Rice Disease Detection Using DenseNet and Convolutional Neural Network

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Abstract– In the research, we investigate the viability of applying machine learning and visual computing to identify various fungal infections of rice. Brown spot and leaf blast illnesses are taken into account. To recognise a specific disease on an image, modern computer vision techniques based on convolutional neural networks are employed. The four most popular and compact convolutional neural network architectures—GoogleNet, ResNet-18, SqueezeNet-1.0, and DenseNet-121—are compared by the authors. The authors demonstrate that the disease can be identified with at least 95% accuracy in the dataset utilized for the investigation. Testing the algorithm on real data that wasn't used for training revealed up to 95.6% accuracy. This is a good sign of the solution's dependability and stability, even when the data distribution changes. The data which is not used in the training gives the accuracy of 95.6%. This is a good sign of the solution's dependability and stability, even when the data distribution changes.

I. INTRODUCTION

One of the most significant grain crops in the world is rice. Throughout the past several years, this cereal has seen a surge in popularity worldwide. In comparison to 437.18 million tonnes in 2008, more than 490 million tonnes of rice were eaten globally in 2019. China and India are the world's two largest consumers of rice, consuming 143 and 100 million tonnes each, while Indonesia, Bangladesh, and Vietnam account for 37,7 million tonnes, 35,8 million tonnes, and more than 56% of global rice production, respectively (21.5 million tons). In Russia, rice is an important food, nutritional, and medicinal item. Consumed cereals are expanding every year. Its proportion in the eaten cereals is growing every year.

In Russia, losses in rice production range from 20% to 40% due to diseases and pests. Fungal infections also inflict enormous economic harm to the rice industry. According to various estimates, losses in Russia due to blast illnesses alone (causative agent, Pyricularia oryzae Cavara) range from 5% to 25% in normal years and up to 60% or even 100% in years when the disease develops epiphytically. As a result of a large drop in the grain's quality derived from the afflicted plants, the harm increases dramatically.

The agrochemicals are sprayed uniformly across the field in today's common pest management techniques as a preventative measure or when any disease symptoms are found. In addition, diseases in their early stages are frequently misdiagnosed, which leads to incorrect complex agrochemical selection. On the one hand, it significantly raises the cost of disease control because, at least initially, the disease infection is concentrated primarily in the vicinity of the original foci. On the other hand, excessive chemical application increases the possibility of groundwater contamination and negatively influences the presence of toxic residues in agricultural products.

Due to these restrictions, a sizable body of research exploring the potential application of machine learning techniques to the issues of automatic detection and classification of crop diseases based on digital images has emerged. Similar basic methodologies are used in these investigations. Initially, cameras or scanners are used to record images of diseases. The second step is to separate the impacted regions (spots) from the background. Thirdly, characteristics are taken from idiosyncrasies of colour, form, or texture. Finally, disease images are classified using algorithms such as neural networks, Bayesian classifiers, k- nearest neighbour (kNNs), support vector machines (SVMs), and others.

A machine learning technique for detecting and identifying rice illnesses such as blasts of rice (RB), leaf blight caused by bacteria (BLB), blight of the sheath (SB), and healthy leaf (HL) (HL) is given. It was paired with an SVM classifier and an advanced convolutional neural network (CNN) extractor of features that had been pre-trained. Preprocessing is given a lot of thought in the research since plants may contain dust, dew droplets, and other particles that produce noise in the data and cause issues in the division and extraction of attributes phases. The kNN classifier was utilized to provide a technique to recognise Blast and Brown Spot illnesses based on geometric factors such as area, main and secondary semi-axes of areas, and the perimeter of the damaged leaf section.

II. RELATED WORKS

One of the intriguing research areas in the computer and agricultural fields is the detection of disease from photographs of the plant. These parameters include picture dataset size, number of classes (diseases), preprocessing, segmentation methods, classifier types, classifier accuracy, etc. [1] The two-stage transfer learning was used in the model training to create an effective model. The proposed method may achieve the intended performance, according to experimental results, with an average recognition accuracy of 99.21% on the public dataset and 97.89% on the local dataset. [2] A survey study was conducted utilizing CNNs technique on eight main rice diseases, including bacterial leaf blight, false smut, rice hispa, blast, stemborer, sheath blight, brown spot, and brown planthopper. [3] In an effort to better understand the variety and identify antagonistic bacteria that are associated with rice in various microenvironments, the endophytic bacteria Deinococcus aquaticus strain 1Re14, Acidovorax sp. isolate 3Re21, and Brevibacillus brevis strain 1Pe2 are the first to be identified as such. [4] By activating the SA-dependent plant defense mechanisms, pre-inoculation with the endophytic fungus P. liquidambaris B3 greatly reduced rice bakanae disease and aided plant growth. Nevertheless, co-inoculation with P. liquidambaris B3 triggered overly aggressive defense reactions, killing plants and exacerbating the bakanae illness. [5]Because RS toxin can be inactivated by the microbial glucosidase enzyme, isolating the gene that codes for the enzyme from T. viride and transferring it to rice plants would result in increased resistance to the sheath blight pathogen through RS toxin inactivation..[6] Polysaccharide-treated seedlings had increased peroxidase and polyphenol-oxidase activity, as well as total phenols concentration. OsPR1.1, OsPR3, OsGLP3-3, OsZFP179, and Oshox24 were upregulated in treated plantlets, while OsACS6 was downregulated[7] Due to a lack of knowledge on RST pathway genes and the lack of a ShBresistant variety, understanding the different metabolic alterations induced in the prone variety by the phytotoxin in contrast with infectious and uninoculated controls allows us to identify important metabolite changes that occur during ShB infection. [8] In vitro antifungal activity against Magnaporthe oryzae, Rhizoctonia solani, Botrytis cinerea, and Fusarium graminearum were investigated for five putative plant growth-promoting rhizobacterial (PGPR) strains isolated from rice rhizospheres. The formation of indoleacetic acid, ammonia, siderophores, and catalase activity, as well as the solubilization of phosphate, were all favorable indicators for all three strains. By using multiplex PCR, it was discovered that these strains have several lipopeptide biosynthetic genes and were capable of forming biofilms.
[9] Bacterial and fungal infections have a serious negative impact on this very valuable crop, significantly reducing crop yield. 11 of the roughly 70 well-known illnesses that have an impact on crop output are caused by bacteria. [10] According to reports from around the world, bacteria from the genus Pantoea can cause rice leaf blight. The symptomatic leaves displayed comparable trends in contamination with X. oryzae pv. Fungus-caused leaf blight,but the disease was capable of significantly reducing rice grain yield.[11] Prediction of illness in rice leaf using DenseNet, a deep learning algorithm. DenseNet training, specifically DenseNet121, DenseNet169, and DenseNet201. DenseNet121 achieved accuracy of 91.67%, DenseNet169 of 90%, and DenseNet201 of 88.33%. 24 seconds pass throughout the model training process. [12] The model first trains on a unique static dataset using Residual Network (ResNet) and VGGNet-based CNN model, and then incrementally learns new information using a network of Gated Recurrent Units (GRU). [13] The dataset for the rice disease patch produced in the first stage was identified using a Siamese Network. The comparison experiment revealed that YoloX had the best detection performance at the detection stage, with a mAP of 95.58% for photos of rice illness. Siamese Network outperformed other models in the identification step, with an identification accuracy of 99.03%. [14]

2.1 Traditional Techniques for Rice Disease Detection

The following methods are currently being used by knowledgeable phyto-pathologists to recognise different rice diseases:

- Visual method: determining the disease's external signs, stage of growth, and frequency.
- Microscopic method: identification of the pathogen and its sporulation, as well as the type of changes occurring in diseased plant tissue.
- Biological methods: Artificial infection ; VNIIF guidelines are used to calculate the percentage of damage.
- Cultural method: The fungus is isolated on a nutritional medium using the and its morphological and cultural characteristics are studied.
- Molecular genetic method: Using polymerase chain reaction, diagnose rust fungi using molecular genetics.

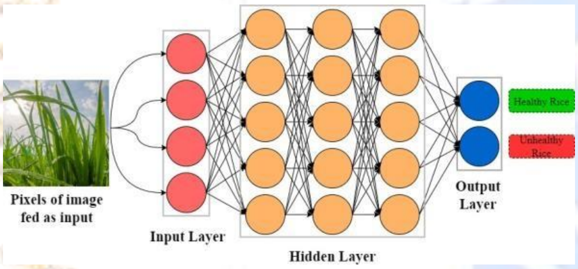
Because substituting the human eye and a professional phytopathologist by a computer algorithm is likely the simplest method to adapt it to modern machine learning techniques. Neural network techniques outperformed all other machine learning algorithms tested for equivalent tasks. They enable one to quickly determine whether an illness is present in the picture. Convolutional neural networks have established one another as the state-of- the-art for recognising digits. Convolutional neural networks have recently actually replaced additional neural network designs as the primary method employed in machine vision to solve issues related to classification, identification, and division of objects on images. Let's quickly go over the fundamental concepts and methods employed by neural networks, as well as some of the factors that contribute to their effectiveness.

2.2 Convolutional Neural Networks: An Overview

Contemporary computer vision approaches using neural network algorithms have proven the greatest efficiency of all learning algorithms utilized for similar applications. They allow you to swiftly identify whether or not an ailment exists in the image. CNNs, on the other hand, have been shown to be the most advanced neural network designs for number recognition. CNNs have lately replaced categorization, detection, and segment of objects on pictures as the dominant technique in computer vision.

Let's quickly go over the fundamental concepts and methods employed by neural networks, as well as some of the factors that contribute to their effectiveness.

The primary goal of CNNs is to simulate the mechanism of human vision as closely as possible. Only a select few of the connections between neurons in the network's neighbouring layers need to be used; not all of them. The simplest explanation of how vision works is when an eye sequentially focuses on different areas of an image rather than the entire thing at once in an effort to find any object within it .By layering identical convolution processes in various ways, one can create distinct CNN architectures. It now serves as a strong basis for contemporary computer vision and aids in the effective resolution of a variety of issues, including categorization, clustering, segmentation, and other issues.



After that, AlexNet was presented. With a test accuracy of 84.6%, it triumphed in the ImageNet 2012 competition. About 1.2 million training images were needed in total for classification.CNNs have emerged as cutting-edge algorithms for working with large colour images, capable of detecting a variety of patterns and shapes on them, thanks to the development of AlexNet. Thanks to the use of numerous parameters and tiny convolution kernels, ImageNet was 92.7% accurate. Convolutional designs had undeniable results by 2013. However, unlike LeNet, this success was primarily attributed to quantitative advancements and increased computing power rather than novel concepts. The total number of variables in networks has grown from a few thousand to hundreds of millions, rendering training them difficult, time-consuming, and expensive. At the time, it was still unclear if the instrument's intricacy was justified by how intricate the problem was, or whether innovative methodologies were required, as in the instance of classic neural networks. Google introduced their GoogLeNet Inception architecture in 2014, which won the ImageNet contest with 93.3% test accuracy, providing another major breakthrough to computer vision. The network only had 6M parameters, which is more than 20 less than VGG-16 and roughly 10 times less than AlexNet. The use of special inception blocks that concatenate convolutions of different sizes was a progressive idea that allowed for a significant reduction in the number of parameters and an improvement in the accuracy of predictions. This made it possible for the algorithm to recognise details at various scales right away and determine which one is most important for a particular image. The designs of SqueezeNet and DenseNet are also noteworthy. SqueezeNet has surpassed AlexNet in terms of quality, despite having 50 times fewer parameters. The number of input channels in each layer was decreased by using 11 convolutions and shrunk larger convolution kernels. ResNet and DenseNet both followed the same qualitative progression, though DenseNet concatenated the earlier layers with the later ones rather than summarizing them. As a consequence, we achieve quicker convergence and a small improvement in quality with a 7M parameter set similar to Google Neural Network.

2.3 Dataset Description

Like any supervised machine learning method, training a neural network requires a decent training set. The hardest part of the job is typically gathering properly preprocessed training data because it necessitates thorough analysis from the viewpoints of both the company and the product's end users. It is specifically stated that difficulties can be reflected by different lighting issues, photo noise, and inadequate illness severity.

It is necessary to know exactly how the learned neural network will be put to use after that. In particular, the following criteria should be established before labor starts: (1) general photographic circumstances, (2) shooting aspect, (3) contrast and brightness levels, (4) potential noise and distortion, (5) lighting issues, and (6) backdrop impact.The finished neural network's quality can be improved by setting photographic restrictions and requiring users to abide by them. Otherwise, no program can ensure the training precision for validation.

In this study, we make use of the dataset while slightly extending it with information that is publicly accessible online. We do not include maize hispa illness because it is unimportant for southern Russia. Finally, we employ a collection of 4,278 pictures, including 1,488 images of healthy individuals, 1,195 images of brown spot disease, and 1,595 images of leaf blast disease.

It should be noted that a single rice stalk can have multiple illnesses on it at once. Multiclass categorization is the job at hand in this situation. However, the information is rigorously marked, and its visual analysis supports this. Therefore, in this study, we take into account the scenario of a rigid multiclass classification:

only one illness per leaf.

Practically speaking, this means that even a perfect model will probably have an upper accuracy limit that is lower than 100% that it cannot beyond without retraining. In this study, we demonstrate that, even with a tight multiclass categorization assumption, a pretty good accuracy of up to 96% may be attained on the validation set.

Only these examples were used in the ultimate quality evaluation of the model's work: wholesome or diseased foliage explosion. These kinds of tests are crucial because the distribution of the dataset used to train the model can frequently be different from the distribution to which it will finally be applied. It is important to understand how robust the model suggested in this work is to distributional changes as machine learning methods are typically fairly sensitive to them.

2.4 Data Preprocessing

But even when gathering data and using a trained model while keeping an eye on the shooting circumstances and quality, a number of basic issues may come up that seriously harm the model's performance. Among them are the following:

- inadequate sample size
- natural rotation/image reflection invariance of forecasts
- volatility of predictions, where even negligible noise can alter the outcome;

the result of overfitting, which occurs when forecasts made on fresh images turn out to be considerably less accurate than those made on training data.

By planning good preprocessing of the initial pictures, all these issues can be addressed to a certain degree. For the initial sample, we use the preparation steps listed below:

- Random angle rotation from 0° to 45°
- Flip a picture along its primary axes.
- RGB picture channel normalization is a standard procedure.

The size of the training sample grows as a consequence, improving prediction stability and guaranteeing their invariance to picture rotations.

2.5 Model Architectures

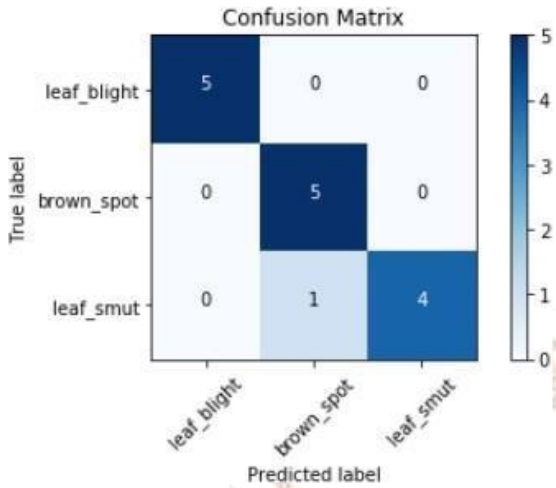
The categorical cross-entropy function, which is usual for multiclass classification issues, has been selected as the primary function. It can be written as (where ynk - ground truth responses (1 or 0), and pnk - softmax model predictions, which rely on model weights w. This applies to our situation of three classes. Since it has a straightforward probabilistic meaning and severely penalizes the model for wrong responses due to the logarithm, this loss function is the most appropriate for categorization tasks.

With PyTorch v1.6.0, a machine learning library built on the Torch library, we can train and use contemporary neural network architectures with all the required features. This framework's ease and extensive features make it very popular. However, the aforementioned architectures are quite well-liked, and you can find versions of them on any other platform, such as TensorFlow, Caffe, etc. The neural network was taught using the following setup on a fixed computer: GeForce GTX 1650 ti 4 GB, Ryzen 5.

The lighter designs that, if required, can be used immediately from a mobile device were the main emphasis of this effort. Using the PyTorch architecture and pre-trained models from the torchvision module, we fully adjusted the models for the aforementioned dataset. We looked at several CNN designs, both traditional and contemporary, and selected the following: SqueezeNeq-1.0, DenseNet-121, ResNet-18, and GoogleNet. They are the most compact while also producing the most hopeful outcomes. Thus, computationally demanding models like VGG and AlexNet, for instance, produced outcomes somewhat worse than those presented below and needing significantly more processing power both during training and prediction.

With only a few settings, DenseNet-121 had the greatest precision and stabilized in the quickest amount of time (roughly 14 epochs). The GooLeNet design came in second place, settling a little more slowly. ResNet-18 finished third in precision, but it already has a lot more factors than the other two. SqueezeNet-1.0's design is something that deserves particular attention. It wasn't significantly worse than the others, displayed comparable accuracy findings, stabilized fast, and had the fewest parameters—roughly 750K.

III. RESULT

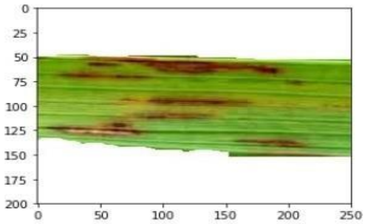


The end quality measures for the models under evaluation are shown in Fig. 2 and include accuracy, micro and macro averaged f1, precision, and recall. It is apparent that DenseNet-121 excels in every trait. GoogleNet and SqueezeNet are the following. In this instance, the heavyweight ResNet design proves to be inferior to the others.

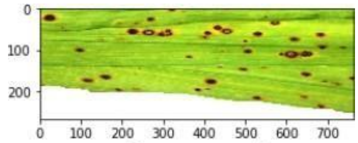
	precision	recall	f1-score	support
bacterial_leaf_blight	1.00	1.00	1.00	5
brown_spot	0.83	1.00	0.91	5
leaf_smut	1.00	0.80	0.89	5
accuracy			0.93	15
macro avg	0.94	0.93	0.93	15
weighted avg	0.94	0.93	0.93	15

The one-vs.-all ROC curves for each class are shown in Figure 3 and were constructed using the validation data and forecasts from the top DenseNet model. Each and every ROC-AUC value is very near 1. GoogLeNet performs marginally better at forecasting the existence of an illness, but it can mistake a brown spot for a leaf blast, according to a deeper examination of the algorithms' mistakes. The overall findings for the ResNet and SqueezeNet architectures are comparable. Only a tiny portion of the diseased plants are detected by even the most accurate DenseNet design, which precisely identifies the remaining instances. (see Figure 4).

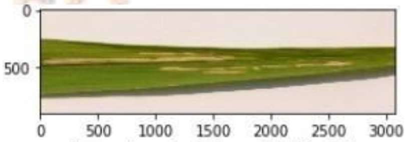
	epoch	accuracy	loss	val_accuracy	val_loss
0	0	0.590476	1.933403	0.400000	3.490494
1	1	0.733333	0.883449	0.666667	2.441292
2	2	0.800000	0.644075	0.533333	3.472850
3	3	0.885714	0.312418	0.600000	1.986271
4	4	0.914286	0.226143	0.866667	1.106820



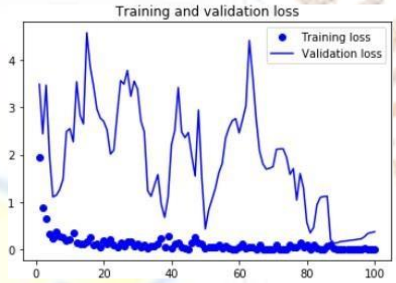
Leaf smut

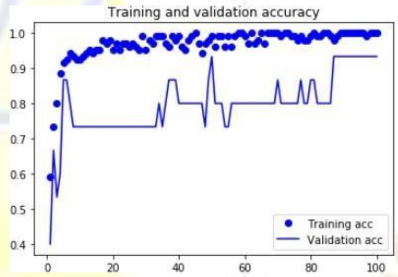


Brown spot



Bacterial leaf blight





IV. CONCLUSION

Convolutional neural network contrasts between various traditional and modern forms show how well these methods can address the problem. The best results were obtained by the DenseNet-121 construction, which achieved a precision of 95.57% on the given dataset. Furthermore, this design displayed the quickest stabilization to values near to the optimum in only 10-20 epochs. We contend that by effectively managing the data collection and early detection systems, the issue of contracting rice fungal infections may be successfully addressed. Furthermore, it is demonstrated that such models may be trained without requiring a significant amount of processing resources. The final proposal could occasionally be used on mobile devices with low computational power needs due to its delicate nature.

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