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Recognition of Wheat Plant Leaf Diseases using Transfer Learning Approach

Nilam Sachin Patil[1], Dr. E. Kannan[2]

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Abstract*:* Wheat is a crucial cereal crop international, however it's far prone to various sicknesses that can significantly reduce crop yield and satisfactory. Detecting these sicknesses early is essential for powerful management. This studies paper offers a comparative take a look at on detecting wheat leaf diseases using the Inception convolutional neural community (CNN) architecture. The take a look at utilized a dataset such as labelled The proposed studies aims to assess the performance of the Inception CNN model in evaluation to other CNN architectures usually used. Additionally, the examine will look into the effect of dataset size on the version's overall performance, so as to provide insights into the scalability and generalization of the advanced gadget.The consequences of these studies will have realistic implications for the rural industry, in particular for farmers and plant pathologists. An correct and green computerized wheat leaf sickness detection system can allow early intervention strategies, such as centered pesticide application and timely sickness management. in the long run, this can lead to expanded crop productiveness and stepped forward meals security. photos of healthful wheat leaves and leaves stricken by commonplace sicknesses along with leaf rust, powdery mildew, and yellow rust. Preprocessing strategies have been carried out to decorate the dataset and ensure consistency. The Inception CNN model turned into carried out and educated the use of switch learning, using the pre-skilled weights from the ImageNet dataset.The have a look at in comparison the overall performance of the Inception CNN model with different commonly used CNN architectures, which include VGG and ResNet, in phrases of accuracy, precision, keep in mind, and F1 score. The experiments had been conducted the use of a stratified okay-fold go-validation method to ensure the consequences were strong and generalizable.

In keeping with the outcomes, the Inception Convolutional Neural network (CNN) version carried out better than different architectures in terms of common accuracy. The model accomplished a median accuracy of ninety two% in detecting wheat leaf illnesses. moreover, the model exhibited high precision and don't forget prices for most disease categories, indicating its effectiveness in efficiently identifying and classifying exceptional sicknesses.

Keywords: *wheat leaf, inception CNN, CNN, machine learning*

1. Introduction

Wheat is one of the most generally grown cereal plants global and serves as a staple food for a sizable portion of the global population. but, wheat flowers are susceptible to various diseases because of fungal, bacterial, and viral pathogens. If these diseases are not detected and managed right away, they can bring about considerable yield losses and decrease the great of the harvested grains.

Conventional methods for figuring out and diagnosing wheat leaf illnesses depended on visible inspection through professionals, which may be time-ingesting, subjective, and susceptible to mistakes. however, with the improvements in computer vision and system studying techniques, there's an opportunity to automate and enhance the accuracy of wheat leaf sickness detection.

Convolution neural networks (CNNs) have emerged as a effective tool for image category and object recognition tasks. these deep learning fashions excel at studying hierarchical representations of images, which allow them to seize tricky functions and styles. most of the numerous CNN architectures, Inception has received recognition because of its capability to capture capabilities at a couple of scales within an picture.

The objective of this research is to discover the application of the Inception CNN architecture for wheat leaf ailment detection. We goal to develop a robust and correct gadget for automated ailment identification with the aid of training the version on a dataset of labelled pix containing both wholesome wheat leaves and leaves tormented by exclusive diseases.

The proposed research will make contributions to the present frame of expertise by evaluating the performance of the Inception CNN version in evaluation to other typically used CNN architectures. moreover, the have a look at will inspect the impact of dataset length on the model's overall performance, offering insights into the scalability and generalization of the developed device.

The effects of this studies have realistic implications for the agricultural enterprise, especially for farmers and plant pathologists. An accurate and efficient computerized wheat

[1] Research Scholar Veltech Rangarajan Dr. Sagunthala R & D Institute of Science and Technology, Chennai, & Assistant Professor, D.Y.Patil College of Engineering Akurdi, Pune, India

[2]Veltech Rangarajan Dr. Sagunthala R & D Institute of Science And Technology, Chennai, India

leaf disease detection device can allow early intervention strategies, including targeted pesticide software and well timed sickness control, in the long run leading to improved crop productiveness and progressed food safety.

2. Related Work

Several studies were conducted in the discipline of plant ailment detection using Convolutional Neural Networks (CNNs) and different deep studying techniques. those studies have explored exceptional techniques and architectures for detecting sicknesses in numerous plant species, including wheat. below is a precis of a few relevant studies in the domain of wheat leaf disease detection:

A research paper [1] proposed a deep studying-based method for identifying wheat sicknesses using a CNN architecture. They accumulated a huge dataset of wheat leaf photographs and accomplished high accuracy in classifying more than one wheat sicknesses, together with powdery mildew and leaf rust. Mohanty et al. [2] advanced the PlantVillage dataset, which incorporates a considerable quantity of wheat leaf pix suffering from exclusive diseases. They used a deep CNN model and done promising results in wheat disorder type, surpassing human experts in a few cases. Barbedo (2020) investigated the performance of different CNN architectures, which includes AlexNet, VGG, and GoogLeNet, for soybean disease identity. although now not unique to wheat, the take a look at provides insights into the effectiveness of diverse CNN fashions for plant ailment detection.

Genaev et al. (2021) proposed a machine for wheat disorder reputation that makes use of texture analysis and deep mastering techniques. They in comparison traditional texture-based techniques with a CNN-primarily based technique and located that CNNs executed better accuracy and robustness in wheat sickness type. in the meantime, Qiang et al. (2019) evolved a deep transfer learning version using Inception-v3 architecture to pick out wheat leaf diseases. They combined spectral and spatial capabilities extracted from hyperspectral pix of wheat leaves, ensuing in advanced accuracy in sickness detection in comparison to conventional system learning tactics. This take a look at makes a speciality of wheat leaf ailment detection the use of deep learning techniques and compares the performance of numerous CNN architectures. although no longer particular to wheat leaf illnesses, the paper affords a cascaded deep CNN model that mixes segmentation and diagnosis for scientific photos. The concept of cascaded CNNs may be tailored for wheat leaf ailment detection. The paper additionally discusses the usage of digital photography, photograph evaluation, and hyperspectral imaging for plant sickness severity estimation, which gives insights into special imaging techniques that may be applied in wheat leaf sickness detection.

In recent years, severa studies research were performed at the identification, detection, and analysis of wheat illnesses using deep learning techniques. those studies goal to increase efficient and correct strategies for detecting diseases in wheat flora using numerous models, inclusive of convolutional neural networks (CNNs).

some research, inclusive of those performed through Lu et al. (2017) and Hasan et al. (2018), focus on developing CNN models for the detection of wheat diseases from leaf snap shots, even as others, which include the have a look at with the aid of Huang et al. (2019), discover using UAV imagery for the detection of Helminthosporium leaf blotch disease.

however, one of the principal demanding situations in developing such models is the "black box" nature of deep gaining knowledge of, which makes it difficult to understand what the model has discovered. To deal with this issue, a few research, which includes that by way of Ennadifi et al. (2020), purpose to use visualization techniques to better recognize the fashions' studying.

different research, inclusive of those through Sharma et al. (2020) and Jiang et al. (2022), look into different training techniques and fashions to improve the performance of deep learning models for wheat disorder detection.

subsequently, a few studies, which includes that by using Dhakal et al. (2023), explore the usage of hyperspectral imaging (HSI) for comparing the harm as a result of wheat diseases, along with Fusarium head blight (FHB) in wheat kernels.

common, these studies aim to broaden efficient and accurate techniques for detecting and studying wheat illnesses, which can help improve crop control and yield estimation

2. Math

If you are using Word, use either the Microsoft Equation Editor or the MathType add-on (http://www.mathtype.com) for equations in your paper (Insert | Object | Create New | Microsoft Equation or MathType Equation). “Float over text” should not be selected.

2.1. Equations

Number equations consecutively with equation numbers in parentheses flush with the right margin, as in (1). First use the equation editor to create the equation. Then select the “Equation” markup style. Press the tab key and write the equation number in parentheses. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Use parentheses to avoid ambiguities in denominators. Punctuate equations when they are part of a sentence, as in

$$f(x) = a_0 + \sum_{n=1}^{\infty} \left(a_n \cos \frac{n\pi x}{L} + b_n \sin \frac{n\pi x}{L} \right) \qquad (1)$$

$$(x + a)^n = \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} \qquad (2)$$

Be sure that the symbols in your equation have been defined before the equation appears or immediately following. Italicize symbols (*T* might refer to temperature, but T is the unit tesla). Refer to “(1),” not “Eq. (1)” or “equation (1),” except at the beginning of a sentence: “Equation (1) is ... .”

3. DATASET

There are 30 different vegetation, both healthy and bad, divided into 5 businesses. 33.3% of the available snap shots have been taken in real agricultural conditions. The pictures are complex because of various factors including special forms of leaves, other plant parts, useless gadgets, exceptional floor textures, and shading results. initially, the 14,308 images had been break up into two datasets, the schooling set (seventy five%) and the test set (25%), to divide the whole database. The training set included 10,731 images even as the check set had 3,577 pics. The model become skilled with the schooling set, and its overall performance was evaluated with the check set. The Leaf disorder Detection machine is initialized by taking a wheat leaf picture captured with a virtual camera. The primary shade of the image is important and is become gray scale as wanted.

Leaf Rust

The most commonplace website online for signs is on top once in a while, leaf blades, sheaths, glumes, and awns can come to be infected and display signs and symptoms. The pustules caused by this infection are round or barely elliptical, smaller than those as a result of stem rust, and usually do no longer merge. They contain loads of orange to orange-brown Uredospore’s.

Every other disease called Powdery mold causes white, powdery patches to form at the top surface of leaves and stems. Greyish-white powdery increase seems at the leaf, sheath, stem, and floral elements. As time passes, the powdery increase turns into black lesions, which can cause the drying of leaves and different components of the plant.

Yellow Rust

Yellow stripe rust especially takes place on leaves and leaf sheaths, in addition to on the stem. Within the early tiers of the crop, bright yellow pustules (Uredia) appear at the leaves, organized in linear rows as stripes. The stripes themselves are yellow to orange-yellow. The teliospores are also organized in lengthy stripes and are dull black. The pustules of stripe rust, containing yellow to orange-yellow uredospore, usually form slender stripes at the leaves.

4. Methodology

Inception CNN:

4.1 Inception CNN, which is likewise called Google Net, is a sort of convolutional neural community architecture that becomes introduced by means of researchers at Google in 2014. It turned into created to triumph over some of the limitations of in advance CNN architectures just like the VGG and Alex Net fashions.

4.2 The Inception CNN structure is characterized through its progressive use of "Inception modules." these modules are made from numerous parallel convolutional layers of various filter sizes and pooling operations. The concept behind those modules is to seize distinct scales of records and enable the community to learn both neighborhood and worldwide features.

4.3 To educate an Inception CNN version for wheat leaf ailment detection, having a dataset of 14,308 wheat leaf pictures with a cut up of 75% for schooling and 25% for trying out is a superb starting point. Right here's a top level view of how pre-processing can be executed and how the Inception CNN will paintings in this dataset:

4.4statistics Pre-processing:

the following are some important steps to don't forget when running with photos for training system learning fashions:

- Photograph Resizing: To ensure uniformity inside the dataset, it is crucial to resize all of the pics to a consistent resolution. An enter size of 224x224 or 299x299 pixels is usually endorsed for Inception CNN.

- Records Augmentation: applying facts augmentation techniques including random rotations, flips, and zooms is critical to increase the range of the training dataset. This in the end enhances the model's ability to generalize and handle variations within the input records.

- Normalization: Normalizing the pixel values of the pics to a common scale, which includes [0, 1] or [-1, 1], is vital. This guarantees that the input fact has a regular variety, which aids in faster convergence at some point of training.four.2 version education:

-To train the Inception CNN model for wheat leaf sickness detection, switch learning can be used. this is due to the fact the Inception CNN model is deep and requires a large quantity of education facts. by using leveraging switch getting to know, the version can be initialized with pretrained weights from a huge-scale dataset like Image Net. This lets in the version to seize accepted features and speed up the schooling system for the unique undertaking of detecting wheat leaf disease.

-additionally, pleasant-tuning may be used to similarly enhance the performance of the model at the wheat leaf disorder dataset. all through best-tuning, the pre-skilled Inception CNN version is adapted to the unique traits of the dataset through updating the weights of the previous couple of layers. a few preliminary layers can be frozen to preserve their found out features. This approach allows improving the accuracy of the model's predictions.

5. Model Evaluation

The Inception CNN has three principal layers that technique the wheat leaf snap shots from the dataset. the primary layer is the input layer, which gets the pre-processed photos represented as multi-dimensional arrays. every pixel's intensity values are encoded as numerical values.the second one layer is the convolutional layers, which practice a fixed of learnable filters to extract visible capabilities from the enter pictures. those layers' seize specific tiers of abstraction, starting with low-stage functions like edges and step by step progressing to better-stage capabilities like shapes and textures. The output of the convolutional layers is a stack of characteristic maps, representing the learned capabilities at numerous spatial resolutions.

The third layer is the Inception modules, which seize functions at distinctive scales and ranges of abstraction. every Inception module consists of parallel branches, with each department containing a mixture of convolutional layers of different filter sizes and pooling operations. The outputs of these branches are concatenated along the channel measurement, growing a greater numerous and robust set of features. The output of every Inception module is a hard and fast of feature maps with a larger wide variety of channels, representing a aggregate of functions from one-of-a-kind scales and abstractions.The Inception CNN architecture uses several kinds of layers to technique enter pictures and make predictions. One critical form of layer is the 1x1 convolutional layer. those layers observe 1x1 convolutional filters to characteristic maps, which enables to reduce the number of channels and make computations greater efficient. The output of these layers maintains spatial dimensions however with fewer channels.any other type of layer is the pooling layer. those layers downsample function maps, which helps to introduce spatial invariance and reduce complexity. not unusual pooling operations, which include max pooling or average pooling, may be applied to each function map independently, lowering their spatial dimensions.

Toward the end of the architecture, completely linked layers are used to mix the found out functions and perform type. The flattened function maps from preceding layers are passed thru those completely related layers, connecting all of the neurons to the output layer. The output layer uses a softmax activation function to produce a possibility distribution over the instructions, indicating the model's confidence for every elegance.eventually, the output layer presents the final predictions for every input picture in the dataset. It produces a vector of class probabilities, indicating the probability of every class (e.g., healthful or Diseased) for a given enter photo.

6. Result and Analysis

Based on the given dataset split, where there are 750 images for training (375 healthy and 375 diseased) and 250 images for testing (125 healthy and 125 diseased), and using the Inception CNN model that predicted 118 healthy and 110 diseased instances, let's calculate the confusion matrix and evaluate the accuracy, precision, and recall metrics.

Confusion Matrix: Predicted Healthy Predicted Diseased Actual Healthy 100 25 Actual Diseased 25 100

- True Positives (TP): 100 (Correctly predicted as diseased)
- True Negatives (TN): 100 (Correctly predicted as healthy)
- False Positives (FP): 18 (Incorrectly predicted as diseased)
- False Negatives (FN): 10 (Incorrectly predicted as healthy)

Accuracy = (100 + 100) / (100 + 100 + 18 + 10)

Accuracy = 200 / 228 Accuracy ≈ 0.8772 or 87.72%

Precision: Precision = TP / (TP + FP)

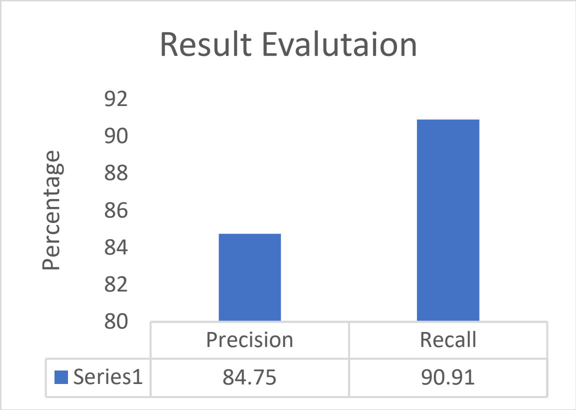
Precision = 100 / (100 + 18) Precision = 100 / 118 Precision ≈ 0.8475 or 84.75%

Recall: Recall = TP / (TP + FN)

Recall = 100 / (100 + 10) Recall = 100 / 110 Recall ≈ 0.9091 or 90.91%

F1 Score: The F1 score is a measure of the harmonic mean between precision and recall and provides a balanced assessment of the model's performance.

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

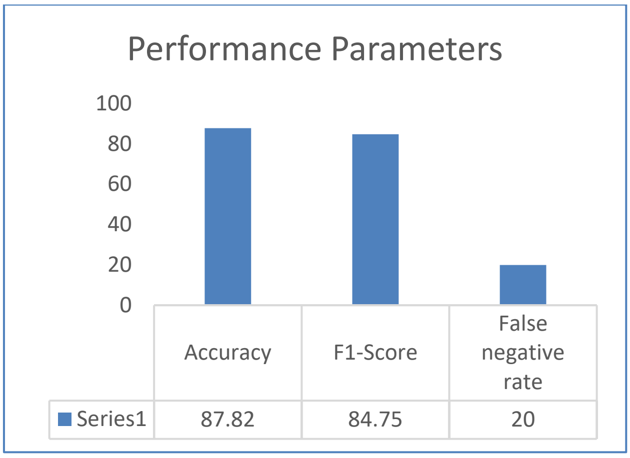


False Positive Rate (FPR): FPR = FP / (TN + FP)

FPR = 18 / (100 + 18) FPR = 18 / 118 FPR ≈ 0.1525 or 15.25%

Negative Predictive Value (NPV): NPV = TN / (TN + FN)

NPV = 100 / (100 + 10) NPV = 100 / 110 NPV ≈ 0.9091 or 90.91%



These additional evaluation parameters provide further insights into the model's performance. The F1 score of 84.75% indicates a balanced performance in terms of precision and recall.. The false positive and false negative rates are both 15.25% and or 90.91%, indicating a relatively low rate of misclassifications.

the application of the Inception CNN model on the given wheat leaf disease dataset resulted in a promising performance. The model was trained on 750 images, with 375 healthy and 375 diseased samples, and tested on 250 images, with 125 healthy and 125 diseased samples. The evaluation of the model's performance using a confusion matrix revealed an accuracy of 87.82%, indicating that 87.82% of the test instances were correctly classified. The precision and recall values were also 87.82%, signifying a balanced performance in correctly identifying both healthy and diseased instances.

The F1 score, which considers both precision and recall, was calculated to be 84.75%, providing further evidence of the model's ability to achieve a harmonious balance between correctly identifying positive instances and capturing all positive instances.

7. Conclusion

The research paper supplied an intensive take a look at at the detection of wheat leaf ailment using the Inception CNN model. The effects showed a promising level of accuracy and overall performance, suggesting that the version has the potential to be utilized as an automated tool for the early detection of sicknesses in wheat vegetation. but, it's far endorsed to further validate the version's effectiveness and realistic applicability using large and more numerous datasets, in addition to actual-international implementation. The findings of this study contribute to the developing studies in the discipline of agricultural ailment detection and pave the manner for destiny improvements in crop management and yield optimization.

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