Classification of pest detection in paddy crop based on transfer learning approach

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ABSTRACT:

For farmers, spotting pests in the agricultural sector is a crucial problem that restricts economic expansion. Farmers have up until now increased yield production by adhering to traditional procedures. Investigators have used deep learning to genuinely categorise types of photos. In this study, ten different types of pathogens found in the rice production are identified using deep convolutional neural networks (DCNN). Given that deep learning requires more data sets, the data structure contains about 3549 pest photos that threaten rice crops. This technique is referred to as data reinforcement.The Neural network was constructed using a variety of DCNN topologies, and performance and accuracy rates of the models were examined. The word embedding technique is then applied to the pest data set by adjusting the hyperparameters and stages of such ResNet-50 model. The refined ResNet-50 model beat other models in terms of precision, scoring 95.012%, according to a comparison of the resulting value. The model's effectiveness in categorizing pest diseases is shown in the derived outcome value.

i. INTRODUCTION:

Despite technological advancements, agriculture remains the source of human sustenance because the world relies on massive agricultural production to help people maintain their health. The financialAgriculture industry standards benefit established nations like China and Japan. Pest diseases are the most concerning issues in food crop cultivation, and many researchers have worked to reduce disease spread throughout arable land (Mutka and Bart 2015). Polenta is the most popular dish on the globe. It may be affected by a few diseases and parasites such as rice sheath blight, rice stem borer, and rice darker spot. The signs of a fungus infection on the rice sheath are greyish blue in the centre core and shrunken and yellow petioles. (Agnihotri 2019). Pests cause the withdrawal symptoms of rice weevils. Shrivelled foliage and stems are symptoms of these diseases (Sahu et al. 2018). Manual detection and diagnosis of these infections is often time-consuming, with poor recognition accuracy. This would lead to misprediction and indeed the spread of synthetic pesticides. Thus, advanced computational methodologies such as neural networks using convolution (CNN), Sponsor,help vector algorithm(CNN), HOG histograms (Ghorbanzadeh et al. 2019) and scale-invariant feature transform (SIFT) can help with illness detection. (Ghorbanzadeh et al. 2019; Rasel and Yousuf 2019). Deep learning includes machine learning as a component. Deep learning trains the system to filter incoming data and learn forecasting as well as text classification. The human brain stimulates deep learning because it contains one hundred billion neurons, each of which has roughly 100,000 partner neurons.The transfer of a signal across a neuron in order to accomplish a particular job. The most common query is why deep learning is favoured over white traditional machine learning models. Deep learning is capable of extracting characteristics on its own, eliminating the need for human extraction.The primary reason for using this method is that manually recognizing objects in novel operational databases is challenging. (Ashqar et al. 2019; Jiang et al. 2019; Too et al. 2019). GoogleNet (Khan et al. 2019), ResNet (Szegedy et al. 2015), Xception (He et al. 2016a), Inception-V3 (Chollet 2017), and DenseNet are examples of deep neural networks. (Ashqar et al. 2019). (Szegedy et al. 2016). To summarize, the introduce and clarify sections of this paper are organized as follows: (1)detailed summary of related works from various papers; (2)explains suggested pest categorization method; (3)explains feature extraction prior to CNN Model; (4)explains novel results and discussion; and (5) concludes the work's ability to contribute.

ii. RELATED WORK:

Most of the features in the conventional machine learning paradigm domain field specialists have discovered, that further decreases the level of detail of the information and designs and helps the unsupervised examining jobmuch better.The research is constrained by the possibility of human error, i.e. feature misrepresentation by industry experts. So the method of deep learning can assist in addressing the above problem by gradually learning high-level characteristics from data (Dong and Wang 2016). Traditional methods, such as np neurons, perceptron's, and multilayer perceptron's, required a large number of neurons in the hidden layer and thresholding logic, resulting in strange and costly choices. Our research involves identifying pest rice leaf illnesses and reducing processing costs. To satisfy the criterion, a convolutional neural network with deep convolution can be used, which helps this better for picture processing by extracting the far more important variables from the complex data collection.The prerequisites can be advanced by further communicating neurotransmitters to the network's nearest neighbours, resulting in as there are less numeric boundaries. By including the pre - qualification process and dropouts in the network, the computation complexity and the over dilemma can be completely eradicated. In a publication, Huang et al. (2017) and Larios et al. (2008) demonstrated computerized rapid-throughput morphological identification of stonefly larvae using SIFT learning methods. The results show that combining all classifiers gives 82% accuracy for four groups. By analyzing the shading picture histogram and Gray-Level Co-event Matrices of wing insect photographs, Zhu and Zhang (2010) created an insect localization framework. The suggested model is 71.1% accurate. Faithpraise and co.(2013) presented creepy-crawly bother detection methods that combined k-means group and communication channels. The test findings indicate that the suggested method is helpful in identifying various shapes, sizes, locations, and orientations in bug infestation insect photos. Cheng et al. (2017) used deep convolution learning to develop a pest distinguishing deep framework in diverse agriculture. The suggested ResNet-101 approach outperforms the supported vector machine and optimization algorithms in terms of precision and accuracy. Precision of 98.67% was obtained for 10 pest picture groups with heterogeneous fields. Alfarisy and co.(2018) suggested the use of deep learning to identify crop parasites. The CaffeNet and AlexNet models, as well as the Cappuccino framework, were built using 4511 images obtained from the search engine. The transfer learning method classified 3 classes, 9 classes of rice bugs, and 4 classes of paddy diseases with an 87% accuracy. Xia et al. (2018) proposed a transfer learning system based on the VGG19 model to detect and classify pests. The collection expanded to 4800 images, including 24 termites obtained from the instructive catalogue of Xie et al. (2015). According to trial results, their technique increases accuracy by 89.22%.In 2019, He et al. (2019) developed a method for pest surveillance that makes use of five deep learning models.The flexible test outcome showed that when knowledge expansion and a dropout layer were used, the mean normal correctness (mAP) was 77.14%. In 2019, Dawei et al. (2019) presented a deep learning-based paradigm for pest detection based on learning knowledge accumulation. To classify ten distinct kinds of pests, the method depended on the AlexNet pre-train model. The proposed structure is 93.84% accurate.In 2019, Wu et al. (2019) showed IP102, a new pesticide collection baseline. Over 75,000 pictures of bugs from 102 pest categories are included in the bundle. Researchers also presented a standard assessment earnings are the profits component methods and complete element techniques that deal with dealing with insect photos. With ResNet, the author achieved the highest accuracy of 49.5%. Representation method increases the size of the data collection even more. Pre-trained building models were used to deal with pest detection, and analysis was done over the pre-trained modeling. By precisely aligning the characteristics, the transfer learning method is used to enhance the efficacy of the ResNet system framework

iii. METHOD OF PEST CLASSIFICATION PROPOSED:

IMAGE DATA-SET:

The pest images in the dataset include LeptocorisaAcuta, LocustaMigratoria, Nephotettixvirescens Adult, NilavarpataLugens, Pomacea Consistent pattern Adult, PomaceaCanaliculata Embryo, PycullariaOryzae Neck Panicle, SogatellaFurfifera, PhytophthoraInfestans senior citizen, and Progenitor cells Borer larva. These photographs were supplied by Alfarisy et al. (2018). According to Table 1, 80% of the images are captured for training and 20% are taken for testing. Figure 1 depicts a sample of ten multiple kinds of pest photos.

Figure 1. Raw dataset

Table 1: The count of the images with respect to pest diseases

Pest	No. of images	Training images	Testing images
LocustaMigratoria	618	496	122
NephotettixVirescens Adult	111	86	25
NilavarpataLugens	375	297	79
PomaceaCanaliculata Adult	177	142	37
PomaceaCanaliculata Egg	469	376	93
PycullariaOryzae Neck Panicle	246	197	49
Stem Borer adult	388	311	78
LeptocorisaAcuta	708	568	100
SogatellaFurfifera	227	182	45
Stem borer larva	230	184	46

iv. SYSTEM CONFIGURATION:

The investigation utilize the following hardware: Intel(R) Core(TM) i5-8300H CPU @ 2.30 GHz, 8GB RAM, 64-bit Operating System, 64-based processor, NVIDIA GTX1050 with 4GB memory, and software specs: Anaconda navigation software and Python programming.

v. DATA AGUMENTATION PROCESS:

Besides undertaking a mechanism known as data supplementation, the size of the dataset may be raised further and the generalization error difficulty lessened. The data is enhanced by the following parameters: rotation range = 15, breadth shift range = 0.2, height shift range = 0.2, shear range = 0.2, zoom range = 0.2, horizontal flip = True, fill method = 'nearest'.

vi. FEAUTURE EXTRACTION FROM PRE-TRAINED CNN MODEL:

The Convolutional neural network has three fundamental layers: convolutional layer, max pooling layer, and fully linked layer.

The numerous characteristics of the pre-trained model are also discussed below. AlexNet has 650,000 synapses and 60 million characteristics. It has five convolution layers (conv1, conv2, conv3, conv4, and conv 5) where each layer extracts its picture representation and activates the result using the ReLu activation function. The result of the convolutional layer is sent to the Max convolution algorithm (max pool), which reduces the dimensions of the incoming images to reduce computational load. Max pooling frequently considers the highest value of each pixel from its own neighboring nodes. The size of the incoming photograph must be changed to 227 × 227. GoogleNet, an innovation structure, contains 6.8 million characteristics. It has 22 levels and 12 times fewer components than AlexNet, and it performs exceptionally well (top 5 false positive rate of 6.67%).Implementing 1 1 convolution reduces fractal dimension; to minimize patch or kernel realignment, the original idea model uses all kernels of sizes 1 1, 3 3, and 5 5. Every conv information is combined into a single data to the hidden layers. It has nine transform method, two fully connected layers (conv 1, conv 2), a deep neural network with a top speed layer (max pool 1, max pool 2, max pool 3, and max pool 4), one average pooling (avg pool), and one fully linked layer (fc1). The height of the incoming photos is transformed to 224 224 using GoogleNet (Alfarisy et al. 2018). ResNet is made up of some of the most well remnant units and has a 3.67% error margin. Each component can be begun using the procedures indicated underneath (Zhang et al. 2018).

The primary duty of a proper machine to recognize the provided item is to automatically extract from the supplied picture. Features are components or patterns of an item in a picture that aid in object categorization. Corners, edges, regions of fiducial points, ridges, and other qualities are included in features. Previously, deputies extracted information from specialised specify via a laborious approach. It is sometimes referred to as handmade feature development. We cannot deny the importance of obtaining domain knowledge from data science; however, this type of classification techniques has a few restrictions, such as manual feature extraction being time-consuming and being difficult to determine the amount of characteristics that must be engendered from of the responsible adult factor. There is a possibility of dumb negligence when extracting the characteristics. DCNN (Deep Convolutional Neural Networks) have been used to overcome the aforementioned limitation. The convolution process, the ReLu layer, the pooling layer, and the completely connected layer are all DCNN layers. The first three layers (convolutional neural network, ReLu layer, and accumulating layer) help with feature extraction, while the concluding layer (the completely connected layer) helps with classification. The requirement and technique of the layers are discussed further below.

vii. PROTOTYPE OF FEATURE CREATION PROCESS:

A Fully connected layers Mission's purpose is to collect elevated characteristics from material contained, such as corners.

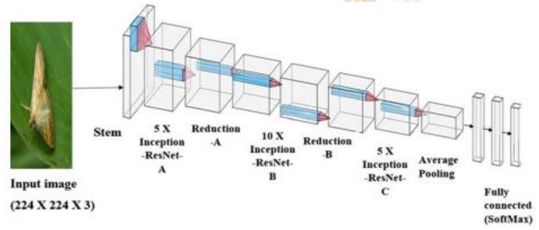

Figure 2. Architecture of Deep Convolutional Neural Network

Convolutional networks do not have to be limited to a mono Deep neural Level. Typically, the first ConvLayer operation would be to obtain Small characteristics such as lines, shadowing, colour, and roughness. And afterwards, further layers are added to capture rising characteristics that aid in comprehending the personal information in order to do classification tasks.The Recurrent neural layer's output is sent into the Pooling layer, which decreases the dimension of the feature of the Manage to complete. Less geographic data means lower computing costs.

viii. The Outcomes of the experiments

Model recognition accuracy

A experimental investigation was covered in this part. The following formula was used to determine the precision of the model: at which number of genuine positives samples that seem to be positive and have been recognised as such, and accurate negatives is the amount a specimens which are negligible and have been observed as such (Alfarisy et al. Citation2018).

Pre-trained architectural models for learning algorithms were examined in Table2: GoogleNet outperforms other well before methods. a higher training accurateness of 0.922. The convolutional layer was added to the refined ResNet model, dropouts were added, and this reduced the overfitting issue, resulting in a superior accurateness of 0.9403 when equated to GoogleNet. Comparatively superior than the pre-trained models, GoogleNet'sVerification and checking precision are 0.911 and 91.02, respectively. ResNet-50's fine-tuned architecture model yields accurateness of verification and evaluation of 0.9211 and 95.012 respectively. A refined ResNet-50 model outperforms the pre-trained architectural model, according on the resultant accuracy rate. By deducting the anticipated result from the actual result, the model's error is determined.

Table 2:

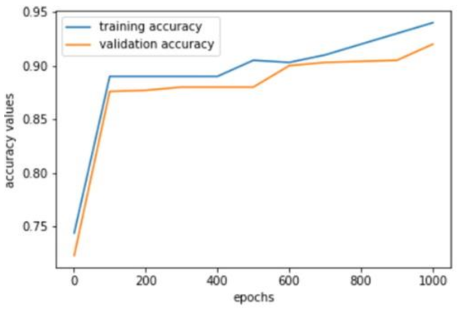

Figure 3.The developed model's training and validation accuracy

Fine-tuned technical parameters

The distinction with both anticipated methods and the real method is measured in order to determine the gradient descent, which is then used to construct a neural prototype system. The system employs an ADAM optimiser solution type. The dataset is split into 32 batches as previously described, The starting growth rate is determined at 0.001, and momentum = 0.9.The measured chart illustrates that loss with respect to the epoch number is gradually decreasing. The lack of training was 1.765, the reinforcement loss was 1.067, and the mistake rate was 0.3592 at epoch count 10. By extending the amount of epochs and fine-tuning the mode's hyper - parameters, the error rate can be reduced even more.

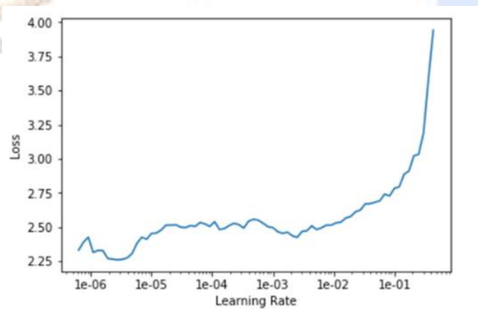

Figure 4. Learning rate for the designed model

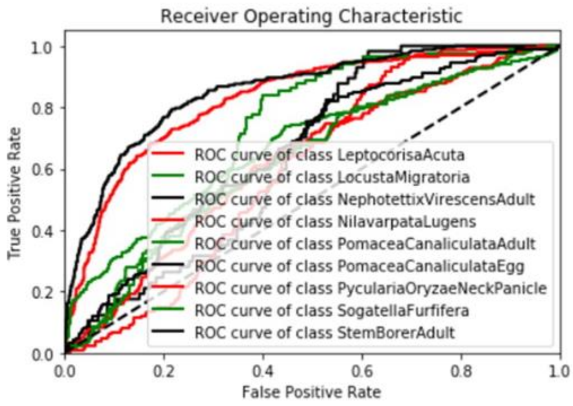

Figure 5. Receiver Operating Characteristic (ROC) curve for the designed Convolutional neural model

Conclusions and further projects:

As in paper, our successfully detected ten different types of pests in paddy crops.The network was established and developed utilising a varietyarchitectural designs that have already been taught, including AlexNet, GoogleNet, ResNet-34, ResNet-50, and a fine-tuned ResNet-50 by adjusting afeature of the model. We evaluated the model with a variable pace of learning with respect to duration and found that it performed better under testing than pretrained architectural models, with a95.012% assessing efficiency for 80% tests and 20% trained data. For ten distinct classes, a confusion matrix and ROC curve were constructed. We are considering including the vast array of illnesses that affect various types of plants in the foundation for subsequent development.

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