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Android-based Corn Disease Automated Recognition Tool Using Convolutional Neural Network

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Abstract: One of the most significant crops in the world today, corn, is under attack from several diseases. Typically, visual review and evaluation are used to identify diseases, but they are regarded as being unreliable. Corn farmers needed an automated disease recognition tool to identify different diseases that affect corn. In this study, a pre-trained convolutional neural network (CNN) was employed to create an android-based recognition tool for recognizing corn diseases. A dataset of healthy corn leaves and three (3) maize diseases—common rust, gray leaf spot, and northern leaf blight—was created using an open-source dataset of Plant Village and field images. The researchers used data augmentation, trained the generated neural network, and put it to the test. The dataset was created using a 75–25 split, trained using the transfer learning concept, then fine-tuned using the VGG-16 CNN model. The CNN model was trained using Tensor flow Keras. The model can identify corn diseases, as evidenced by its accuracy of 93.42 percent and F1-score of 93.53 percent. A mobile application employing the Dynamic System Development methodology (DSDM) was created using the methodology. The trained CNN model file was used to create the android application, which serves as a tool for identifying maize diseases. The produced application was deemed to be extremely compliant according to the participants' assessment of the android application using the ISO 25010 software quality standard, with an overall weighted mean of 4.22. The results show that the participants recognized the CDARS application's potential to offer farmers important information and as an automated corn disease recognition tool that could promote more sustainable and secure food production.

Introduction

In most nations, a sustainable agriculture sector is a major force behind a paradigm shift that fosters long-term growth in the economy. However, it has been noted that the Philippines' economic growth has been hampered by the country's poor growth in agricultural production (Rosegrant et al., 2015). This impeded development has a connection to climate change effects. It affects the development and consequences of plant diseases and pests (Garrett et al., 2022). Climate change has contributed to the continuous growth of weeds, pests, and fungi that creates problems for crops (Bebber, 2019; Fones et al., 2020) . Furthermore, studies demonstrate that climate change affects pathogen development rates and stages (Chakrabortya et al., 2000). Crop diseases that damage various parts of the plant reduce agricultural productivity and, as a result, have an impact on the global economy. Corn, as one of the most significant agricultural commodities in the world, has experienced yield impacts (Baskin, 2022; Tripathi et al., 2016; Ummenhofer et al., 2015).

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Crop diseases contribute significantly to production losses in modern agriculture. Various harmful crop diseases are emerging on a wide scale around the world, posing major problems for agriculture. Despite of the great amount of money spent on crop disease prevention, insufficient technical support is usually provided, resulting in poor disease control. If neglected and handled effectively, this can result in yield loss and an increase in agricultural production costs. Crop surveillance is essential for detecting early symptoms and preventing the spread of various diseases. These diseases are typically seen in a variety of crop sections, including fruits, stems, roots, and leaves. Manual human eye detection is the most widely utilized method. Making the correct diagnosis frequently necessitates the knowledge of trained humans. However, these knowledgeable and trained diagnosticians are not usually available, especially in rural areas in developing nations. It can also be difficult, expensive, and imprecise in giving proper disease diagnosis because it is based primarily on the examiner's experience. Thus, early and precise identification of crop diseases in plant health surveillance is critical for predicting outbreaks and managing disease infections (Wason, 2018). To successfully respond to developing plant diseases and pests, technological advancements and improved workflow are needed (Anandhakrishnan and Jaisakthi, 2022). The emergence of an efficient image-based crop disease recognition tool can significantly aid in the early diagnosis of crop diseases due to the development of consumer devices, such as smartphones, that can capture high-quality images and the rise of computer vision technologies, including the development of mobile applications (Ngugi et al., 2021).

The agricultural sector has benefited from the utilization of computer vision and deep learning in precision agriculture. Deep learning improves traditional machine learning by including additional complexity and hierarchical data representations into the model. One example of a deep learning algorithm is called convolutional neural networks (CNNs). These are deep artificial neural networks that are utilized in image and video identification, image classification, and natural language processing tasks (Wason, 2018). It initially scans and analyzes the input data with convolutional layers, then down samples the data with pooling layers, and then uses fully connected layers to make predictions based on the analysis.

CNN was used to diagnose leaf diseases in various crops (Anandhakrishnan and Jaisakthi, 2022; Ngugi et al., 2021). A CNN was used in several studies to diagnose diseases in corn by training a model using photos of impaired corn plants. The model was highly accurate in recognizing the various illnesses, implying that this strategy shows a potential to improve crop management and disease control in corn (Mishra et al., 2020; Tian et al., 2019). In another study, CNNs and data augmentation techniques were utilized to identify plant illnesses based on leaf photos from a small dataset. The model correctly identified the diseases, indicating that this method is useful for identifying plant diseases when data is limited (Afifi et al., 2021; Gasparetto et al., 2018). In another work, CNN was employed in crop disease recognition by utilizing the concept of transfer learning (De Oliveira and Romero, 2018; Xia et al., 2019). It is a technique that allows a CNN model that has been trained for one task to be used for another related task. To do this, a new model is trained on the second task using the pre-trained weights of the previous model rather than beginning from scratch. This enables the new model to benefit from the old model's knowledge, lowering the quantity of training data necessary and enhancing performance on the second job. Several studies show that transfer learning can be an effective strategy for crop disease identification and can considerably enhance disease diagnosis accuracy (Chen et al., 2020; Mukti and Biswas, 2019). It outperforms existing machine learning algorithms in identifying crop diseases with high accuracy, even with a limited dataset.

Image recognition and classification can be revolutionized by Convolutional Neural Networks. However, to optimize the power of CNN models in detecting crop diseases, they must be deployed in a more portable device, such as mobile devices. Several research have shown that a mobile application and CNN models can be used to diagnose plant diseases particularly in developing nations where laboratory facilities are few (Ahmed and Harshavardhan Reddy, 2021; Oraño et al., 2020; Sudana et al., 2020; Valdoria et al., 2019).

In this study, CNNs was used as image recognition tool to automatically detect corn diseases. It utilized training data that contained images of several corn diseases to enable image recognition. The researcher trained corn disease images using a pre-trained CNN called Visual Geometry Group 16 (VGG 16) based on PlantVillage leaf images and other field and web images. The researchers trained the VGG 16 network using transfer learning concepts, fine-tune it, then test its accuracy to find the best trained CNN model. Although deep learning has gained recognition in plant pathology in recently, its functional application for automated disease identification remains limited. As a result, this work explores how to combine the benefits of image

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processing and deep learning principles and apply them as a mobile application on a smartphone to recognize diseases that may impact corn leaves. The CNN model that was created was integrated into an Android application. As a corn disease recognition tool, the Android application was created with Android Studio. The Dynamic System Development Model is used in the application's development. It recognizes various corn disease images using the created corn disease CNN model. The built application was also utilized to transfer corn disease images to a web server for further storage and as basis for analysis.

Table 1. The total images used as corn disease dataset

Class	Train	Test	Total
Corn Healthy	341	114	455
Common Rust	341	114	455
Gray Leaf Spot	341	114	455
Northern Leaf Blight	341	114	455
Total	1,364	456	1820

Table 2. The total images used as corn disease dataset based from source

Source	Total
Field Images	136
Online Images	292
PlantVillage	1392
Total	1820

Materials and Methods

This study used a descriptive-developmental research design.

The design and development of the image recognition CNN model

Image Collection

Images of corn diseases were obtained from the Plant Village dataset. It is an open-source crop disease resource. The corn diseases dataset is composed of images of leaves with Northern Leaf Blight, Gray Leaf Spot, and Common Rust and healthy corn leaves. Additional images of the identified cordn diseases and healthy corn leaf images were also collected. The dataset includes more images obtained from other websites via Google search and other free online sources. Furthermore, field images collected by the researcher from various barangays in Echague, Isabela were included in the dataset.

Image Preprocessing

To achieve consistency, the corn disease images were pre-processed. This is due to the fact that some of the images acquired from the internet have varying resolutions and quality. To improve feature extraction, pre-processing was done to provide a final image dataset that is nearly identical at best. Using Adobe Photoshop, photographs are cropped, their backgrounds are removed, and the attention is mostly on the area where the disease is depicted. This is done to ensure that the images include the information required by the convolutional neural network for feature learning. For uniformity, each image was downsized to 256 by 256 with a black backdrop, as is the case with the Plant Village dataset images.

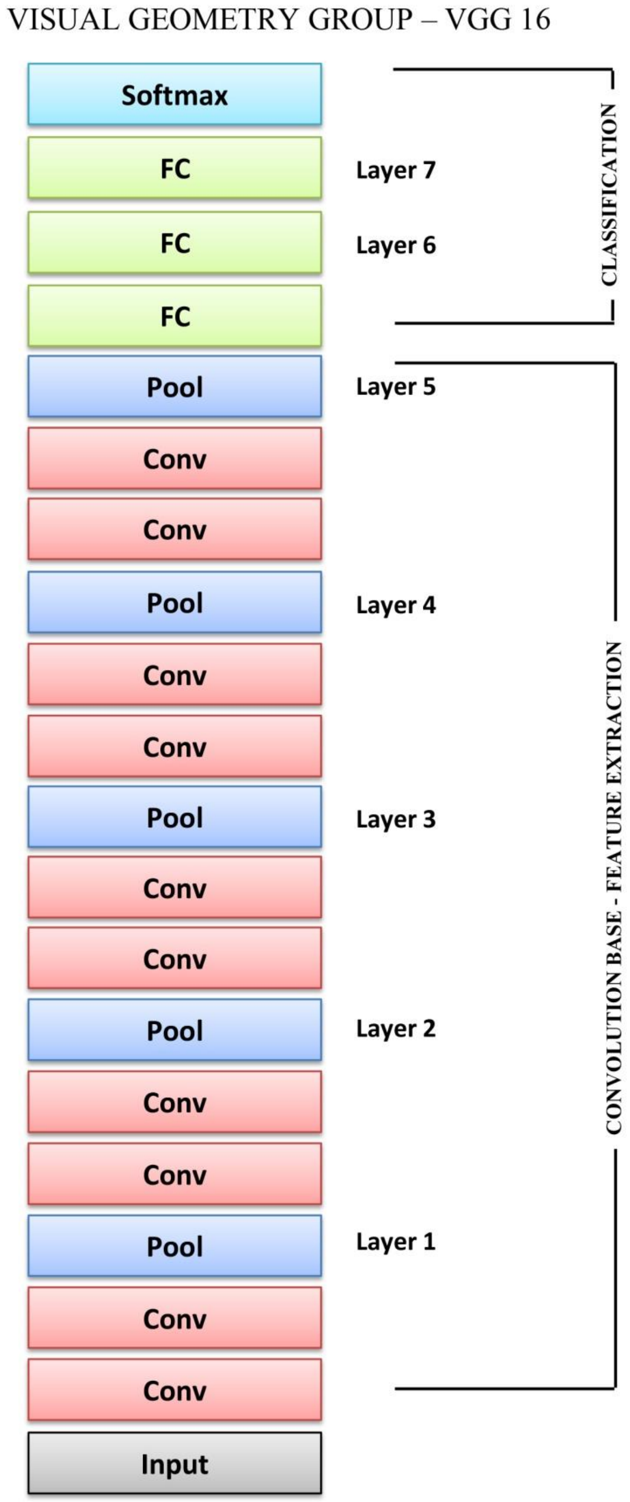

Figure 1. The pre-trained VGG 16 CNN Architecture

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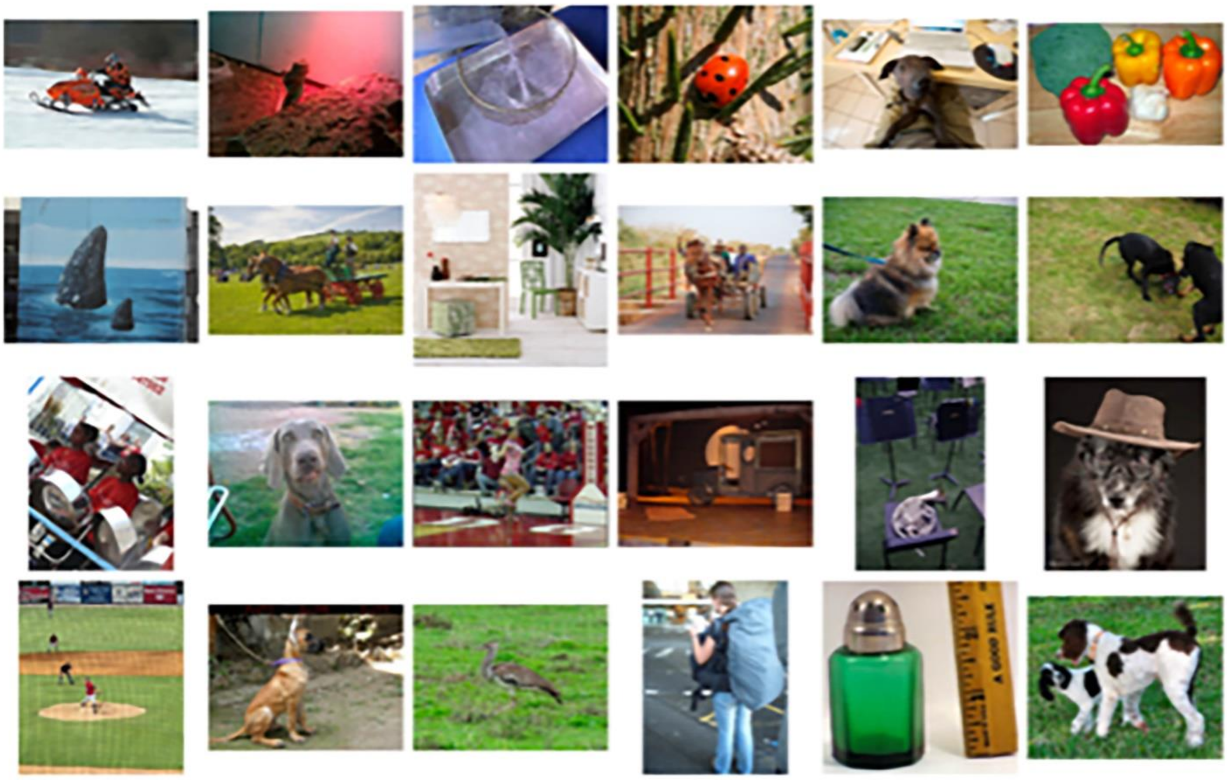

Figure 3. Images from the ImageNet Dataset

Table 1 show that a total of 1820 images were used for the entire dataset, which was consisted of four classes. Images from PlantVillage were combined with images from the field and from online sources. The Plant Village dataset provided 1392 images, including 136 images coming from field images. Following that, 292 images were acquired from various web sources (see Table 2).

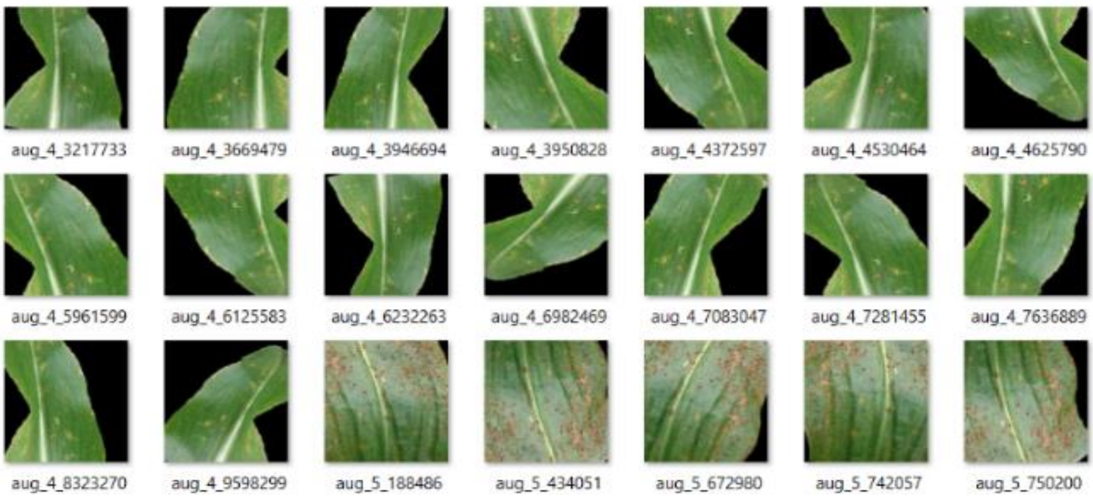

Figure 2. Sample images of the corn disease dataset using different data generator

Data Augmentation

For data augmentation, the following parameters were set: zca_whitening was set to false to apply ZCA whitening, zca_epsilon was set to 1e-06 to apply epsilon for ZCA whitening; rotation_range was set to 20 to rotate images in 20 degrees randomly; width_shift_range was set 0.1 to shift images horizontally randomly; height_shift_range was set 0.1 to shift images vertically randomly; shear_range was set 0.1 to to set range for random shear; zoom_range was set to [0.9,.5] to set the range for random zoom; channel_shift_range was set to 0 to set the range for random channel shifts; fill_mode was set to constant; cval was set to 0 to set the value used for fill_mode when it is set to constant; horizontal_flip was set to true to flip images horizontally randomly; vertical_flip was set to true to flip images vertically randomly; vertical_flip was set to true to randomly flip images vertically; rescale was set to 1./255 to set rescaling factor; and data_format was set to none to set image data format to either "channels_first"

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or "channels_last." All of these data augmentations were set prior to training on the images programmatically.

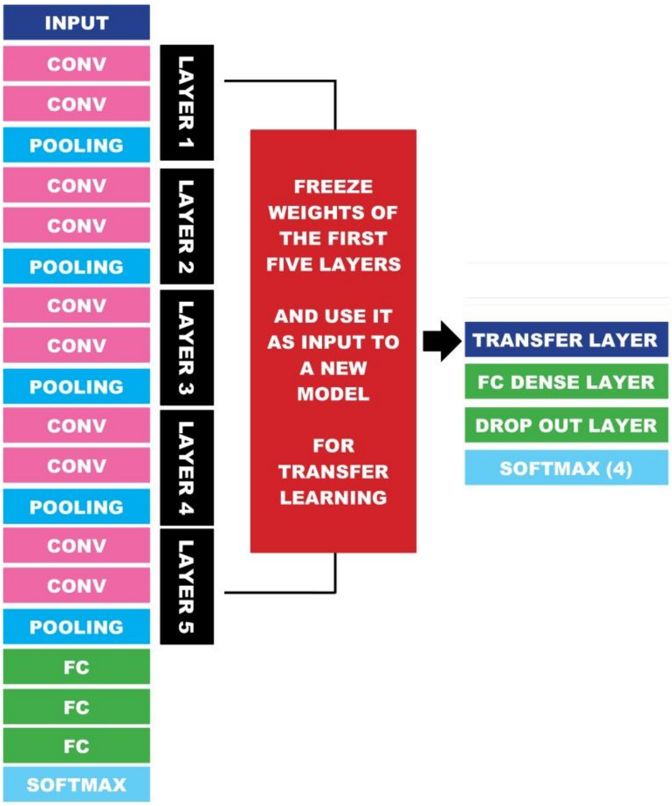

Figure 5. Application of transfer learning concept in the pre-trained VGG16 CNN model

Dataset Training

The deep CNN was trained utilizing a pre-trained neural network named VGG16 by applying the transfer learning approach. The CNN was trained using Tensorflow Keras. Prior to training, the image dataset was separated into 75% Training Dataset and 25% Test Dataset.

The researchers used the ImageNet dataset to pretrain the Visual Geometry Group (VGG16) CNN model shown in Figure 1. ImageNet is a research effort that aims to create a massive library of photographs with annotations, such as images and descriptions. Since 2010, the photos and their annotations have served as the foundation for the ImageNet Large Scale Visual Recognition Challenge, or ILSVRC. It is made up of hundreds of millions of photos divided into 1,000 distinct categories, as seen in Figure 2.

The corn image collection is then sent into ImageNet's pre-trained CNN model VGG16 model. Figure 3 depicts the usage of data augmentation to create a larger collection of augmented corn diseases photos.

Transfer learning was achieved by freezing the convolution base of the VGG16 model. It was used as an input to a new sequential model, but it was flattened before being joined to additional layers. A new dense

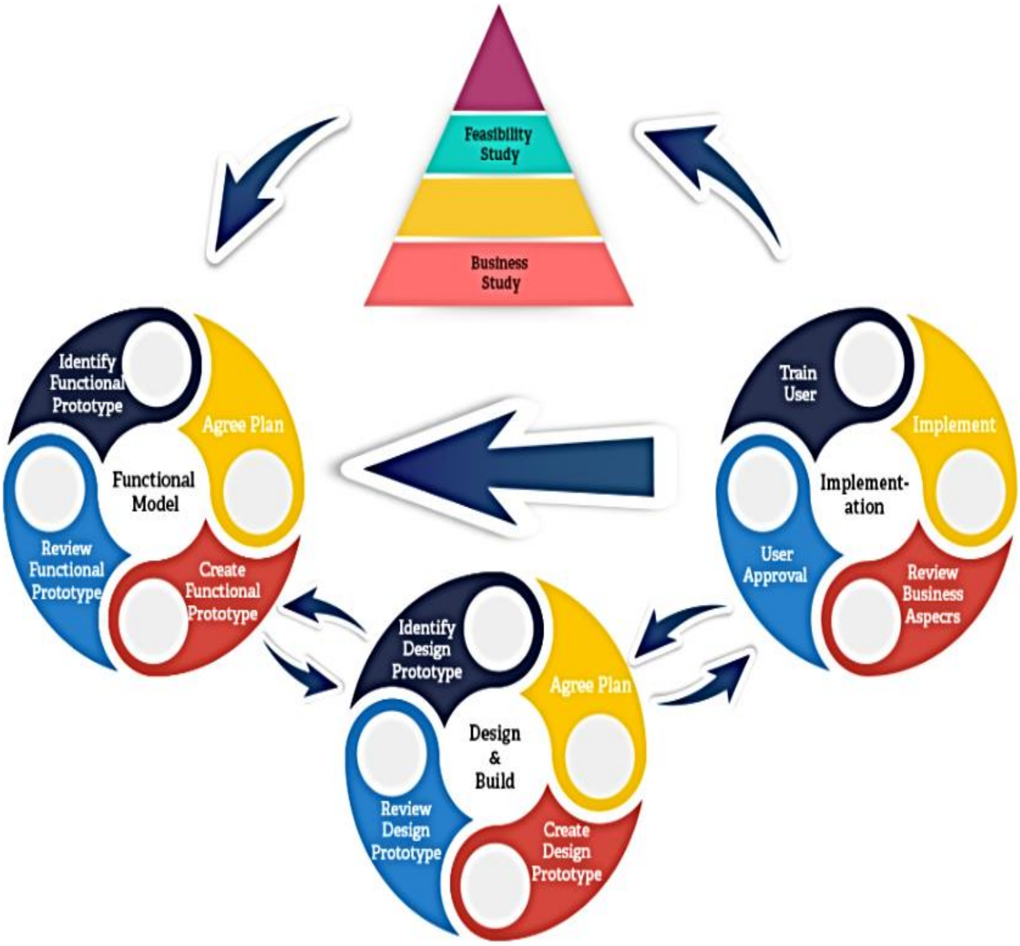

Figure 4. The Dynamic System Development Method (DSDM)

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fully connected layer has been developed for training, which is used to integrate features recognized by the VGG16 model in the corn disease images.

To prevent the model from over fitting, the researcher added a dropout layer with a value of .55. Finally, a fully connected layer with softmax activation was implemented for the four classes of corn images. This layer is used to categorize corn disease images based on the four classes provided.

The optimizer used was Adam Optimizer. It's learning rate of 0.00001 was set during training. Each epoch, it is repeated 20 times with 100 steps. The performance metric set employed was categorical accuracy (CA). Jupyter Notebook, which uses Python as its programming language, was used for the training.

Following the completion of training and verification of the model's correctness, the model was fine-tuned once more. The VGG16 models as well as a new classifier were improved. It was performed by unfreezing and training the final two blocks of layers from the original VGG 16 convolution base. The new model is trained once more to improve its accuracy even more.

Data Validation

Training accuracy and training loss were compared to test accuracy and test loss to confirm the validity of the data. It was crucial for the model's reliability to maintain acceptable training and test accuracy. Furthermore, because training and learning are on-going, the accuracy loss and test loss must be low.

Performance Measurement

During training, the CNN model's performance was automatically measured. The performance criteria used was category accuracy (CA) prior to training. The accuracy and confusion matrix are generated programmatically after training. To evaluate performance of the CNN, the accuracy, precision, recall, and F1-score were also computed.

The Implementation of the developed CNN Model in a Mobile Architecture using Dynamic System Development Model (DSDM)

The system development life cycle (SDLC) model utilized in the project's construction is the Dynamic System Development Method (DSDM). The use of DSDM framework in mobile application development offers opportunities for lightweight development processes, while addressing changing user requirements. It is a methodical, practical way to offering business solutions quickly and effectively. DSDM stresses the delivery of the business solution rather than just teamwork. It was necessary to take action before developing a project to ensure that it was practical and profitable. It places a premium on communication and collaboration among all parties concerned (Rusdiana, 2018) . The Android-based Corn Disease Automated Recognition Tool Using Convolutional Neural Network was following the different phases of the DSDM model.

Phase I: Pre-Project

The research project begins with the conduct of a feasibility study and identified issues related to crop disease identification and reporting. The researcher also looked for potential study participants specifically corn farmers and conducted an initial interview with the head and personnel of the Municipal Agriculture Office in Echague, Isabela.

The next step done was the conduct of a business analysis, which was done to assess the business process that was related to the system that was going to be constructed. The researcher then creates a framework for the suggested solution and determines how to construct, test, deploy, and maintain the system, as well as the technologies needed to build and implement it.

Phase II. Functional model / prototype iteration

At this stage, the researcher had already created a working system prototype. A functional prototype is a representation of the tasks and processes that the system should do. Iterative prototype development and user testing are simultaneously. The researchers developed the functional model with feedback from users and Municipal Agriculture Office staff from the Local Government Unit of Echague, Isabela.

Phase III: Design and Build Iteration

The researchers have planned and created the system application at this point. Iterations were used to design and develop the software. It was created with a context diagram and a use case diagram to explain the user's role and functionality.

Phase IV: Implementation

During this phase, the system is completed, documentation is generated, and a review document is created, which compares the requirements with how well they were met by the product. The system is approved by the end users after they receive training on how to utilize it. The researcher sent the director of the Municipal Agriculture Office a report on the system's pilot testing. The farmer participants received the Android app, which they downloaded on their smartphones. The farmer participant is shown the application to determine whether or not it is acceptable. Through careful coordination with the Municipal Agriculture Office, the system was put into place.

Through orientations and training, the researcher also equips the system's users (farmers and municipal agriculture office workers) with the knowledge they need to operate it effectively. The system was evaluated for its compliance with ISO 25010:2011 Software Quality Requirements and Evaluation (SQuaRE) using a survey questionnaire adopted based on the said ISO standard.

Result

The designed and developed CNN model for corn disease automated recognition tool

The convolutional neural network was trained using a multi-class dataset of corn diseases obtained from Plant Village, other online sources, and actual field images. The accuracy test result is depicted in the confusion matrix in Table 3 below.

Table 3. The Confusion Matrix of the Developed CNN Model

Actual Class	Predicted Class: Common Rust	Corn Healthy	Gray Leaf Spot	Northern Leaf Blight
Common Rust	113	0	1	0
Corn Healthy	0	112	0	2
Gray Leaf Spot	2	0	107	7
Northern Leaf Blight	17	0	3	94

The different performance measures are generated based on the resulting confusion matrix of the developed convolutional neural network. This pertains to precision, accuracy, recall, and the F1 score. The overall accuracy was 93.42 percent, and the others were computed as follows:

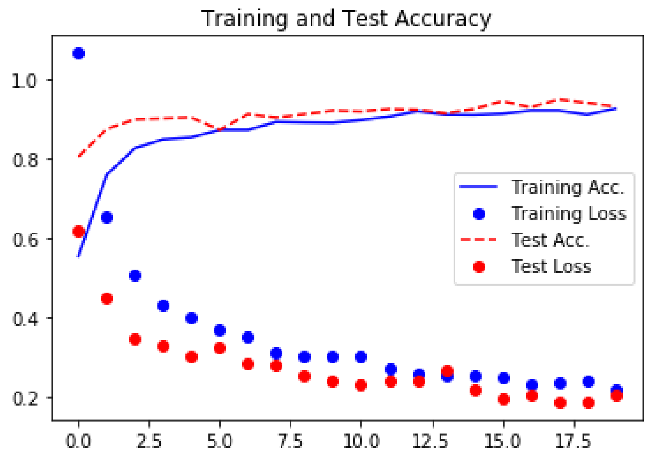

Figure 6. The training and test accuracy of the developed CNN model

The performance measurement of the developed CNN model is shown in Table 4 above. The model's average precision has an overall weighted mean of 93.65 percent, and its recall has an overall weighted mean of 93.42 percent. Meanwhile, the model's F1 score has a overall weighted mean of 93.53 percent.

Table 4. The performance measurement of the developed CNN Model

Classes	Precision	Recall	F1 Score
Corn Healthy	100.00	98.25	99.12
Common Rust	86.92	99.12	93.02
Gray Leaf Spot	96.40	93.86	95.13
Northern Leaf Blight	91.26	82.46	86.86
Mean	93.65	93.42	93.53

This means that the proposed model was accurate enough to be employed as a recognition model for identifying corn diseases. This finding relates to the findings of Mishra et al. (2020), who discovered that deep convolutional neural networks may reach outstanding disease diagnosis accuracy in corn.

The Developed Android-based Corn Disease Automated Recognition Tool Using Convolutional Neural Network

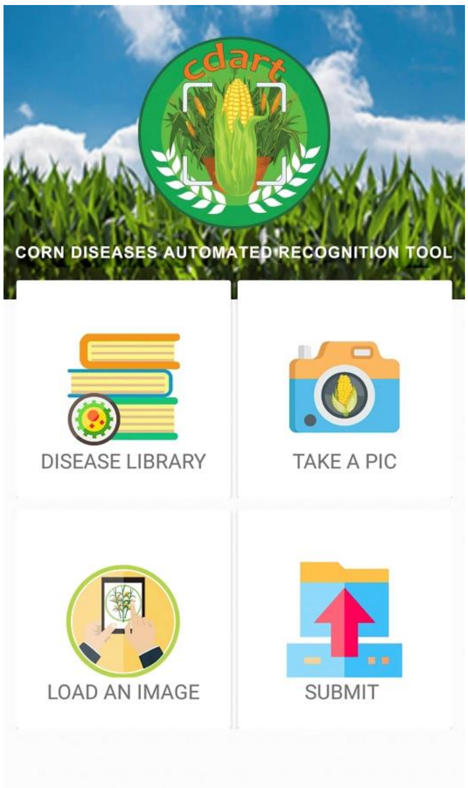

Figure 7. The Interface for the Users of the Mobile Application

The developed application was composed of a mobile application and a web application. The mobile application is developed in Android Studio as an Android application that can run on any Android smartphone. The farmers can use it in an offline mode for identifying selected corn diseases. User farmers may also view corn disease information and submit corn leaf images to a web server. The web application is a repository of all submitted images that is managed by a designated system administrator. The administrator is tasked with managing the submitted images and messages on the web server.

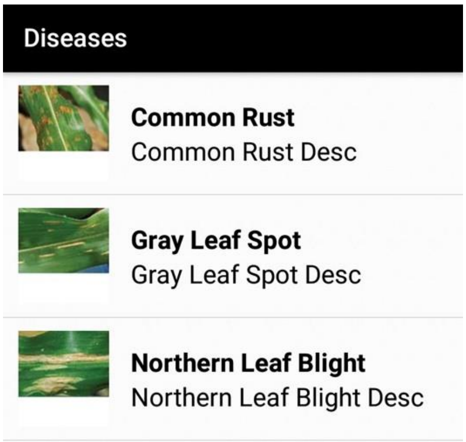

Figure 8. Corn Diseases Sub Module

Through the use of a convolutional neural network model, the researchers have developed deep learning-driven mobile application. The smartphone application is utilized by taking a picture of a corn leaf with a suspected disease and uploading it to the app. The app predicts what disease might be present or visible on the leaf and displays the likely origin, symptoms, and remedies. Aside from the mobile app, a website where uploaded photographs of corn diseases can be accessible using the XAMPP development framework can be found at http://cdars.com.ph.

Figure 9. Diseases Sub Module

The developed Android application's mobile interface for users (Figure 7) contains the ability to show a list of corn diseases, load and identify corn diseases, and submit images to the server.

Figure 10. Take a Pic Sub Module

Figure 11. Load Image Sub Module

The corn disease's submodule is shown in Figure 8. It displays corn diseases that may be found on leaves of corn that could affect yields.

The Disease Information submodule is shown in Figure 9, and it is accessed by selecting and clicking one of the images of corn diseases in the corn diseases module. It will display the entire description, symptoms, controls, treatments and so on. of the corn disease chosen.

The Take a Pic submodule is shown on Figure 10. It allows the user to take images of a corn leaf with suspected disease. It also allows the user to crop the image to focus and display the part of the leaf where the disease is manifesting. After that, the user can press done to load it into the Identification Module (Figure 12) for recogntion of the corn disease.

The Load Image submodule is shown on Figure 11. It allows the user to take or load a corn diseases image from the gallery, crop it, and load it into the identification module as shown on Figure 12.

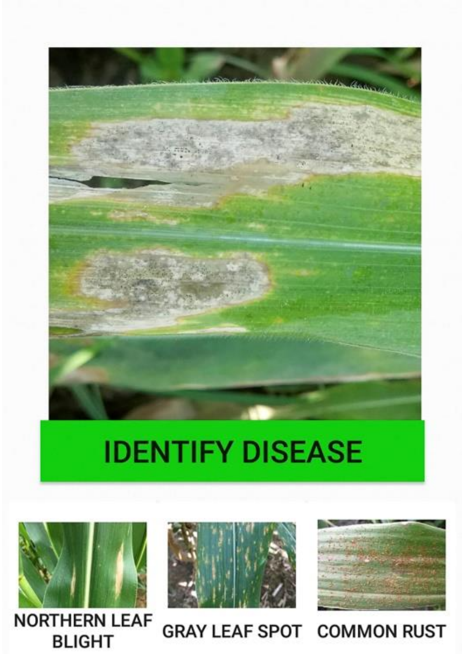

Figure 12. Identify Sub Module

The Identification module is shown on Figure 12. It depicts the identified corn disease using the trained convolutional neural network model on the various corn diseases dataset.

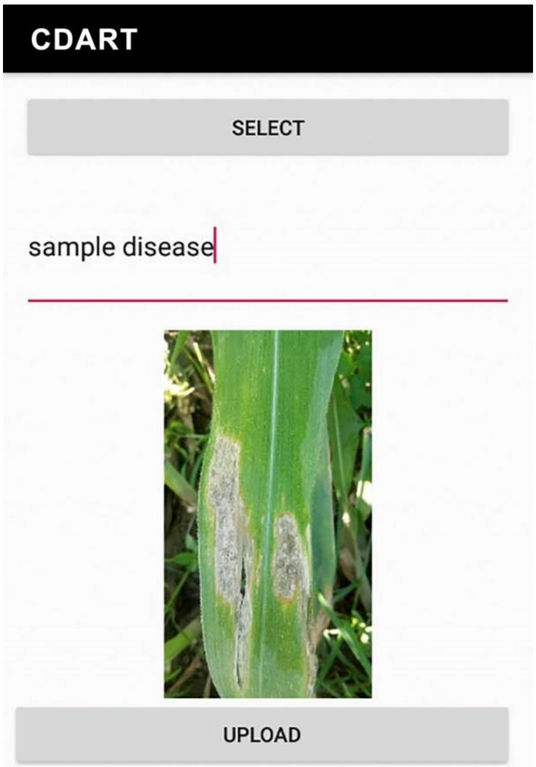

Figure 13. Submit Sub Module

The Submit submodule is shown on Figure 13. It enables farming users to upload images to a web server administered by MAO employees. The images provided are for further study and inclusion in the corn disease dataset. This would allow the enrichment of the corn disease dataset to include new corn diseases or expand the number of images in the dataset. The dataset will be used again for the convolutional neural network model's continual training to improve its accuracy.

Table 5. The extent of compliance of the developed application to ISO 25010 Software Quality Requirements and Evalaution (SQuaRE) Standard

Software Characteristic	Weighted Mean	Descriptive Interpretation
Functional Suitability	4.18	High Extent
Reliability	4.20	Very High Extent
Performance Efficiency	4.22	Very High Extent
Compatibility	4.27	Very High Extent
Usability	4.28	Very High Extent
Security	4.15	High Extent
Maintainability	4.22	Very High Extent
Portability	4.20	Very High Extent
Overall Weighted Mean	4.22	Very High Extent

The extent of compliance of the developed Android based Corn Disease Automated Recognition Tool Using Convolutional Neural Network to ISO 25010:2011 Software Quality Standards

Following formal consent, a presentation, and actual usage, the degree of conformance of the CDARS application to ISO 25010 software quality characteristics was assessed. The researchers assessed the degree of compliance with the Android-based Corn Diseases Recognition Tool using the characteristics and sub-characteristics of standard metrics from ISO 25010's Quality Model for External and Internal Quality. The functional suitability, performance efficiency, compatibility, usability, dependability, security, maintainability, and portability are the characteristics or dimensions of the analysis evaluation.

Table 5 shows the overall evaluation of the 40 participants to the developed corn disease recognition tool. The participants gave the Android-based Corn Disease Automated Recognition Tool using Convolutional Neural Network application descriptive interpretation of "very high extent", with a mean score of 4.22. This means that the CDARS application achieved a significant level of compliance to ISO 25010 software quality requirements.

The study's participants acknowledged that the developed Android application was effective during the study's execution since it is functional, efficient, compatible, useable, reliable, secure, maintainable, and portable. Furthermore, the findings indicate that the participants highly valued the potential of the android-based corn disease detection tool in giving important information to farmers as well as as an viable automated corn disease recognition tool that farmers could utilize.

Conclusion

The use of a convolutional neural network as a crop disease recognition model for corn disease demonstrated significant potential, with 93.42 percent accuracy in identifying selected corn diseases. It also demonstrates that transfer learning and fine-tuning may be applied to Convolutional Neural Networks to develop a high-recognition-accuracy recognition model. Furthermore, the developed Android application, Android-based Corn Disease Automated Recognition Tool Using Convolutional Neural Network, was found to be ISO 25010 software quality compliant. It was determined to be compliant to a "very high extent" with a grand mean of 4.22. It signifies that the mobile applications' features and functioning have met all the standards for excellent software. It also demonstrates how using the Dynamic System Development Model (DSDM) in software development could boost the speed, quality, and development of mobile applications, resulting in better outcomes for the developer and users. Finally, the Android-based Corn Disease Automated Recognition Tool Using Convolutional Neural Network provides a practical and efficient automated corn disease recognition tool.

Conflict of Interest

The author(s) of these research declare(s) that there is no conflict of interest regarding the publication of this paper.

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