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RESEARCH ARTICLE

Batch size impact on enset leaf disease detection

Temesgen A. Asfaw

Abstract

Enset, also known as the "false banana," is a staple food in southern and southwestern Ethiopia that could potentially alleviate poverty among smallholders. Recently, a bacterial wilt disease that damages enset leaves has resulted in massive economic losses for farmers. The use of deep learning for automated plant leaf disease diagnosis in crops has grown in popularity in recent years; however, the impact of hyperparameter selection, particularly batch size, on model performance in the context of enset leaf disease detection remains unidentified. In this research, we looked at how batch size affects the effectiveness of a deep learning model to detect enset leaf disease. The study investigated how different batch size settings affected model performance during the detection of enset leaf disease. To confirm this, five commonly used batch sizes [16, 32, 64, 128, and 256] were combined in the proposed experiments. For the study, we have collected a total of 2132 infected and healthy leaves of enset from the south-west area of Ethiopia. Before training the convolutional neural network (CNN) model, the images in the dataset are preprocessed to enhance feature extraction and consistency. Based on the results of the experiments, we determined that the model's efficiency was even better, but only when the batch size employed in the model was less than the size of the test dataset. The study uses deep learning to detect bacterial wilt in enset leaves and provides academics and practitioners with heuristic information to help boost enset production when CNN is used in agriculture.

Keywords: Deep learning, CNN, Enset, Batch size, Agricultural technology.

Introduction

Agriculture is a critical component of Ethiopia's economic development. The sector that receives the most attention in the government's overall economic growth strategy. It accounts for 41% of GDP, over 90% of export value, and directly sustains livelihoods (FDRE 2014). Different varieties of annual and perennial crops flourish in Ethiopia's distinct agro-ecosystems. Among them, there are a number of others. Enset is one of the most important food crops for over 20% of the Ethiopian population living in the southern and southwestern parts of the country. Enset plantations are found at altitudes between 1,200 and 3,100 meters above sea level (M.Wolde 2016). Most enset-growing areas have an average annual rainfall of 1,100 to 1,500 mm, a mean temperature of 10 to 210°C, a relative humidity of 63 to 80%, and an estimated area of enset production of over 321,362.43 hectares (Birhanu, Adiko, and Duraisamy 2023). Enset is expounded to and resembles the banana plant, which is an indigenous plant classified under the monocarpic genus enset and monocot family. This can be commonly called the false banana, the Ethiopian banana, or the herbaceous plant (Borrell *et al*. 2020). Locally, the plant is termed Enset. Botanically, it's named the Ethiopian banana. The enset crop is an important indigenous food crop known for its tolerance to transient drought, high productivity, gender equity, and environmental sustainability. It also helps to confirm food security in a country like Ethiopia (Buntine and Weigend 1994).

Currently, however, its growth is threatened by many production constraints, while the productivity and area coverage of the crop are declining because of various biotic and abiotic factors. From those factors, a disease that is caused by bacteria, fungi, viruses, and nematodes is the most severe biological problem. Among these, bacterial wilt of enset is the most determinant constraint on enset production (Kudama, Tolera, and Gebeyehu, 2022). Bacterial wilt of enset, caused by *Xanthomonas* campestris PV. Musacearum, was first reported from Ethiopia and is currently found in all the enset-growing regions. It is the most serious in terms of its effects on production. Its disease symptoms are characterized by:

Department of Computer Science, Mizan-Tepi University, Tepi, Ethiopia.

***Corresponding Author:** Temesgen A. Asfaw, Department of Computer Science, Mizan-Tepi University, Tepi, Ethiopia, E-Mail: temesgenabera@mtu.edu.et

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- An initial symptom appears on the central heart leaf or one of the inner leaves of enset, whose tip becomes yellowish, limp, and droopy.
- A cut made through the petioles of a newly infected enset plant reveals browning of the vascular strands and yellowish or grayish masses of bacterial ooze out of the strands.
- Cross sections at the base of the pseudostem and corm show discoloration of the vascular strand with a large bacterial pocket and grayish or yellowish exudate with brownish to black spots. In the later stages of the development of the disease, most of the leaves wilt, and the petioles break and wilt. Eventually, the entire plant dies and rots to the bottom (Figure 1).

In recent years, the application of deep learning has shown remarkable results in detecting plant leaf disease (Brahimi *et al*., 2018; Kalaivani *et al*., 2022; Zhong and Zhao, 2020; Nagila *et al*., 2023). However, the effectiveness of the deep learning model depends on various factors, and one critical aspect of the training hyperparameters, batch size, holds particular importance. To date, various studies have shown the application of deep learning in detecting Enset leaf disease (Chen *et al*., 2022; Ganore and Tigistu, 2020; Gezahegn and Mekbib, 2016; Rashid *et al*., 2021). However, there isn't much research that has examined how batch size affects deep learning models to detect Enset leaf disease in the agriculture industry.

This research seeks to address this gap by systematically examining the impact of different batch sizes on model convergence, accuracy, and computational efficiency in the context of enset leaf disease detection.We collected a total of 2132 infected and healthy leaves of enset from the Gecha farm area and Masha Agricultural Fields in South-West Ethiopia. To improve feature extraction and increase consistency, the images in the dataset for the deep convolutional neural network (CNN) are preprocessed before the model is trained. One of the most significant operations is the normalization of image size and format. In this study, image preprocessing is performed by resizing the image to 128x128 pixels and converting to grayscale. Finally, the proposed CNN model was evaluated using performance evaluation metrics such as accuracy, precision, recall, and F1-score.

The research laid its focus on the impact of batch size for training deep learning models in the domain of enset leaf disease detection. This study aims to provide valuable insights for researchers, practitioners, and stakeholders involved in agricultural technology. The findings contribute not only to the advancement of enset farming practices but also to the broader field of agricultural deep learning.

Related Works

Ignoring early symptoms of plant disease in the agricultural sector may result in losses to crops, which might potentially destroy the world economy (Rizzo *et al*., 2021). This section

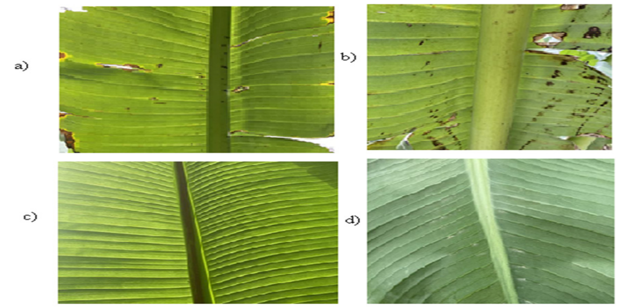

Figure 1: Sample images of (a and b) Bacterial wilt enset leaf and (c and d) Healthy enset leaf.

provides a comprehensive review of cutting-edge research on the subject of disease leaf identification. In addition to novel deep learning algorithms, we reviewed various traditional classification algorithms in the literature, such as neural networks (HECHT-NIELSEN 1992), support vector machines (Kumar Sahu and Pandey 2023; Deena *et al*. 2023), and rule-based classification (Rajesh, Vardhan, and Sujihelen 2020), that are mostly used in plant leaf disease identification.

The research proposed by Kalaivani *et al*. (2022) presented plant seedling classification using deep learning. They used convolutional neural network (CNN) algorithms, a deep learning technique extensively applied to image recognition. A dataset that contains approximately 5,608 images with 960 unique plants that belong to 12 species in a few developing phases is 99.48% of accuracy.

The study by Owomugisha *et al*. (2014) presented automated vision-based diagnosis of banana bacterial wilt disease and black sigatoka disease. They used a machine-learning approach to detect and classify banana bacterial wilt and banana black sigatoka. The seven classifiers used for classification were: nearest neighbors, decision trees, random forests, extremely randomized trees, naive bayes, and support vector classifiers (linear SVM and RBF SVM). After testing the seven different classifiers, extremely randomized trees gave a classification accuracy of 96% for banana bacterial wilt and 91% for banana black sigatoka.

Ganore and Tigistu (2020) proposed a novel approach using image processing and machine learning techniques to detect Ethiopian enset diseases. Image processing and multiclass support vector machine (SVM) techniques are used to classify a given Enset leaf image as normal or infected.

To detect disease in enset leaves, Afework and Debelee (2020) designed a deep learning-based model. The designed model is trained and tested using the collected dataset, and it is compared with different pre-trained convolutional neural network models, namely VGG16 and InceptionV3. The dataset contains 4896 healthy and diseased enset images. From this, 80% of the images are used for training and the rest for testing the model.

The research proposed by Brahimi *et al*. (2018) has used deep learning techniques for plant disease detection and saliency map visualization. They have tested multiple state-of-the-art CNN architectures using three learning strategies on a public dataset for plant disease classification. The accuracy is 99.76%.

Sweetwilliams *et al*. (2019) have developed an internet of things (IoT) and machine learning model for the detection of Sigatoka disease in plants. The acquired leaf images were further processed using two image descriptors, namely the scalable color descriptor (SCD) and the Histogram of oriented gradient (HOG), to extract discriminative color and texture features, respectively. The best accuracy of 98% was produced using the HOG descriptor.

An Ethiopian coffee leaf disease detection model was developed by Mengistu, Alemayehu, and Mengistu (2016) using imaging and machine learning techniques. Artificial neural networks (ANN), k-Nearest Neighbors (KNN), Naïve, and a hybrid of self-organizing maps (SOM) and radial basis functions (RBF) are used. The total number of data sets is 9100. From the total of 9100, 70% were used for training, and the remaining 30% were used for testing. The result showed that color features represent more than texture features regarding the recognition of coffee plant diseases, and the performance of the combination of radial basis function (RBF) and self-organizing map (SOM) is 90.07%.

The study by Amara, Bouaziz, and Algergawy (2017) has developed a deep learning-based approach for banana leaf disease classification. They use the LeNet architecture as a convolutional neural network to classify image data sets. The leaves infected by the disease are determined based on the color difference between the healthy and infected leaves. The authors perform feature extraction and classification by applying the CNN algorithm. The trained model gives an interesting classification with 97.3% accuracy.

Material and Methods

This study utilizes an experimental research approach to detect the bacterial wilt disease of enset leaf using deep learning techniques and the impact of batch sizes on the performance of deep learning model detection. The proposed study was separated into four sections: Data acquisition, dataset preparation, model development, and evaluation techniques. The flowchart for the proposed Enset leaf disease detection is shown in Figure 2.

Data Acquisition

The dataset utilized for these studies was gathered from the Gecha and Masha zones of south west Ethiopia. The study area map of the proposed system was illustrated in Figure 3. The gathered dataset contains 2132 images of enset leaves that are separated into two groups: healthy and infected. There are 1000 images of healthy enset leaves and 1132 images of infected leaves. The images were all thought about for the review.

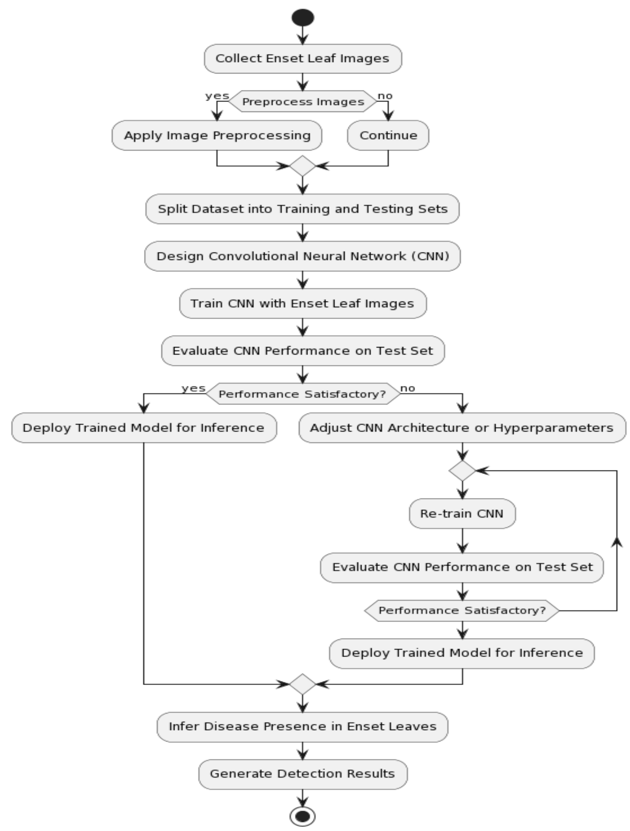

Figure 2: Flowchart of the proposed enset leaf disease detection process

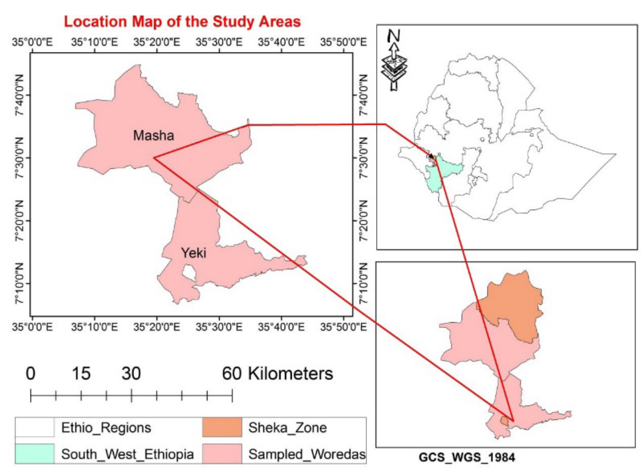

Figure 3: Location map of the study area

Dataset Preparation

The gathered image sizes fluctuated, making learning troublesome for the model. Subsequently, prior to partitioning the gathered image dataset into the training, test, and validation sets, we performed image pre-processing, for example, resizing, normalization, and dataset splitting. The images have been diminished in size to 224 x 224 pixels. The image's pixel value is rescaled to the span [0, 1] by means of information standardization. The dataset was divided into three segments: training, testing, and validation. The validation and test datasets were utilized to survey the exhibition of the proposed model, while the training dataset was utilized to prepare the CNN model. Subsequently, we isolated the training, validation, and testing datasets by 80, 10, and 10%, respectively.

Model Development

This study examines the impact of different batch sizes on CNN model convergence, accuracy, and computational efficiency in the context of enset leaf disease detection. The proposed CNN model consists of an input layer and output layer with multiple hidden layers, including the convolution layer, pooling layer, rectified linear unit, dropout layer, and normalization layers. The input layer accepts RGB images of size 128x128 with two classes (healthy leaf and infected leaf). The convolution layer extracts features from the input image by convolving it with different learnable filters to produce a 2-dimentional activation map called the feature map. The basic architecture of CNN shown in Figure 4. The ReLu activation function is performed after every convolution to introduce nonlinearity to the CNN model. The pooling layer reduces the dimensionality of each feature map while preserving important information in the input for further analysis. The dropout layer randomly switches off or drops out some input node elements while training data to learn features less dependent on its surroundings. Dropout regularization is added to the proposed architecture to overcome overfitting.

A fully connected layer connects every neuron in the previous layer to every neuron on the next layer, combining all the features learned by the previous layer to facilitate classification. Two fully connected layers are used: FC1 with 64 dense and ReLU activation functions, and FC2 with 2 dense and sigmoid activation functions. Feature extraction is a type of dimensionality reduction that represents an interesting part of the image, such as color features. The classifier is placed at the end of the CNN model, which is also called a dense layer, where data dimensions are transformed so that data can be classified linearly.

Evaluation Techniques

Model evaluation is the process of estimating the generalization accuracy of the model with unseen data (in our case, test data). It is not recommended to use training data for evaluating a model because the model remembers all data samples that were fed during training, i.e., it predicts correctly for all the data points in the training but not for data that wasn't seen during the training. For the evaluation of the model, we used the following performance measurement factors:

Accuracy

Accuracy is the ratio of the number of true predictions to the entire number of input examples.

Accuracy = (TP + FN)/(S) (1)

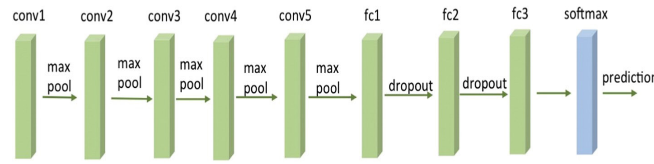

Figure 4: A basic representation of a convolutional neural network.

Precision

It is the number of true positive outcomes divided by the number of positive outcomes expected by the classifier.

Precision=TP/ (TP+FP) (2)

Recall

It is the number of true positive outcomes divided by the total number of patterns that should have been known as positive.

Recall=TP/ (TP+FN) (3)

F1-Score

The F1 score is the choral mean of recall and precision. Therefore, this score returns both false positives and false negatives as reasons to assault a strength between recall and precision.

F1-Score= (2 * Precision * Recall)/(Precision + Recall) (4)

where TP is true positive, TN is true negative, FP is false positive, FN is false negative, and S is the total number of samples.

Results and Discussion

The goal of this study is to examine the impact of different batch sizes on model convergence, accuracy, and computational efficiency in the context of enset leaf disease detection. The models were built with a convolutional neural network using python 3.9 machine learning software. The data analysis and classification were carried out using the Sklearn Python library. Python provides three options to partition the dataset into training, testing, and validation data. These are: preparing distinct files for the training dataset and the test dataset; validation with the possibility of setting a variety of numbers of folds; and percentage split.

Results

In the experiment, we tested the most commonly used batch size combinations for examining the impact of different batch sizes on CNN model convergence, accuracy, and computational efficiency in the context of enset leaf disease detection. This experiment employed BS = [16, 32, 64, 128, 256] batch sizes, an SGD optimizer, and a 0.001 learning rate. The number of epochs was chosen to be 100 to ensure consistency in the results and because of the magnitude of the dataset. Table 1 shows the effect on different batch sizes. The larger batches (BS_256) had the lowest accuracy. The use of a smaller batch size resulted in the maximum performance; the greater the performance, the smaller the batch size. Due to the batch size of 32, the

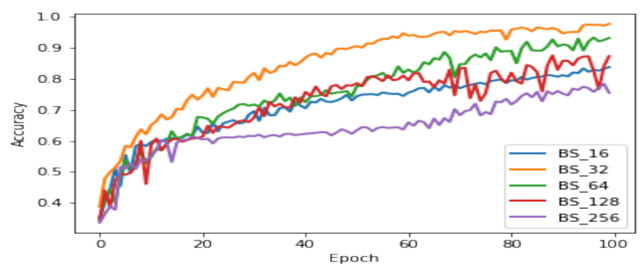

Figure 5: Accuracy plot of different batch sizes result

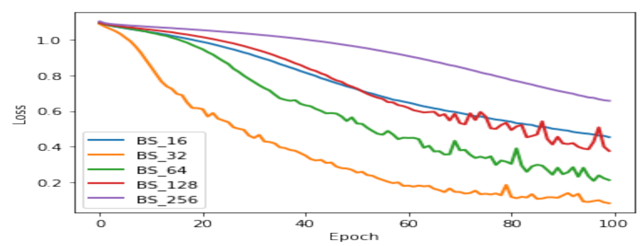

Figure 6: Loss plot of different batch sizes results

Table 1: Comparative effect of batch size on CNN performance.

Batch sizes	*Accuracy*	*Precision*	*Precision*	*F1-Score*
16	86.0%	86.3%	84.0%	86.3%
32	91.3%	91.3%	92.3%	92.3%
64	90.1%	90.0%	89.6%	89.6%
128	82.5%	83.4%	83.3%	84.1%
256	75.7%	80.0%	75.6%	76.4%

experiments had the best overall accuracy. Our findings are consistent with those of Masters & Luschi (2018), where the authors recommended using smaller batch sizes. Despite the fact that our study does not advocate using large batch sizes, the outcomes of Radiuk (2017) concur with our conclusions on batch size. Bengio (2012) indicated that an acceptable default setting for the batch size is 32. While our experiments (in which a batch size of 32 produced positive results) support this, the highest performance was obtained with a batch size of 32. Figures 5 and 6 show, respectively, the comparative results of accuracy and loss acquired from the effects of batch size.

Discussion

The data from the experiment indicates that the best results are obtained by using a CNN with a smaller batch size (BS_32). A CNN model can effectively detect leaf images in this situation. A crucial aspect of the new study is its theoretical and applied contribution. First, a few studies in the agricultural field examine how the hyperparameter setting affects the effectiveness of deep neural networks. It wouldn't be too far to conclude that our research would surely add to theoretical information, especially by providing the framework for a deeper comprehension of the influence work of hyperparameter setups. In contrast to earlier studies, its purpose is to make it easier for us to understand the effects of several commonly used batch sizes in the model when it is used to detect enset leaf disease using CNN. We looked into how different batch sizes affect CNN performance when it comes to detecting enset leaf disease.

On a practical level, this study lays the foundation for creating valuable heuristic information that can help scientists using deep learning techniques in the agricultural sector detect enset leaf disease. This study enhances the performance of hyperparameter tuning for CNN training to identify enset leaf disease.

Despite the encouraging findings, the study had some limitations. To begin with, the dataset used for the study was too small to train the CNN model. However, this limitation offers a chance for further investigation to evaluate the reliability of the results, and we eventually intend to consolidate findings from more extensive databases gathered from a range of agricultural suppliers throughout agricultural sectors.

Conclusion

Agriculture is a critical component of Ethiopia's economic development. Enset crop is employed as a staple and co-staple food and represents a possible pathway to bringing several smallholders out of poverty in southern and southwestern Ethiopia. This plant is additionally rich in carbohydrate, found in an exceedingly false stem (pseudostem) and an underground bulb (corm). Detecting diseases plays an important role in the field of agriculture because most of the diseases in plants are not easily visible when they happen for the first time. In this research, we looked at how batch size affects the effectiveness of a deep learning model to detect enset leaf disease. The study investigated how different batch size settings affected model performance during the detection of enset leaf disease. To confirm this, five commonly used batch sizes [16, 32, 64, 128, and 256] were combined in the proposed experiments. For the study, we have collected a total of 2132 infected and healthy leaves of enset from the south-west area of Ethiopia. To improve feature extraction and increase consistency, the images in the dataset for the CNN are preprocessed before the model is trained. Based on the findings of the experiments, we discovered that the model's performance was even better, but only when the batch size used in the model was smaller than the size of the test dataset. The work is based on deep learning to identify bacterial wilt in enset leaves and provide researchers and practitioners with heuristic knowledge to help increase enset production when CNN is employed in the agricultural sector.

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