Classification of Diseases in Paddy using Deep Convolutional Neural Network

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Abstract: Paddy disease detection is decisive in the field of automatic pathogens diagnosis machine. Currently, Deep Convolutional neural network typically examined the state-of-the art results in image classification. In this work, we proposed a novel DCNN model to identify previously known bacteria leaf blight, brown spot, leaf blast, leaf smut and narrow diseases in prior knowledge. A unique repository of data holds 1260 images of different diseases, 80\% of data carried out for training and 20\% for testing the samples. To add advantages to our model, we built our model using ADAM optimizer and conducted comparative research over SVM (support vector machine), KNN (K-Nearest neighbor) and ANN (Artificial Neural Network). The dataset given to the novel DCNN model with keras framework and achieved testing accuracy of 0.940 with less training error rate of 0.013. The interpretation outcome demonstrates that high level image classification accuracy with less error rate was achieved by novel DCNN model than traditional methods. Therefore, our model performs best for recognizing 5 paddy diseases and can be possibly implemented in day to day life application.

Keywords: Artificial neural network, Back-propagation, Deep Convolutional Neural Network, Support Vector Machine, keras framework.

1. Introduction

Agriculture is the fountainhead of human sustenance in spite of the overwhelming developments in technology because the world depends on large scale rice cultivation to help people lead healthy lives. Rice is consumed as the primary food in China, India, and Japan. Nowadays, the population has dramatically increased worldwide, leading to an increase in rice production. In order to meet global needs, rice cultivation must be increased to a minimum of 40\% by 2030 [1]. The production of rice crops currently falling due to the spraying of excessive pesticides, pests, weeds and diseases includes bacterial leaf blight, brown spot, leaf blast, leaf smut and narrow spot [2]. Currently, farmers face problems identifying rice diseases in prior knowledge. The result of inaccurate classification of the disease leads to showering excessive dangerous pesticides in the field. In today’s trend, the best solution to the above issue is to develop an inexpensive system to automatically monitor the crop field. Although there are various techniques available on the market, such as statistical approach, Bayes theorem, data mining, image processing, they face certain issues. Data analysis technique can be used to identify and classify numerous diseases in the agricultural sector [3] Images are also compressed, enhanced or transformed using Image processing (PCA, Auto coder) and computer vision technique to understand and diagnose the diseases [4]. Machine Learning Technique (Regression, SVM, and Decision Tree) was developed to obtain an optimal solution and reduce the error rate. Machine Learning cannot handle huge data-set and accurate feature need to be extracted before passing data into the Machine Learning algorithms, in order to overcome these drawbacks, Deep Learning technique...
(CNN, FFNN, RBFNN, Back-propagation, and Gradient Descent) were introduced, which enhanced the Machine learning concept. Separate machine is not essential for the process of extraction of features. The feature part can be skipped, and images can be fed directly to deep learning sources instead. Output is produced in terms of accuracy.

Since image processing techniques are complex to process huge data set and due to the lack of automated system, a new proposal was made in 1980 to propose machine learning techniques to handle dynamic problems in real time [5]. It makes effective use of the resource and automated system was developed using machine learning models. In ML, additional errors are generated during the prediction period. To avoid this problem, Deep learning was proposed in 2010. CNN is a learning algorithm that learns about the data during the classification period and generates the best percentage classification accuracy in the predictive period compared to Machine Learning classification approaches. Recently, in order to avoid diagnosing complexity, we have developed a Deep Convolutional Neural Network (DCNN) system that recognizes five different diseases, namely bacteria leaf blight, brown spot, leaf blast, leaf smut and narrow.

The framework is given below, section 2 describes related work based on various category; section 3 explains methodology; section 4 presents results and discussion; section 5 explains conclusion.

2. Related works
This section explains in-depth survey of the repository of rice disease, rice classification technology and implementation process.

2.1 Diseases repository
This subsection explains the detailed review of the paddy dataset used by numerous authors. First, let’s look at the term pathogens. Pathogens are disease creating agents; they can be bacteria, viruses or fungi. Usually extreme bruise in the leaves portion. The content below explains the paddy repository survey, authors [2] has collected 4,511 leaves images of 13 different classes from different search engine to classify pest disease and achieved 87% accuracy. Authors [6] focused only on pest detection in paddy field, 5,000 images are collected from Google, achieved accuracy of 0.95. Author [4] focused to identify blast diseases from 5,808 images of 2906 infected leaves and 2902 healthy leaves. The image repository collected from Institute of plants protection, China. The authors [7] detect blast diseases in south India, the system produce 85 % accuracy for infected leaves and 86 % accuracy for healthy leaves. The repository is built by collecting images from Internet. As result so far there is no huge dataset repository available for free cost for paddy diseases and pest.

2.2 Technology for Image Classification
Till dated DCNN is the best practice methods in Deep learning [8] to recognize the leaf diseases, as illustrated in Table 1.
Table 1: Evolution of Image Classifications

| Year | Author          | Proposed Techniques | Description                                      |
|------|-----------------|---------------------|--------------------------------------------------|
| 1992 | Mauuachusetts   | Object recognition  | Objects are identified based on certain set of features |
| 1970 | (Papert et al., 1996) | Computer vision    | This techniques extract edges, lines,             |
| 1980 | (Takeo et al., 2012) | Mathematical formulas | Recognize shading, texture from the image         |
| 1990 | (LeCun et al., 1989) | Neural networks    | Identify handwritten digits.                      |

2.3 Implementation
Author [2] used unique dataset over 4,511 images to recognize both pest and paddy diseases and achieved accuracy over 87%. The cons of this paper are accuracy can be improved gradually by fine-tuning the model and using better framework. Since caffe framework does not support well for the trained model [9] used ANN to recognize blast diseases. Proposed novel rice blast [1] recognition system using CNN, SVM, LBP, and Haar-WT [10]. The cons of this paper where limited images were recognized [12]. Proposed a method to recognize pest using bad-of-words approach. This model doesn’t support for low resolution pixel images [11]. Used K-Means clustering techniques to recognize the percentage of infected area [13]. Identifying K value is difficult. Relevance vector machine algorithm used for classifying feature affecting and achieved desired results. Support vector machine, neural networks and Decision tree are compared aging thyroid dataset. CNN is used for classifying breast cancer feature from thermal images. SVM is used for classifying breast cancer feature from thermal images [14]. SVM is used for classifying UCI breast cancer dataset.

3. Materials and methods
3.1 Data-Sets
A unique dataset has been created, which contains 1,260 images for five different classes, including bacteria leaf blight, brown spot, blast, leaf smut, and narrow. The images are downloaded from the repository of github and kaggle. Example images of paddy diseases are shown in Figure 1.

![Figure 1: Example images of Paddy diseases](image)

The count of respective diseases as follows: bacteria leaf blight holds 232 images, brown spot holds 788 images, leaf blast of 162 images, leaf smut holds 40 images, narrow consists of 38 images, totally 1,260 images as, illustrated in Figure 2 is considered for image identification.

3.2 Pre-processing task

The image input is resized to 224 X 224 pixels and the number of filters applied over the model is 3. The images are transformed into a matrix structure array using the function convert to array. The label binarizer function is used to reform the label to binary values.
3.3 Data augmentation
Over-fitting problem arises when the network learns to remember the training dataset, resulting in no chance of viewing negative impact on the testing dataset. In order to avoid the aforementioned problem, data augmentation comes into the picture. The generated image data is used to perform the augmentation task, the parameter used.

3.4 Deep Learning module
From various state-of-the-art framework available in deep learning, we decided to select the keras framework that supports the high-level standard library. It works above the Theano or Tensor flow. The simplest way considered for training and 20% for testing and random state is set to 42. Comparison was made on novel model with the pre-trained AlexNet and fine-tuned AlexNet model. Number of epochs is 25 and the batch size set to 32.

To reduce the loss and improve accuracy, the number of epochs is updated to 1000 and the training accuracy reached is 0.9987, training loss 0.0149, validation accuracy 0.9409, validation loss 0.1533 and test accuracy 94.0869.

3.5 Convolutional layer
Convolutional layer mines the feature of the input image. The input image is transformed into matrix structure in the preprocessing task. Convolutional layer holds filter to perform a convolutional. In a convolutional task, slide the filter matrix over the image and compute the dot product to detect the patterns.

\[ CL = f(WK \ast y) \] 

\( F = \text{activation function}, \ W = \text{weight applied over each input neurons}, \ K = \text{kernel}. \) Our developed CN model contains 32 filters with 3X3 kernel.

3.6 Activation function
Relu is a frequently used activation function in CNN among sigmoid, tanh, linear function. The reason behind Relu is low computational cost, it takes less time to train and test the model. Finally, it is a sparse network, so that only less information needs to be processed.

\[ \text{Relu} = \max(0, X) \] 

In our model Relu activation layer utilized in six different levels with convolution layer.

3.7 Pooling
The intention of adding pooling layer is to down-sample the pixel values, since the convolution layer has more network parameters to reduce the parameter pooling layer performs down-sampling operation. There are 3 kinds of pooling operation namely max, min, and average. Max pooling operation is performed in our model, i.e. the highest pixel value is considered.

3.8 Dropouts
Hinton recommended that dropout ease the circumstance of less training set in neural system by forestalling the collaborations of specific features. In our model to overcome over-fitting problem in our model, we added dropouts of 0.25. Dataset for rice crop diseases is shown in Table 2.
Table 2: Dataset for rice crop diseases

| Classes                | Images | Training images | Testing images |
|------------------------|--------|-----------------|----------------|
| Bacteria leaf blight   | 232    | 185             | 47             |
| Brown spot             | 788    | 630             | 158            |
| Leaf blast             | 162    | 129             | 33             |
| Leaf smut              | 40     | 32              | 8              |
| Narrow                 | 38     | 30              | 8              |
| **Total**              | 1260   | 1006            | 254            |

3.9 Optimizer
The main purpose of importing optimizer in the designed model is to reduce the errors generated by the model. The error is usually calculated by subtracting actual with predicted value [20]. In order to improve the designed model, we are using ADAM (Adaptive moment estimation) optimizer. The pros of utilizing ADAM optimizer is, it can easily converges and learns the model in less time [21]. Comparison over different models is shown in Table 3.

Table 3: Comparison over different models

| Model       | TA     | TL     | VA     | VL     | Testing Accuracy |
|-------------|--------|--------|--------|--------|------------------|
| AlexNet     | 0.8812 | 0.2924 | 0.7722 | 1.0417 | 77.217           |
| FT- AlexNet | 0.7285 | 0.7159 | 0.4261 | 3.0377 | 42.608           |
| NV- Model   | 0.8636 | 0.3022 | 0.8417 | 0.4763 | 84.173           |

4. Results and Discussions

The results of the study carried out by training the whole dataset using novel Deep convolutional neural network and achieved testing accuracy of 94.08%, training accuracy of 0.998 is shown in Figure 2.
Training loss of 0.149, validation accuracy of 0.9409 and validation loss of 0.1533 in 1000 iteration as shown in Figure 3.

Comparison was made on different algorithms like KNN, ANN, and SVM and it is shown in Figure 4. It is clearly understood that the novel DCNN Model produces the best results in training compared to the previous approach [22]. During implementation, we build our own data repository that was collected from the internet. Till now nobody has classified 5 paddy diseases together with less error rate and best accuracy. Testing accuracy can be improved further by improving the epoch count.

5. Conclusion and future work
We survived and designed a novel Deep Convolutional Neural Network in this research to classify 5 different paddy diseases and achieve 94.08 percent accuracy. The developed system can help farmers recognize 5 paddy diseases in previous knowledge. The extension of this work is gathering huge paddy images from different languages and improving system performance by applying transfer learning over a huge dataset. Another future work is to predict pests, weeds and more paddy diseases in the agricultural field, as well as developing smart IoT.

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