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PLANT DISEASE DETECTION ON SOME SELECTED PLANTS USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract

Crop diseases pose a severe danger to food security, yet because many parts of sub-Saharan Africa lack basic infrastructure, it is still challenging to identify them quickly. Smartphone-assisted illness recognition is now possible thanks to the growing popularity of smartphones and recent developments in computer vision made possible by deep learning. Using a locally collected dataset of 268 photos of both healthy and sick plant leaves of maize, beans, rice, guinea corn, and sunflower, aggregated at optimum environments, we trained a profound CNN to recognize plant illnesses. The developed model's response rate was 41.02%–94.03%, signifying the approach's usefulness. Generally, the practice of utilizing ImageNet open source data in profound models training, and learning avails a precise chronology for mobile devices embedded in plant illnesses identification and control in Nigeria, and the whole world.

Keywords: Deep learning, machine learning, crop diseases, Detection and Management Convolutional neural networks, Computer vision.

1. Overview

More than 7 billion people can eat the food that can be produced today thanks to modern technology. (Hughes, D. P., and Salathé, 2015) Plant diseases pollinator decline Food security continues to be threatened by matters like climate variation (Tai et al., 2014), (Working Report of the 4th assembly of the Inter-governmental Science-Policy Platform on Biodiversity Ecosystem and Services, 2016), and others. Crop diseases pose a severe danger to food security, but because so much of sub-Saharan Africa lacks the necessary infrastructure, it is still challenging to swiftly diagnose.

Smartphone-aided disease diagnosis has been made possible by the rise in smartphone usage with the recent computer vision developments through deep learning. Plant illnesses present as a hazard to global nutrition safety, nevertheless, they may also have disastrous effects on smallholder farmers, whose survival depends on producing abundant harvests. In industrialized countries, more than 80% of agricultural production is produced by smallholder farmers. Reports of yield losses of more than 50% caused by pests and diseases are frequent (UNEP, 2013). (2014) Harvey et al. A demographic that is particularly vulnerable to a disease is smallholder farmers. interruption of the food supply because the majority of hungry people (50%) dwell in these homes (FAO, 2017).

In the past ten years, integrated pest management (IPM) strategies have progressively augmented historical methods for the extensive administration of pesticides (Ehler, 2006). Accurate disease detection at the time of first manifestation, regardless of the method is a core step towards crop illnesses control.

Over time, institutions like local plant clinics or agricultural extension services have helped identify diseases. Additional assistance for these efforts has recently come from making disease diagnosis information available online, utilizing the expanding global internet resources. Even more recently, mobile phone-based tools have expanded quickly, capitalizing on the historically unprecedented global adoption of mobile phone technology (The Global Information Technology Report 2015).

Due to their powerful computational capabilities, sharp screens, and comprehensive built-in accessory sets, such as high-definition cameras, smartphones in particular provide a particularly new method of aiding in the diagnosis of diseases. As of April 2022, 5 billion individuals, or around 63% of the world's population, used the Internet (WDP, 2022). Thanks to the enlarged smartphone market, mobile devices, high-definition cameras, and powerful processors are available., it is now possible to diagnose diseases using automatic photo identification on a scale that was never before possible. In this study, we demonstrate that it is technically possible to employ a deep learning strategy (or healthy) using locally gathered 268 pictures of five crop species with five illnesses. Figure 1 displays an illustration of each crop-disease combination. The fields of computer vision and object recognition have seen considerable advancements, particularly in the past. ILSVRC, or the huge graphics detection, PASCAL VOC Challenge (Everingham et al., 2010) and trials based on the ImageNet dataset (Deng et al., 2009) have been utilized as benchmarks for a range of visualization-related issues in computer vision, including object categorization. With a top-5 error of 16.4%, a massive, deep convolutional neural network was able to categorize photographs into 1000 different categories in 2012. (2012) Krizhevsky et al. Profound CNN advancements during the subsequent three years reduced the fault percentage to 3.57%. Although training large neural networks might take some time, Models are excellent for consumer applications on smartphones because they can quickly classify images after training. Several applications have lately used deep neural networks with success. A damaged plant image as an input and a crop disease pair as an output are mapped using CNN. In a CNN, precise nodes produce arithmetical outputs as outgoing edges and take mathematical inputs from the edges coming in. In profound neural networks, the input deposit is plotted to the productivity deposit using multiple stacked deposits of nodes. The difficult part of building a deep network is ensuring that the network's structure, functions (nodes), and edge weights accurately map the input to the output. To train neural nets constraints are changed so that the mapping grows better over time. Due to numerous conceptual and engineering developments, this computationally challenging technique has lately witnessed considerable advances (LeCun et al., 2015; Schmidhuber, 2015). In this article, we demonstrate how 268 photo images were categorized to categorize using the CNN approach, we identified 5 illnesses in 5 crop species.

2. Literature Review

In the past few years, especially, developments in computer vision and object identification have been enormous. The Large-Scale Visual Recognition Challenge based on the ImageNet dataset, and many others have been widely used as benchmarks for a variety of visualization-related issues in computer vision, including object classification. Recently, deep neural networks have been successfully used in a wide range of applications. An image of a damaged plant as an input and a crop disease pair as an output are mapped using neural networks.

A sizable, deep convolutional neural network managed to classify photos into 1000 different categories in 2012 with a top-5 error of 16.4. Deep convolutional neural network advancements during the subsequent three years reduced the error rate to 3.57%. The trained models can swiftly classify photos, which makes them acceptable for consumer applications on smartphones even though training big neural networks can take a long time.

Table 1: Summary of some related works

S/No	Paper Title	Authors	Year	Major Findings
1	Custom Convolutional Neural Network for Detection and Classification of Rice Plant Diseases	Sanasam Premananda Singh et al	2023	Achieved 99.66% accuracy in Strawberry disease detection. This approach will enable the farmer to diagnose various rice diseases and take preventive measures in time
2	TomConv: An Improved CNN Model for Diagnosis of Diseases in Tomato Plant Leaves	Preeti Baser et al	2023	Early work using CNNs for tomato disease recognition. TomConv model helps to identify diseases found on leaves and achieved an accuracy of 98.19% for training data of tomato plant leaves.
3	Plant Disease Detection Using CNN	Nishant Shelar et al	2022	Achieved 95.6% accuracy in Strawberry disease detection.
4	Convolutional Neural Networks in Detection of Plant Leaf Diseases	Bulent Tugrul et al	2022	Deep convolutional neural networks (DCNN) trained on image data were the most effective method for detecting early disease in plants.
5	Grape Leaf Black Rot Detection Based on Super-Resolution Image Enhancement and Deep Learning	Jiajun Zhu et al	2021	Proposed a CNN-based method for detecting Grape Leaf Black Rot.

Aim and Objectives

Leveraging the advancement in technology and the increased access to smartphones and mobile devices, we aim to solve the problem of plant diseases which is a major threat to food availability to the masses. This will be achieved by:

- Collect images of diseased and healthy crop leaves
- Training a deep convolutional neural network with locally collected dataset
- Develop an application for the detection of these diseases along with their management practices

Methodology

Dataset Description

Two hundred and sixty-eight (268) images of diseased crop leaves (of maize, beans, rice, guinea corn, and sunflower) were collected on crop farms of Teaching and Research Farms of the University of Abuja, Abuja Nigeria, and were analyzed and categorized. The collected crop leaf samples were assigned five class labels. From several plants, crop leaf diseases were predicted. The infected image sample is shown in Fig.1. In Most methods used, and defined herein, each image was resized to 224 × 224 pixels, Furthermore, On the downscaled photos, predictions and model optimization were both carried out. In this study, the entire dataset was used for training and validation. Grayscale and color versions of the locally sourced dataset were used for the training. The goal of the study was to establish if the Neural Network (NN) sincerely picks up instead of merely detecting the biases in the dataset, the "notion" of plant diseases. We evaluated the model's potential to acquire high-level structural patterns that are specific to certain illnesses and crops, as well as its ability to adjust without color details. When planning the tests, it was taken into consideration that CNN could be able to preference up on innate predispositions related to the illumination, and the data-gathering. equipment.

1 2 3 4 5

FIGURE 1: Example of leaf images from dataset. (1) Anthracnose, **(2)** Cercospora leaf spot, **(3)** Phosphorus deficiency, **(4)** Rice brown leaf spot, **(5)** Sunflower leaf blight.

Approach

More accurate classification outcomes and quicker classification times can both be achieved with a sound model design. The three main network types that are now available are CNN, generative adversarial networks, and recurrent neural networks. CNN is the most frequently used feature extraction network for the task of identifying and categorizing plant diseases and is thus the strategy that will be used in this project.

CNN is a specialized kind of neural network model with a sophisticated network architecture and the ability to execute convolutional operations. Figure 3 shows the input deposit, convolution layer, pooling layer, full connection layer, and output layer of a convolutional neural network model. The convolution layer and the pooling layer alternate throughout the model, and when the convolution layer's neurons are coupled to the pooling layer's neurons, a complete connection is not required. A main computational component of a CNN is the convolution layer, which is also where most of the calculation takes place. It can be thought of as a local receptive field, and the convolution neural network's local receptive field is its biggest benefit.

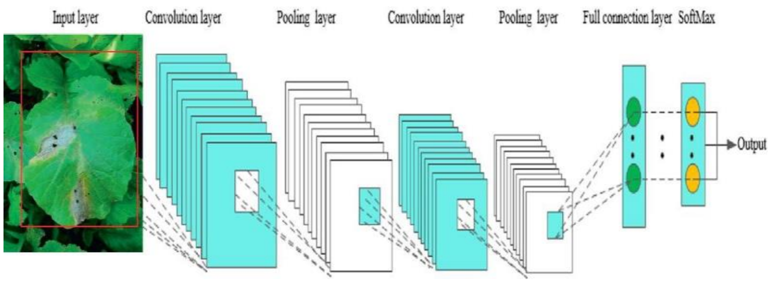


Figure 3: Structure of a CNN

Profound CNN suitability in detecting agricultural disease indicated above was assessed. LeNet-5 (LeCun et al., 1998) and EfficientNetB0 (ICML 2019) were the types of algorithms, or architectures, that were employed. A series of fixed convolutional coatings are In the LeNet-5 architecture variations, one or more completely linked layers are used to track the network. ReLu (Rectified Linear Unit) non-linear activation units are frequently connected to all network layers. Optionally, a standardization deposit and a pooling deposit may come before a convolution deposit. In this scenario, a model was either completely trained from scratch in one instance or transferred learning in the other instance to examine how well the architectures performed on the dataset. The learning of any layer was not restricted during model training, as commonly done transfer learning is used. To put it another way, the main distinction amongst both methods of learning is a condition of the few trained classes., allowing the erudition strategy to benefit from the sizable quantity of graphic acquaintance previously obtained through transfer learning. EfficientNetB0 model extracted from ImageNet.

In this study, the following experimental configurations were used:

I. Choice of deep learning style:

LeNet

EfficientNetB0

II. Choice of training mechanism:

Training from Scratch

Transfer Learning III. Choice of dataset type:

Color

Grayscale

IV. Training, and testing dataset circulation:

Training set: 80%, and then testing set: 20%,

An epoch is the total number of training iterations that a specific neural network has gone through. traveling through the filled training set. Each experiment lasts for a total of 30 epochs. Several epochs were selected depending on observation in the experiments where the learning always converged well (at 30).

The subsequent hyper-parameters were used in experimentations:

- Optimizer: Adam
- Loss: categorical cross-entropy
- Base learning rate: 0.005,
- Gamma: 0.1,
- Batch size: 128

TensorFlow, a quick, open-source deep learning context, was used in the aforementioned experiments. Additionally, Google Colab was used for the training, and GPU clusters were used to speed up the training.

To understand how approaches (models) achieve or generalize on new datasets, and also memorize them, the experiments were run at a ratio of 80 - 20 train-test set splits (80% of the training dataset, and 20% was used to test).

It should be noted that the collected data frequently contains many pictures of the same leaf (shot from various angles). Throughout the test, and training data splitting, it was ascertained a common leaf sample is either for test or training purposes.

Results

It was noted at the outset that arbitrary guesswork produces an average overall accuracy of 3.13% with a dataset of 5 labels. Our inclusive accurateness varied between 41% and 94% of all investigational arrangements, which comprised two photographic illustrations of image data (Figure 2). This indicates that there is a lot of potential for deep learning to solve comparable estimate issues.

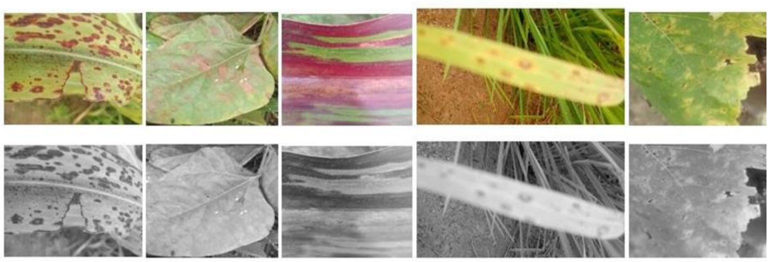


FIGURE 2: Sample images from dataset used in various experiments (A) Colour **(B)** Grayscale.

After the first step decreases after running for a total of 30 epochs, all experimental configurations virtually evenly converge on the learning rate. With training and validation using an 80:20 ratio, the model's accuracy was respectable. As anticipated, by Increasing the test set to train set ratio further, the model's overall performance will begin to deteriorate.

The performance of the two varieties of the dataset (color and grayscale), when the rest of the experimental setup was left unchanged, differed noticeably across all experiments. As anticipated, presentations degraded in comparison with studies of the colored variety. As a result, models performed well when used with the colored dataset variety (Figure 4). In Figure 3, the result of loss and accuracy after 30 epochs across experiments for color and grayscale images are shown. From the graph of the colored and grayscale images, it was indicated that accuracies for training and validation increase while the losses decrease. This is an expected and normal trend. Also, Table 2 demonstrates the evaluation of our models' accuracy, precision, recall, and f1 score.

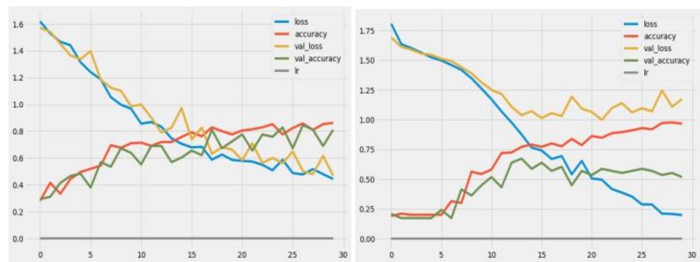
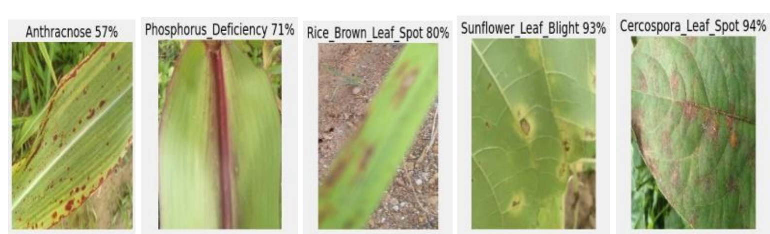


Figure 3: Loss and accuracy after 30 epochs across experiments for color and grayscale images.

Finally, the models from our experiments were tested on a held-out sample of colored and grayscale images with an accuracy range between 41.02%-94.03% i.e., the model was correct 94 out of 100, as shown in Fig. 4



Tests from models trained on a colored image dataset

Tests from a model trained on a grayscale image dataset

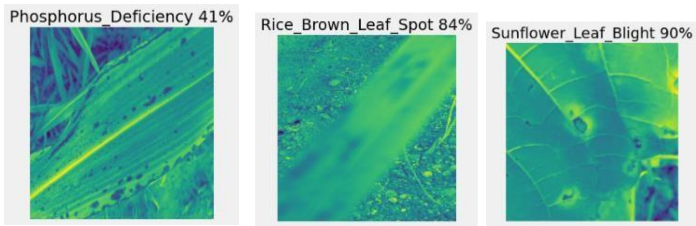


Figure 4: Results obtained from test samples

Table 2: Evaluation of model meticulousness, recall, accuracy, and f1 score

Model	Accuracy	Meticulousness	Recall	F1 score
Model 0	0.81	1.0	0.24	0.38
Model 1	0.79	1.0	0.18	0.31
Model 2	0.81	1.0	0.22	0.36

Discussion

CNN has suggestively better-quality results over time in classifying images and identifying substances. He et al. (2015); Szegedy et al. (2015); Zeiler and Fergus (2014); Simonyan and Zisserman (2014); Traditionally, learning algorithms have been utilized in feature spaces created by hand-engineering features like SURF (Bay et al., 2008), HoG (Dalal and Triggs, 2005), SIFT (Lowe, 2004), for image classification tasks. Thus, these techniques's effectiveness was strongly inclined by the fundamental preset structures. It is necessary to repeat the feature engineering process whenever the current circumstance or the relevant dataset drastically changes because it is challenging and intricate. This issue arises in the majority of attempts to detect plant diseases using computer vision since they mostly rely on manually produced features, picture augmentation techniques, and a variety of other complicated and time-consuming methodologies. In addition, traditional approaches to disease classification using machine learning frequently focus on a small number of classes, frequently within a single crop. Samples comprise the feature to distinguish between healthy tomato leaves and tomato powdery mildew, a stereo and thermal image extraction and classification pipeline was utilized (Raza et al., 2015).

Apple scab was identified using RGB images. (Chéné et al., 2012), and Powdery mildew detection in uncontrolled situations Citrus huanglongbing is detected via fluorescence imaging spectroscopy (Wetterich et al., 2012) Aircraft-based sensors and near-infrared spectral patterns have been used to detect C. huanglongbing (Sankaran et al., 2011). (Garcia-Ruiz et al., 2013), the tomato plant yellow foliage curl disease was identified utilizing several customary feature extraction techniques, and then the virus was classified utilizing a pipeline for support vector machines. a recently published study on the application of machine learning to plant phenotyping (Singh et al., 2015) provides a complete overview of the effort implemented in the field. Although CNN has ever been implemented to categorize and detect plant diseases in Phalaenopsis seedlings, such as Phytophthora black rot, bacterial soft rot, and bacterial brown spot (Huang, 2007), the technique obligated that the imageries be represented using a chosen before the neural network classifying them, a list of texture features was constructed.

Recent studies have shown that administered training by means of a profound CNN can successfully tackle picture classification problems with a very large number of classes, and serve as the basis for the technique, Krizhevsky et al. (2012). By means of finger concocted landscapes, exceeding traditional techniques. in conventional benchmarks. They are a particularly enticing choice for a practical and scalable method for the computational inference of plant diseases since they do not require the time-consuming feature engineering stage and the answer is generalizable.

To diagnose crops, their presence, and their identification, as well as diseases on previously unseen photos, We developed a model utilizing a profound CNN style and qualified it on images of crop leaves. This objective has been accomplished as evidenced by the top accuracy of 94.03% within the dataset of 268 photos encompassing 5 classes of 5 plant varieties and 5 illnesses. Thus, the prototypical properly categorizes crops and diseases from 5 possible classes in 94 out of 100 photos without the use of feature engineering. Since the categorization procedure is quick, a smartphone can apply, despite the model training taking a considerable time (between a few minutes and hours on Google Collab). This demonstrates a direct route to the widespread global use of smartphone-assisted crop disease diagnostics.

Nevertheless, there are still other problems that must be addressed in further study. with an evaluated image batch, the model's accuracy is slightly worse when measurements are made under settings other than those used for training. Even though our accurateness seems magnificent compared to other based on a sample with five modules chosen at random (2.6%), it can still be improved by using data variety. Our most recent research indicates that merely incorporating more data won't be effective enough to greatly increase precision, hence prompting us to get more data.

The second disadvantage is that we can only categorize single leaves that are up against a consistent background at this time. Despite the simplicity of these scenarios, when a disease first appears on a plant, a factual app must be in a position to catalog photographs of it. In reality, many diseases affect both the upper, and lower sides of the plant leaves.

New picture collection tools should therefore make an effort to gather images from various angles, ideally in settings that are as realistic as is practical. Even though growers are expected to be aware of the crop they are cultivating, the usage of five categories that cover plant types and illness grades has complicated this task eventually compared to the normal state. Restricting cataloging problems to illness conditions won't make much of a difference given the extraordinarily high accuracy of the locally acquired information. We can on real-world datasets observe appreciable accuracy increases. The effectiveness of our models was assessed by selecting the appropriate crop-disease match among 38 different classes. The top model's accuracy score was 94.03% overall, demonstrating the technical validity of our technique. Overall, this technique is fairly effective with more training data, it is predicted to become considerably more knowledgeable of crop species and illnesses.

It's important to recall that procedures defined here are predestined to complement instead of completely substituting existing disease-diagnosing techniques. It is frequently difficult to make an early-stage diagnosis only by visual inspection, and diagnostics exclusively based on visual symptoms are inherently erroneous. We do, however, believe that the method is a practical addition to help reduce crop loss given the expanding smartphone prevalence in the world, with around a billion of them in Africa (GSMA Intelligence, 2016). In the future, location and time information may be added to image data from a smartphone to further increase accuracy. Not to add that it is advisable to keep in mind how quickly mobile expertise has advanced recently and shall improve further in the future. We believe in very accurate diagnostics given the continuously expanding quantity and Caliber of sensors on mobile devices, it might only be a matter of time before via a smartphone.

Conclusion

A clear road for smartphone-assisted crop disease identification and management in Nigeria is provided by using the increasingly vast and freely accessible image datasets to train deep learning models. Our model's accuracy should be improved in subsequent training to almost 100%. Each of Nigeria's agroecological zones should develop local data banks for crop and weed diseases to facilitate collaboration with the worldwide plant village engaged in the collecting of plant data.

References

Bay, H. E. (2008). Speeded-up robust features (surf). Comput. Vis. Image Underst. doi:10.1016/j.cviu.2007.09.014 .

Chéné, Y. R. (2012). On the use of depth camera for 3D phenotyping of entire plants. Comput. Electron. Agric. , 122–127.

Dalal, N. A. (2005). Histograms of oriented gradients for human detection," in Computer Vision and Pattern Recognition. IEEE Computer Society Conference on.

Deng, J. D.-J.-F. (2009). "Imagenet: A large-scale hierarchical image database," in Computer Vision and Pattern Recognition. IEEE Conference on. (IEEE).

Ehler, L. E. (2006). Integrated Pest Management (IPM): definition, historical development and implementation, and the other IPM. Pest Manag. Sci. 62, doi 10.1002/ps.1247, 787–789.

Everingham, M. V. (2010). The Pascal Visual Object Classes (VOC) challenge. Int. J. Comput. Vis. 88. doi: 10.1007/s11263009-0275-4 , 303–338.

FAO. (2017). The future of food and agriculture – Trends and challenges. Rome.

Garcia-Ruiz, F. S. (2013). Comparison of two aerial imaging platforms for identification of huanglongbing-infected citrus trees. Comput. Electron. Agric. 91. doi:10.1016/j.compag.2012.12.002, 106–115.

GSMA Intelligence. (2016). The Mobile Economy- Africa 2016. London: GSMA. GSMA.

Harvey, C. A. (2014). The extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. Philos. Trans. R. Soc. Lond. B Biol. Sci. 369:20130089. doi: 10.1098/rstb.2013.008.

He, K. Z. (2015). Deep residual learning for image recognition. arXiv:1512.03385.

Huang, K. Y. (2007). Application of artificial neural network for detecting phalaenopsis seedling diseases using color and texture features. Comput. Electron. Agric. 57. doi:10.1016/j.compag.2007.01.015, 3-11.

Hughes, D. P. (2015). An open-access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv:1511.08060 .

Krizhevsky, A. S. (2012). Advances in Neural Information Processing Systems. DOI: 10.1145/3065386.

Russakovsky, O. D. (2015). ImageNet Large-Scale Visual Recognition. DOI: 10.1007/s11263-015-0816-yarXiv.

Tai, A. M. (2014). Threat to future global food security from climate change and ozone air pollution. Nature Clim Change, https://doi.org/10.1038/nclimate2317, 817–821.

The Global Information Technology Report. (2015). ICTs for Inclusive Growth. weforum.org. The Global Information Technology Report.

WDP . (2022). Worldwide digital population July 2022. Statista Research.