

Detection of Paddy Diseases using Deep Learning Methodologies

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Abstract -----Now a days, Farmers are facing loss in crop production due to many reasons one of the major problem for the above issue is crop diseases. To ensure healthy and proper growth of the paddy plants it is essential to detect any disease in time and prior to applying required treatment to the affected plants. Since manual detection of diseases costs a large amount of time and labour, it is inevitably careful to have an automated system. This paper presents a paddy disease detection system using deep learning approaches. Three of the most common paddy diseases namely leaf smut, bacterial leaf blight and brown spot diseases are detected in this work. Clear images of affected paddy used as the input. After necessary pre-processing, the dataset was trained on with a range of different learning algorithms including that of K-Nearest Neighbour, Decision Tree, Naive Bayes, Logistic Regression and Convolutional Neural Network. Convolutional neural network algorithm (CNN), achieved an accuracy of over 98.80%

Key Words----- *Disease detection, Deep learning, paddy, supervised learning, CNN*

I. INTRODUCTION

In India most of its economy comes from Agriculture itself and it is the second largest producer of wheat and Rice. It provides employment to 60% of the Indian population and generates 17% to the total GDP of India. This consequently also contributes towards almost half of the rural employment (49%). While providing a vital role in the country's economy, paddy serves as a staple food for the mass population and provides two-thirds of the per capita daily calorie intake. As per the USDA's report, total paddy yielding area and corresponding production are projected to be 11.8 million hectares and 35.3 million metric tons respectively for 2019-2020 (May to April) [1]. These economic gatherings clearly indicate that proper paddy cultivation is a high priority for Indonesia. Disease free paddy cultivation would play a foremost role in ensuring stable economic growth and maintain the desired targets. Moreover, to keep pace with the emerging fourth industrial revolution, Indonesia needs to work for its industrial advancements which will involve smart systems that can take decisions without any human interventions. To that end, we have come up with an automated system using deep learning techniques, a system that will contribute in country's agricultural development by automatically identifying and classifying diseases from the images of paddy. Paddy blast and brown spot were considered as the most prominent diseases then, but now brown spot and

bacterial blight are considered as the most prominent and dangerous paddy diseases [2]. In this paper, we have focused on the identification of three paddy disease detection namely bacterial blight, brown spot and leaf smut.

The features of the diseases [3] is described below and illustrated in Fig.1:

- Leaf smut: small black linear lesions on leaf blades, leaf tips may turn grey and dry.
- Bacterial blight: elongated lesions near the leaf tips and margins, and turns white to yellow and then grey due to fungal attack.
- Brown spot: dark brown colored and round to oval shaped lesions on rice leaves.



Fig. 1. (a) Leaf Smut, (b) Bacterial leaf blight, (c) Brown Spot disease

This paper proposes such an approach that makes disease prediction and classification of the three mentioned paddy diseases. The novelty of the paper lies in the detection of paddy diseases using deep learning approaches with high accuracy. The proposed solution of this paper has been described in section III. The comparative study among the five has been analyzed in section IV for better representation and understanding of the efficiency and accuracy of the model trained with different algorithms.

II. LITERATURE REVIEW

Sladojevic and colleagues [4] aimed to detect plant diseases using Deep Learning techniques that will help the farmers to quickly and easily detect diseases which in turn would enable the farmers to take proper steps at early stage. They

used 2589 original images in performing tests and 30880 images for training their model using the Caffe deep learning framework [5]. For achieving a higher accuracy in evaluating a predictive model, the authors used 10-fold cross validation technique on their dataset. The accuracy of prediction of this model is 96.5%. Depending on only the extracted percentage of the RGB value of the affected area of rice leaf using image processing, a model was developed in [6] to classify the disease. The RGB percentages were fed into Naive Bayes classifier to finally categorize the diseases into three disease classes: Bacterial leaf blight, Rice blast and Brown spot. The accuracy of the model to classify the diseases is over 89%. In another study [7], the affected parts were separated from the rice leaf surface using K-means clustering and the model was then trained with SVM using color, texture and shape as the classifying features. Maniyath et al. used random forest, an ensemble learning method, to classify between healthy and diseased leaf [8]. For extracting the features of an image, the authors used Histogram of Oriented Gradient (HOG). Their work has claimed an accuracy 92.33%. Image Processing and machine learning techniques were also used in [9] for the detection and classification of rice plant diseases. Authors of this paper used K-means clustering for the segmentation of the diseased area of the rice leaves and Support Vector Machine (SVM) for classification. They achieved a final accuracy, 93.33% and 73.33% on training and test dataset respectively. The same dataset was also used in our work but our methodology resulted in a higher accuracy both in training and test dataset.

III. PROPOSED WORK

The main idea of this work is to create a paddy disease detection model using deep learning algorithms that can be helpful for disease recognition. The data for this task is collected from the UCI Repository [10]. Python [11] an open source, has been used to apply different deep learning algorithms to train our model.

Classifiers used

Supervised classification algorithms were applied on paddy Disease Dataset to detect three diseases of paddy. In this work, four classification algorithms were applied to detect the diseases. At first we applied classification algorithms before attributes selection and achieved different results for four algorithms. After that we applied classification algorithms using five selected relevant attributes with applying 10-fold cross validation and achieved better results.

1) Logistic Regression:

Logistic regression can only be applied if the target class has categorical values. As the aim was to predict and categorize the disease of the affected rice leaf, logistic regression was a suitable model to train our dataset with. This paper works on predicting three distinct diseases, so we used multiclass logistic regression. In multiclass logistic regression, for given i classes, i different binary classifiers $h_{\theta}^{(i)}x$ are trained for each class i to determine the probability of y , the target class [12]. Then, a new input x

can be predicted to belong to the class i if it maximizes $h_{\theta}^{(i)}x$

$$h_{\theta}(x) = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}} \quad (1)$$

where,

$$g(\theta^T x) = g(z) = \frac{1}{1 + e^{-z}} \quad (2)$$

h_{θ} is the hypothesis that determines the predicted output; y is predicted to be 1 if h_{θ} is greater or equal to 0.5 and it is predicted to be 0 if h_{θ} is less than 0.5. $g(z)$ maps real valued numbers within a range of 0 to 1 and it plots an S-shape curve as Fig.5:

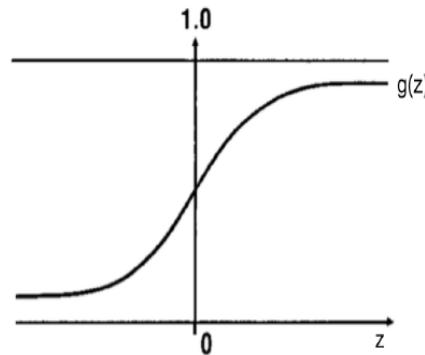


Fig. 2. S-shaped sigmoid function

Here we performed 10-fold cross validation using logistic regression algorithm and achieved 75.463% accuracy on training set and 70.8333% accuracy on test set in detecting three diseases.

2) K-Nearest Neighbour:

It calculates the distances of the query point from each of the instances and finds the K minimum distances that is, it determines the K nearest neighbours for the query point from which it can predict the class of the query point. The value of K needs to be chosen by inspecting the data; in case, we found when $K = 1$ the accuracy is 98.8426% on training set and 91.6667% on testing set after performing 10-fold cross validation. And when $K=3$ the accuracy is 85.6481% on training set and 72.9167% on testing set after performing 10-fold cross validation. We found, if the value of K is increased then accuracy is decreased.

3) Decision Tree:

Decision tree [13] is one of the most commonly used machine learning classifiers. Taking the best suitable attribute at the root, this algorithm breaks the dataset into partitions. The goal of the partition is to unmix the dataset. The splitting iterates until eventually the partitions group the data such that they are homogeneous. Iterative dichotomiser 3 (ID3), which uses a greedy approach, is the core algorithm for decision tree. In this approach, entropy and information gain, concepts borrowed from information theory, are used for constructing the tree. Entropy measures

the impurity of arbitrary attributes; zero entropy means all instances belong to the same class. As entropy becomes more and more positive, the instances become more and more heterogeneous.

$$E = \sum_{i=1}^c -p_i \log_2 p_i \quad (3)$$

Here c is the number of classes. Information gain allows to determine attribute to be selected as the next node in the tree. The attribute with the most information gain would be selected for this purpose.

$$Gain(S, A) = Entropy(S) - \sum \frac{|S_v|}{|S|} Entropy(S_v) \quad (4)$$

Here, A is the known attribute and S_v is the subset of A for which, A has the value v . Using five selected attributes decision tree algorithm was able to correctly classify 94.9074% data on training set where 10-fold cross validation is performed. The model achieved 97.9167% accuracy on test data.

4) Naive Bayes Classifier:

Naive Bayes [14] algorithm is a probabilistic algorithm that is based on Baye's theorem. Based on this theorem, the best hypothesis [16] is chosen based on equation 5

$$\hat{y} = \operatorname{argmax} P(y) \prod_{i=1}^n (P(x_i|y)) \quad (5)$$

In this work Naive Bayes algorithm achieved the lowest accuracy to correctly classify three diseases.

5) Convolutional Neural Network:

CNN[15] consists of an input layer, multiple hidden layers and an output layer. In hidden layers consist of Convolution layer, Rectified Linear Unit, pooling layer and fully connected layer. The input layer takes the resized, gray scaled image and output layer produces the detection of the disease and provides remedies. The detailed explanation of the remaining layers as follows,

(i) Convolutional Layer

The training data (images of the diseased and healthy rice plant) was sent to input layer of CNN. The convolution operation is then performed on input samples; the input is convolved with filters called kernels, that is, a number of filters slide over the feature map of the previous layer, to produce output feature maps.

(ii) Rectified Linear Unit (ReLU)

In this layer is usually called as activation function layer, types of activation function available such as sigmoid, Tanh, ReLU, Softmax, etc. In our model ReLU activation function is used in hidden layers. It is the most widely used activation function. In ReLU layer the image with negative pixel values are replaced with pixel value 0 and remaining pixel retain as it is. The ReLU function can be written in the mathematical form in equation 1, 0

$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases} \quad (1)$$

where x is a pixel value.

(iii) Pooling Layer

A pooling layer performs reduction operation along the dimensions of image (Width, Height), resulting dimensionality reduction. The primary aim of pooling operation is to reduce the size of the images as much as possible. This scans across the image using a window and compresses the image extracting features. Average pooling and Max pooling are the most commonly used methods in pooling layers. In max pooling largest value of the pixel is taken from the selected window of the image, while average pooling takes the average of all pixel values within the window.

(iii) Fully Connected Layer

After the convolution + RELU + Pooling layers, we stack up these layers many times until the image is reduced to a vector. In this layer actual classification will happen. In this layer all the neurons are interconnected; this layer produces an N -dimensional vector, where every neuron in this layer contains the vectors of the features extracted from the image. The proposed system has concentrated on detecting the paddy diseases and provides the suitable remedies, thus leads to increase in paddy crop production. In this system it detects the most common and frequently occurring paddy diseases (Rice blast and bacterial blight) and provides pesticides or insecticides as a remedy to control the disease. The type of paddy disease is detected by CNN algorithm.

IV. RESULTS AND DISCUSSION

Training and Test dataset contains 432 and 48 instances respectively and 5 attributes were chosen. Table I shows the accuracy of five classification algorithms after performing 10-fold cross validation on training data (90% of dataset) and test data (10% of dataset) where best five attributes were selected.

TABLE I ACCURACY ON TRAINING AND TEST DATASET

Algorithms	Accuracy On Training Set	Accuracy On Testing Set
Logistic Regression	75.463 %	70.8333 %
KNN(K=1)	98.8426 %	91.6667 %
KNN(K=3)	85.6481 %	72.9167 %
Decision Tree	94.9074 %	97.9167 %
Naive Bayes	58.7963 %	50 %
CNN	96.81 %	98.80 %

The comparison between the accuracy of the four classification algorithms are represented in Figure 6. Besides accuracy, other performance measures like TPR (True Positive Rate), FPR (False Positive Rate), Precision value (Positive Predictive Value), Recall value (Sensitivity), F-Measure and AUC (Area Under ROC) are also evaluated to compare among the five algorithms and it reveals in Table II and Table III that in each case, decision

tree algorithm outperforms all other algorithms in detecting and classifying the diseases.

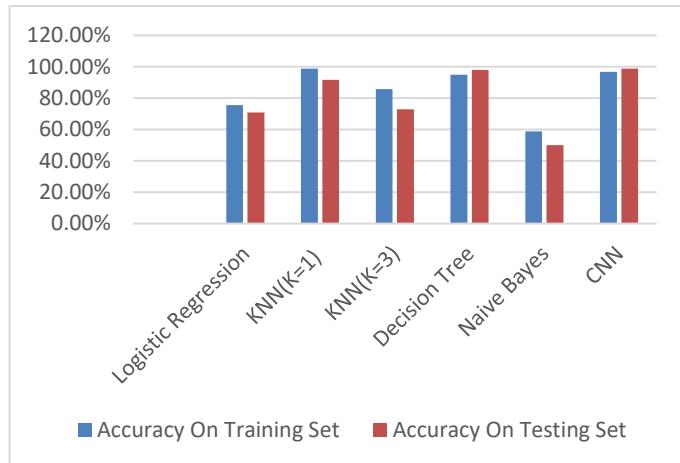


TABLE II DETAILED EVALUATION ON TRAINING SET

Algorithms	TP	FP	Precision	Recall	F-measure	Area under ROC
Logistic Regression	0.755	0.123	0.757	0.755	0.754	0.882
KNN(K=1)	0.988	0.006	0.988	0.988	0.988	0.987
KNN(K=3)	0.856	0.072	0.858	0.856	0.857	0.978
Decision Tree	0.949	0.026	0.950	0.949	0.949	0.980
Naive Bayes	0.588	0.207	0.670	0.588	0.580	0.816
CNN	0.95	0.027	0.960	0.95	0.96	0.99

TABLE III DETAILED EVALUATION ON TEST DATA

Algorithms	TP	FP	Precision	Recall	F-measure	Area under ROC
Logistic Regression	0.708	0.141	0.720	0.708	0.699	0.882
KNN(K=1)	0.917	0.042	0.933	0.917	0.915	0.899
KNN(K=3)	0.729	0.131	0.755	0.729	0.731	0.931
Decision Tree	0.979	0.009	0.980	0.979	0.979	0.985
Naive Bayes	0.500	0.238	0.554	0.500	0.477	0.782
CNN	0.95	0.008	0.970	0.980	0.98	0.97

The empirical error rate for a classifier is given by equation 6. This is then used to determine the accuracy.

$$Error = \frac{\sum_{i=1}^n \delta(h(x), y)}{n} \quad (6)$$

Where

$$\delta(h(x), y) = 1 \text{ if } y \neq h(x)$$

and

$$\delta(h(x), y) = 0 \text{ if } y = h(x)$$

V. CONCLUSION AND FUTURE WORK

This paper presents a deep learning approach to detect three different paddy diseases: leaf smut, bacterial leaf blight and brown spot disease. A comparison between five deep learning algorithms in the realms of paddy disease detection has been made. The algorithms predicted the paddy diseases with varying degrees of accuracy. It was found that CNN performed the best with 98.29% accuracy on test data. Having thus identified a near-optimal algorithm, we hope to extend this study further as higher quality datasets become available in the future. In Future other Paddy diseases can be trained and Mobile Application can be developed and make it available free on the Google play store. Other diseases can be trained and integrate with the paddy crop model, so that model can be able to predict other diseases.

REFERENCES

- [1] "Usda: Rice output continues to see growth." <https://www.dhakatribune.com/business/economy/2019/04/09/usd-a-rice-output-continues-to-seegrowth>. Accessed: 2019-08-25.
- [2] S. Miah, A. Shahjahan, M. Hossain, and N. Sharma, "A survey of rice diseases in bangladesh," International Journal of Pest Management, vol. 31, no. 3, pp. 208–213, 1985.
- [3] "Rice disease identification photo link." www.agri971.yolasite.com/resources/RICE/DISEASE/0IDENTIFICATION.pdf. Accessed: 2019-08-25.
- [4] R. Kaur and V. Kaur, "A deterministic approach for disease prediction in plants using deep learning," 2018.
- [5] "Caffe." <https://caffe.berkeleyvision.org/>. Accessed: 2019-08-26.
- [6] T. Islam, M. Sah, S. Baral, and R. RoyChoudhury, "A faster technique on rice disease detection using image processing of affected area in agro-field," in 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), pp. 62–66, IEEE, 2018.
- [7] F. T. Pinki, N. Khatun, and S. M. Islam, "Content based paddy leaf disease recognition and remedy prediction using support vector machine," in 2017 20th International Conference of Computer and Information Technology (ICCIT), pp. 1–5, IEEE, 2017.E, 2018.
- [8] [9] "Caffe." <https://caffe.berkeleyvision.org/>. Accessed: 2019-08-26.
- [10] S. R. Maniyath, P. Vinod, M. Niveditha, R. Pooja, N. Shashank, R. Hebbar, et al., "Plant disease detection using machine learning," in 2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C), pp. 41–45, IEEE, 2018.
- [11] H. B. Prajapati, J. P. Shah, and V. K. Dabhi, "Detection and classification of rice plant diseases," Intelligent Decision Technologies, vol. 11, no. 3, pp. 357–373, 2017.
- [12] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann, 2016.
- [13] C.-Y. J. Peng, K. L. Lee, and G. M. Ingersoll, "An introduction to logistic regression analysis and reporting," The journal of educational research, vol. 96, no. 1, pp. 3–14, 2002.
- [14] M.-L. Zhang and Z.-H. Zhou, "MI-knn: A lazy learning approach to multi-label learning," Pattern recognition, vol. 40, no. 7, pp. 2038–2048, 2007.
- [15] J. R. Quinlan, "Induction of decision trees," Machine learning, vol. 1, no. 1, pp. 81–106, 1986.
- [16] I. Rish et al., "An empirical study of the naive bayes classifier," in IJCAI 2001 workshop on empirical methods in artificial intelligence, vol. 3, pp. 41–46, 2001.
- [17] Mrs. Shruti U, Dr. Nagaveni V, Dr. Raghavendra B K "A review on machine learning classification techniques for plant disease detection" 5th International Conference on Advanced Computing & Communication Systems (ICACCS) 2019.