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DETECTING SUGARCANE DISEASES THROUGH ADAPTIVE DEEP LEARNING MODELS

Sammy V. Militante[1] and Bobby D. Gerardo[2]

[1]Technological Institute of the Philippines
Quezon City, Philippines.

[2]West Visayas State University
Iloilo City, Philippines.

[1]sammy.militante@antiquespride.edu.ph

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ABSTRACT: Sugarcane diseases are a major threat in the sugarcane industry which leads to the vast destruction of disease-ridden crops, decreases farming and large financial loss on small-scale farmers. The loss and farming disaster can be prevented if the early detection of such diseases can be detected and applying new technologies such as machine learning technology is implemented. Subsequently, deep learning is a current technology in machine learning that delivers a process to solve this problem. This paper proposes various deep learning models of CNN architecture trained using a sugarcane image dataset containing 20,000 images of healthy and unhealthy or diseased sugarcane. The five trained models used in the study include StridedNet, AlexNet, LeNet, VGGNet, and GoogleNet. The VGGNet model achieves the highest accuracy rate of 95% and GoogleNet achieves the lowest rate of 65% among the trained models. The trained models serve its objective by detecting and classifying images of sugarcane leaves into a diseased category based on the pattern of a defect and healthy leaves. Early detection of sugarcane diseases through deep learning models could help farmers sustain their production and income.

KEYWORDS:*Sugarcane leaf disease detection; Deep learning; StridedNet;AlexNet; LeNet; VGGNet; GoogleNet*

1.0 INTRODUCTION

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The study of plant diseases offers a wide knowledge in the scientific area and the biological characteristics of plant diseases. Nowadays, detection and recognition of plant diseases show to be challenging and somehow requires a special need. Plant diseases are a threat to global food security and devastating to the small-scale farmers whose income only rests on healthy cultivation. Early detection of these diseases benefits the good quality of sugarcane yield or production and expected a higher income for the farmers.

One critical task in crop disease management is the avoidance of greater loss which can be done through preventive measures by early detection of the crop diseases. The traditional way of sugarcane disease detection and recognition is usually done manually. With the recent development of technology, an automated system was introduced to do these tasks to prevent inconveniences and reduce the time spent in doing it manually or traditionally.

To help overcome these problems in the detection and recognition of diseases in plants, there are several methods have been used and the popular method used is Convolutional Neural Network. The CNN method includes a deep learning method that uses artificial neural network architectures [1]. The introduction of deep learning techniques in agriculture [2], and in particular in the area of plant disease identification [3], has only begun to take place in the last couple of years, and to a rather limited extent. The Convolutional Neural Networks (CNNs) is the basic deep learning tool used in this study [4]. CNN's constitute one of the most powerful techniques for modeling complex processes and performing pattern recognition in applications with large amounts of data, for example, the pattern recognition in images.

The objective of this paper is to provide an application to predict the type of sugarcane diseases based on the features of leaves and compare the several deep learning models of CNN architectures and determine the best deep learning model among five identified models to detect and recognize sugarcane diseases. The dataset containing 20,000 images of healthy and diseased sugarcane leaves is used to train the models. The data has 7 classes composed of 6 types of sugarcane diseases and one healthy class of sugarcane leaves. The early diagnosis of sugarcane disease can be used to prevent further damage that can be done to the crops which helps sustain the cultivation.

The remaining part of the paper is organized as follows. Section II deals with the convolutional neural network. Section III describes the proposed model and the methodology used to solve the problem. Section IV deals with experiments performed on the given problem and results obtained for the same. Finally, the results are concluded which includes a comparison

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between different models and future scope.

2.0 CONVOLUTIONAL NEURAL NETWORK

Deep learning is composed of several numbers of neural networks in which each neuron is represented as a single node and the entire activity is controlled by processing unit primarily the Central Processing Unit or Graphics Processing Unit (GPU) [5-7]. Recently, deep learning is initiated in several applications of agriculture like disease detection and recognition [8], plant identification and classification [9], fruit grading of fruit images [10] captured from a mobile camera or any camera devices or fixed on any robot [11]. Various deep learning models like AlexNet, GoogleNet, and VGG are applied for plant disease detection and diagnosis. LeNet, AlexNet, GoogleNet architecture is used by Amara et al. [10] and Mohanty et al. for leaf disease classification utilizing the Plantvillage dataset [9]. Pawara et al. compared the GoogleNet and AlexNet for classification purposes using the agrilplant, leaf snap, folio datasets [6]. Among these models, VGG achieved the best result while classifying 17,548 test image datasets to their respective classes with an accuracy of 99.53% and a very less error rate.

Artificial neural networks are mathematical recreations that imitate the brain function that interconnects the neurons and synapses. The key characteristic of ANN is the ability to be trained over the supervised learning process. Throughout the process, neural networks are "trained" along with the dataset to the model system containing specific matchings of inputs and outputs of the system. CNN's [4] are an evolution of traditional artificial neural networks, concentrated mostly on applications with repeated patterns in diverse areas like image recognition or image detection. ANNs key characteristic is that, with the procedure used in the layering, it reduces the required number of basic elements (number of artificial neurons) in comparison to traditional feedforward neural networks. For image recognition applications, several baseline architectures of CNNs have been developed, which have been successfully applied to complicated tasks of visual imagery.

Convolutional Neural Network (CNN) is a supervised deep learning technique, which has covered an innovative force on various computer vision and image-based applications. The areas where CNN is widely used are face recognition, object detection, image classification, etc. Components of a CNN model includes convolutional layers, pooling layers, fully connected layers, activation functions, etc. as shown in figure 1.

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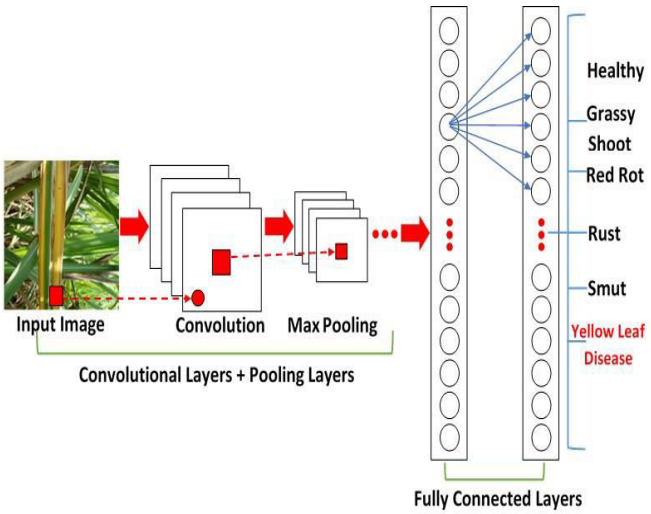

Figure 1: Design of CNN Architecture

Five CNN architectures were tested in this study using the images of sugarcane leaves to identify sugarcane diseases. These are the following: (i) StridedNet [12], (ii) LeNet [13], (iii), VGG [12], (iv) AlexNet [15], and (v) GoogleNet [14]. These models together with their training and testing process were implemented using Keras and OpenCV machine learning computational framework.

2.1 Convolution Layer

This layer consists of a set of convolutional kernels with each neuron act as a kernel. These kernels are linked with a small area of the image known as a receptive field. It works by dividing the image into small blockscalled the receptive field and convolving them with a specific set of weights [14]. The operation of Convolution is explained in equation (1).

$$F_l^k = (I_{x,y} * K_l^k) \quad (1)$$

The input image is represented by$I_{x,y}$, x, y shows spatial locality where K_l^k represents the Ith convolutional kernel of the kth layer. The division of an image into small blocks helps in extracting locally correlated pixel values. This locally aggregated information is also known as feature motifs. A different set of features is extracted by sliding convolutional kernel on the image with the same set of weights. Convolution operation may further be categorized into different types based on the type and size of filters, type of padding, and the direction of convolution [1].

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2.2 Activation Layer

This layer helps in learning a complex image pattern and serves as a decision function. The selection of an appropriate activation function can accelerate the learning process. The activation function for the convolved feature map is defined in equation (2).

$$T_l^k = f_A(F_l^k) \tag{2}$$

2.3 Pooling Layer

Pooling layers are used for the downsampling to lower neuron size and reduce overfitting. A downsampling layer is applied after the activation layer to reduce the spatial dimension with no change in-depth. A filter of size 3x3 is applied to the pooling layer to produce an output based on the type of pooling although filters with different sizes may also use. The pooling layer reduces the size of the feature map which reduces the number of parameters and weighs, decreases the training time and cuts the rate of computation and in general, it controls overfitting [10].

Overfitting is a state where the model achieves a maximum of 100% on the training dataset but an average of 50% on the test data. This can be overcome by activating a random set of dropped out setting the value to 0. Dropout is a function that increases simplification by learning numerous representations of patterns.

2.4 Fully Connected Layer

This layer identifies very high-level features that highly correlate to an object or class. Input to a fully connected layer is a set of features for classifying images without considering the spatial structure of the images Fully connected layers are used to calculate the class probabilities or scores and its result can be the input of the classifier. A well known and used classifier is a softmax classifier. Recognition and classification are implemented in this layer.

3.0 METHODOLOGY

The workflow diagram showing the experimental design of CNN to predict whether the sugarcane leaves are infected or not by monitoring the leaf images presented in figure 2. Different stages in processing include the following:

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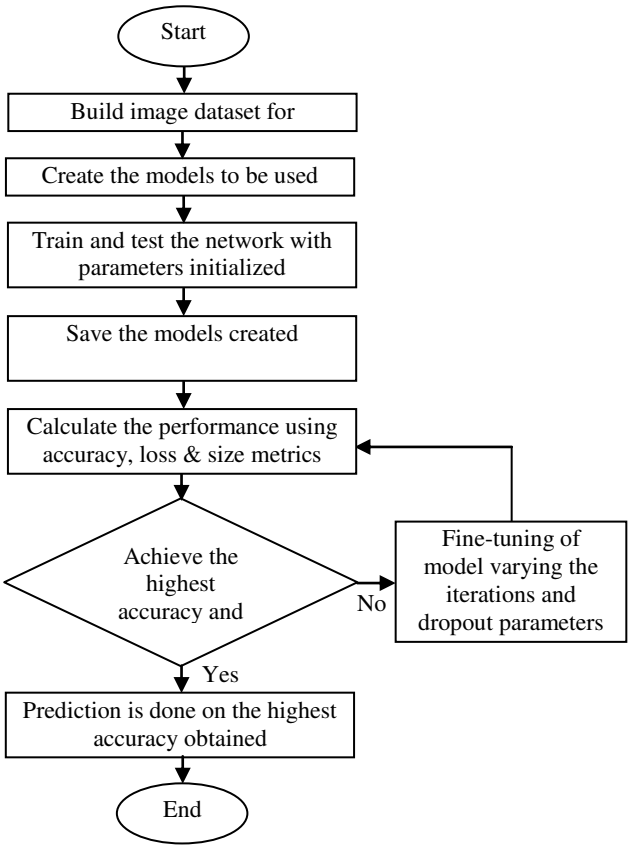

Figure 2: Workflow diagram for sugarcane disease prediction

3.1 Image Data Acquisition

Dataset is captured manually with different digital camera models, enhances and segments it if required and saves it in a folder distinguishing the different diseased images and healthy images for sugarcane plant leaves. The acquired dataset consists of 20,000 images belonging to seven different classes. Each image downloaded belongs to the RGB color space by default and stored in the uncompressed JPG format.

3.2 Pre-processing of Images

Preprocessing includes a reduction in image size and cropping the image to a

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specified size and region of interest respectively. It enhances the image to the required color scale and processed it. A segmented and grayscale kind of image does not give high performance when compared to the processed RGB images. Therefore, the proposed work takes color images and resized to 96x96 resolution for further processing.

3.3 Pre-trained CNN Architectures for Feature Extraction

The convolutional layers extract features from the resized images. Feature extraction and fine-tuning are the core methods in training modeling of the study. CNN learns weights and biases of different feature maps to specific feature extractors. Subsection 3.3 describes the use of CNN architectures for modeling sugarcane disease detection.

3.3.1 AlexNet

AlexNet is a CNN architecture that won the most difficult ImageNet Challenge for visual object recognition in 2012 developed by Alex Krizhevesky [10]. In terms of accuracy and recognition rates, it outperformed traditional computer vision methods and it is considered as the first state-of-the-art deep learning approach [16]. AlexNet is the most well-studied CNN architecture due to its impact on most image classification tasks [17]. The basic structure of AlexNet architecture is composed of 5 convolutional layers with max pooling, 2 fully connected layers, and a softmax layer. The softmax layer is the activation layer that connects the architecture to 1000 classes while earlier layers treated as feature extractors. AlexNet can induce a 4096-dimensional feature vector from each image at the final layer which contains activations of hidden layers.

3.3.2 VGGNet

Simonyan and Zisserman introduced VGG network architecture in 2014 [12]. VGG architecture consists of 16 convolutional layers and using only 3×3 convolutional layers stacked on top of each other in increasing depth on which this network is characterized by its simplicity. Reducing volume size is handled by max pooling. Two fully connected layers, each with 4,096 nodes are then followed by a softmax classifier. VGGNet consists of 138 million parameters and considered the most used image recognition architectures.

3.3.3 GoogleNet

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GoogleNet is incarnated from the Inception architecture and 22 layers deep composed of Inception modules for a total depth of 142 layers [24]. GoogleNet is a deep architecture, but its main goal is to learn with reduced parameters. GoogleNet uses small convolutions, batch normalization, and factorization and because it uses smaller convolutions, parameters are drastically reduced within the network. GoogleNet's parameter is approximately 4 million which is 15-times smaller than AlexNet.

3.3.4 StridedNet

StridedNet uses strided convolutions rather than pooling operations to reduce volume size. The first convolutional layer uses 7×7 filters but all other layers in the network use 3×3 filters like VGG network architecture. The use of batch normalization inclines to stabilize training and make tuning hyperparameters easier. The utilization of dropout is to help the network generalize and minimizing overfitting. StridedNet's parameter is approximately 1 million which is 60-times smaller than AlexNet.

3.3.5 LeNet

The LeNet architecture consists of two sets of convolutional and average pooling layers, followed by a flattening convolutional layer, then two fully connected layers and finally a softmax classifier. LeNet is straightforward and small, making it perfect for teaching the basics of CNNs, it can run on the central processing unit (CPU) even if your system does not have a suitable graphical processing unit (GPU). LeNet parameter consists of 60 thousand parameters only.

3.4 Classification

Each block comprises a convolutional, activation and max-pooling layer. Three such blocks followed by fully connected layers and softmax activation used in this architecture. Convolutional and pooling layers used for feature extraction whereas the fully connected layers are used for classification. Activation layers applied in introducing non-linearity into the network.

4.0 EXPERIMENTAL SETTINGS

To increase the dataset, data augmentation techniques have been used automatically at random by rotating the images on 20 degrees, horizontal flipping, vertical and horizontal shifting of images. The optimization using

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Adam optimizer has been carried out with categorical cross-entropy as the loss function. Batch size of 32 has been used and all the models have been trained for 100 epochs. The initial learning rate has been set to 0.01 and it is reduced by a factor of 0.3 on a plateau where the loss stops decreasing. Early stopping is also implemented to monitor the validation loss and stop the training process once it has been increased.
Each architecture is trained and fine-tuned with the same configuration. Each model is architected to learn 7 classes of sugarcane diseases including the healthy leaves with a weight rate and neuron bias rate of 20 on both the fully connected layers and softmax or activation to further accelerate the process of learning on new layers. Fully connected, softmax and classification layers are replaced in each architecture. All the experiments were performed on an ASUS laptop with the 8th generation Intel Core i7 processor, 16 GB memory and a 4 GB graphics processor. The laptop runs a Windows 10 operating system with OpenCV and Python 3.7 application program installed.

5.0 RESULTS AND DISCUSSION

Adam optimizer was chosen as a training function to be used in CNN architectures in this study instead of using stochastic gradient descent momentum or SGDM due to the effectivity in achieving good results in most deep learning applications. The highest validation accuracy of 95% obtained by the VGGNet model over 100 epochs of training and the lowest is 65% achieved by the GoogleNet model. The plots of the train and test accuracy and loss against the epochs in figure 3 delivers the visualization of accuracy and loss on the LeNet model in the left image and on the right image presents the visualization of accuracy and loss on StridedNet model. Figure 5 displays the accuracy and loss of the VGGNet model.
The results show that the models perform the process well on the classification of six different classes of sugarcane leaf diseases with minimum requirements with regards to resources. Figure5 shows the detection and recognition of a sugarcane leaf with an accuracy rate of 53.59% recognized as a sugarcane plant infected with 45.47% rust disease using a stridedNet model.

Table 1: Individual Sample Images of Sugarcane leaves with test results in detecting sugarcane diseases using various models.

CNN Arc	**Individual Test Results of Sugarcane Disease Detection Models**

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hitecture											
	Red Rot	Red Rot	Grassy Shoot	Rust	Rust	Smut	Smut	Yellow Leaf Curl	Yellow Leaf Curl	Healthy	Healthy
											
AlexNet	16.56	30.02	34.52	35.12	38.25	28.17	23.85	33.13	44.63	41.52	26.71
GoogleNet	8.16	22.64	7.59	15.70	33.10	16.95	7.32	5.44	41.34	33.55	28.05
VGGNet	28.45	44.26	35.67	36.94	72.18	53.80	34.34	44.38	58.68	51.93	42.70
StridedNet	15.35	33.09	33.47	45.92	65.05	48.21	33.92	45.78	43.03	47.42	34.64
LeNet	10.10	42.46	8.89	16.57	35.24	16.93	6.52	6.40	45.24	32.36	30.20

Figure 3: Plots of accuracy and loss against epochs on LeNet and StridedNet

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Figure4:Plots of accuracy and loss against epochs on VGGNet and AlexNet

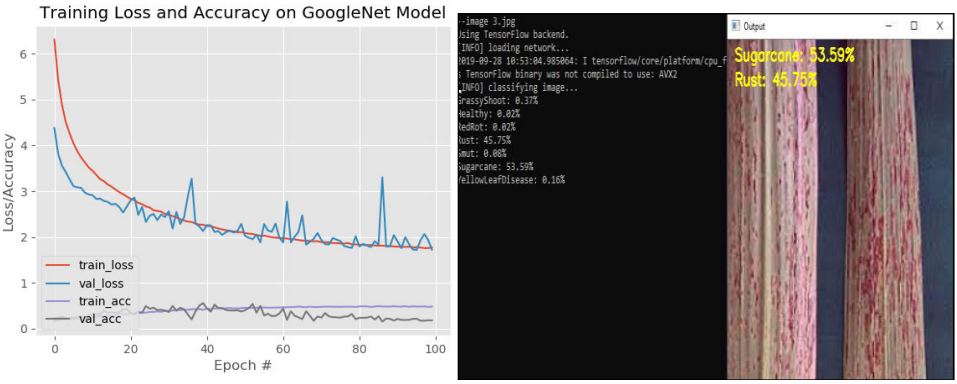

Figure 5: Plots of accuracy and loss against epochs on GoogleNet and evaluation result of an image recognized as 53.59% sugarcane plant infected with 45.47% rust disease using stridedNet model.

6.0 CONCLUSION

This paper applied five deep learning models to detect and recognize six classes of sugarcane leaf diseases and one healthy class of sugarcane leaf. The architecture used in the study compares StridedNet, AlexNet, LeNet, VGGNet, and GoogleNet models and determines which model has the highest accuracy in identifying and recognizing the sugarcane leaf diseases. With the least number of layers to identify and classify the sugarcane leaf diseases with seven (7) classes, among these three models, the VGGNet model achieves the highest accuracy rate on identifying sugarcane leaf diseases while GoogleNet achieves the lowest rate. For future work, an increasing number of datasets to validate and increase the learning rates and optimizers may be used for the models above-mentioned. It perhaps also includes experimentation with newer and different models for a better

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performance of the model on the training set. Thus, this study can be used as a decision tool to assist and provide farmers the familiarity in identifying and recognizing the sugarcane diseases that can be found in the study.

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