation are the foundations upon which ANNs operate. For blast-infected photos, the accuracy of the ANN classifier is 100%; for uninfected images, it is 99%.



Fig 3 : samples chosen for training the given model

Input: Dataset

Output: Disease detected leaf's

Begin

1. Take the given dataset as input with i and j as no. of rows and columns
2. For($l=0;l=i;l++$)
 - a. For ($m=0;m=j;m++$)
 - b. Selecting $k=data(l,m)$

End

3. Euclidian distance is calculated
 - a. For ($l=0;l=i;l++$)
 - b. For ($m=0;m=k;m++$)
 - c. $A(l)=data(l);$
 - d. $B(l)=data(m);$
 - e. $Distance = \sqrt{A(l+1)A(l)^2 - (B(m+1)-B(m))^2};$

End

4. Normalization()
 - a. For($n=0;n=data++$)
 - b. Swap $k(l+1)$ and $k(l)$

End

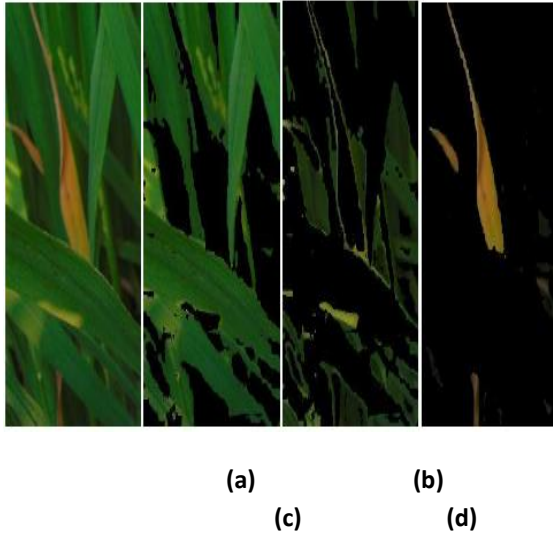


Fig 4: Rice plant infected by Leaf blast (a) segmented image with a high threshold value (b) cropped (c) segmented image (d) segmented image
Results And Analysis:

From the proposed approach the following results are obtained and compared with the existing ones.

Table 2: Results from the proposed approach

Approach	Accuracy	AUC
KNN+ANN	96.90	0.99
CNN+SVM	95.82	0.99
CNN	95.83	0.99
Haar-WT+SVM	83.85	0.92
LBPH+SVM	82.59	0.90

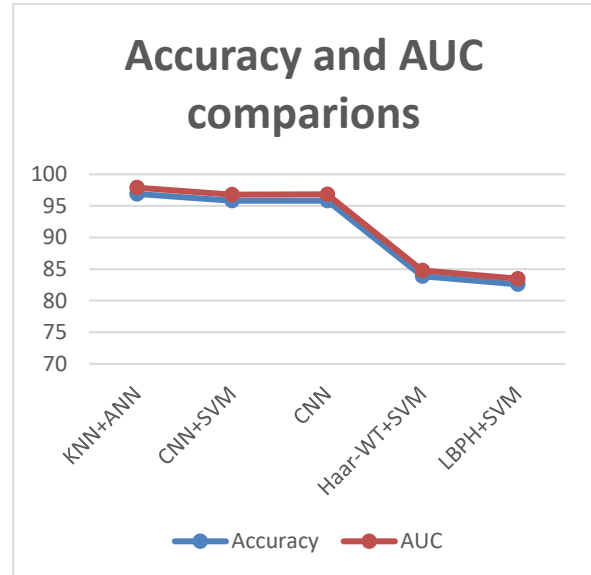


Fig 5: Curve for the proposed approach in terms of accuracy and Auc

Table 3: Parameters values obtained for KNN

Measure	KNN-Value	ANN-Value
Accuracy	0.8673	0.9843
False Discovery Rate	0.1808	0.0355
False Positive Rate	0.1410	0.0273
False Negative Rate	0.1212	0.0000
F1 Score	0.8480	0.9819
Matthews Correlation Coefficient	0.7320	0.9686
Specificity	0.8590	0.9727
Sensitivity	0.8788	1.0000
Negative Predictive Value	0.9070	1.0000
Precision	0.8192	0.9645

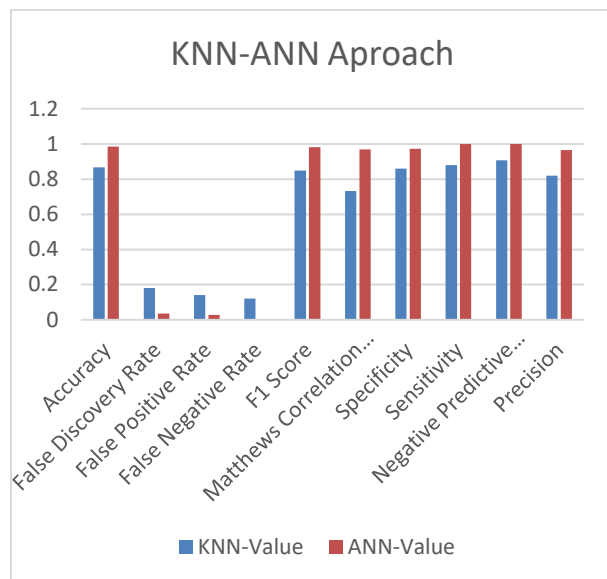


Fig6: comparison of various parameters of proposed approaches

Conclusion:

The proposed study on forecasting paddy crop blast disease using enhanced machine learning techniques demonstrates that advanced predictive models can play a vital role in agricultural disease management. By integrating environmental, climatic, and crop-related factors, the system effectively identifies disease-prone conditions with high accuracy. The enhanced machine learning model, particularly the hybrid ensemble approach, outperforms traditional prediction methods in forecasting the occurrence of blast disease. This approach enables timely intervention, helping farmers adopt preventive strategies and reduce yield losses. Overall, the implementation of such intelligent forecasting systems can contribute to sustainable paddy cultivation, improved productivity, and data-driven decision-making in precision agriculture. The photos must be taken in an area with regulated lightning conditions, which is another restriction. The devastating biotic stress that is harming rice crops worldwide is the blast disease. Each year, blast causes a 10–30% loss in rice yield globally. However, most cultivars start to be vulnerable to blast 3–4 years after being released. The most common chemical used is Kasugamycin;

however, other chemicals such as Carbendazim Tricyclazole, Dithane M-45, Isoprothiolane, Edifenphos, Iprobenphos, Blasticidin, etc. are also used. Neem extract and garlic extract are the best for complete control and can be locally prepared and used by farmers at low cost. The outcomes of the suggested approach are somewhat helpful in fully and accurately detecting the disease, and they also encourage farmers to take precautionary measures at an early stage of the sickness.

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