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Identification of maize leaf diseases using red, green, blue-based images with convolutional neural network (CNN) and residual network (ResNet50) models

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ABSTRACT

Maize (*Zea mays*) is a crucial global staple crop that serves as a primary source of food and income, especially for smallholder farmers. However, it is susceptible to diseases that drastically reduce yields if not controlled. Traditional methods of disease detection of visual inspections are often inaccurate and uncertain. Recent advances in computer vision and deep learning techniques have shown promise in improving image recognition for crop disease detection. This study aims to develop models for detecting maize leaf diseases at the subfieldlevel using red, green, and blue (RGB)-based images using convolutional neural network (CNN) and residual network (ResNet50) models. A dataset of 1500 maize leaf images representing seven categories of maize disease symptoms was collected from the maize fields in Mopani District, Limpopo, South Africa. The data were processed to train and compare two deep learning models, CNNs and ResNet50. Both models demonstrated good classification accuracy with ResNet50 outperforming CNN, achieving an accuracy of 78.76% compared to 71.01% for CNN. The findings underscore ResNet50 enhanced capability to classify maize leaf diseases more accurately than CNN, attributed to its deeper architecture. This study illustrates the potential for deploying deep learning model in detecting maize leaf diseases. This study supports the transformative potential of deep learning in advancing agricultural practices, serving as a vital tool for early disease detection and contributing to food security in maize-producing regions, particularly smallholder farming systems. Therefore, this study trains the models that can be included in the mobile applications to be used to detected diseases in a sub-field level of the smallholder farms.

1. Introduction

Maize (*Zea mays*) is one of the most important crops after wheat and rice, consistently yielding more than other cultivated cereal crops ([27]; FAO, 2018). With the global population projected to increase by about 30% to reach 9.7 billion by 2050 [32], food production must rise to meet this growing demand. In sub-Saharan Africa (SSA) maize is a crucial source of food and income for over 300 million smallholder households [26]. Despite its high production, maize is highly vulnerable to various diseases throughout the growing season, which poses significant challenges. Numerous maize diseases have been reported globally [18], which cause annual maize yield losses of 4-14% annually [25]. Traditionally, maize diseases are identified through visual inspection, which relies heavily on the farmer's experience in the field. This reliance leads to difficulties and inconsistencies in disease identification [30]. This challenge is compounded by the fact that symptoms can appear similar in the early stages of crop growth, making accurate visual diagnosis difficult. The application of remote sensing technology has reformed

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the way of monitor crop health. Computer vision and machine learning techniques have been widely used in numerous studies to analyse images for detecting infected crop plants [8,11]. These approaches have experienced exponential growth, leading to new methodologies and models for identifying and discriminating features [9]. Deep learning is a subset of machine learning, employs artificial neural network architectures with a large number of processing layers [3,9]. These models have revolutionized tasks such as image recognition [6], voice recognition [15], and other similar complex processes that involve analysing large volumes of data. For example, the operation of self-driving vehicles and machine translation and interpretation [3]. Convolutional Neural Networks (CNNs) are the cornerstone of deep learning, recognized as one of the powerful techniques for modelling complex processes and performing pattern recognition in applications involving large datasets [29]. These networks have been successfully utilized for end-to-end learning through deep neural architectures. For instance, Ferentinos [9] demonstrated a CNN system for automatic plant recognition based on leaf photographs. Grinblat et al. [12] developed a relatively simple, yet robust neural network that effectively identifies three different legume species based on the morphological patterns of leaf veins. Mohanty et al. [22] compared the AlexNet and GoogleNet CNN architectures, to identify 26 diseases across various plants, achieving accuracies of 99.27% and 99.34%, respectively. Similarly, Ferentinos [9] employed different CNN architectures to identify 58 distinct plants plant diseases, achieving a classification accuracy of 96.3%. Geetharamani and Pandian [10] proposed a nine-layer CNN model to identify plant diseases using the Plant Village dataset, employing data-augmentation techniques to enhance the data size and analyses performance. The authors reported an accuracy level of up 96.4%, which outperformed traditional machine-learning-based approaches [10]. Among various CNN architectures, He et al. [14] introduced the residual network (ResNet50), which has proven effective for identifying crop diseases using RGB-based images. Wang et al. [34] applied an improved ResNet50 model for maize disease recognition achieving an accuracy of 97.83%. Similarly, Shaheed et al. [27] utilized Resnet-50 to classify plant leaf diseases with RGB-based images, achieving an accuracy of 99.12%. While deep learning models, have been employed to detect maize diseases, previous studies have primarily focused on detecting single disease either from one crop or from multiple crops. There is a notable lack of research on detecting multiple diseases at the sub-field scale. In detecting crop diseases, frameworks that uses advanced machine learning and deep learning have recently emerged. Kaur et al. [20] proposed a novel hybrid CNN methodology that combines handcrafted and automated features to improve classification accuracy for different crop leaf diseases. More work has also been done to investigate collaborative learning strategies to address data privacy, generalisability, and scalability. Aggarwal et al. [2] proposed a federated transfer learning (FTL) framework was proposed for rice leaf disease for classifying rice diseases using multi-client cross-silo datasets. This method allows decentralised model training across geographically distributed datasets while maintaining data privacy. Similarly, Aggarwal et al. [1] advanced a resource-efficient federated learning model for IoAT (Internet of Agricultural Things), demonstrating real-time rice leaf disease detection using federated transfer learning and feature extraction. Although the application of remote sensing technologies was implemented in most existing studies focusing on field-wide or regional analyses, the sub-field scale remains limited. This approach may overlook the significant difference in disease spread within the smaller areas of the field. Disease detection at the sub-field level, particularly for smallholder farms, allows targeted interventions for the infected crops. This goes a long way in reducing costs associated with treatment application to the whole field. This approach holds an important potential in enhancing disease management strategies in small holder farms and contributing to sustainable agricultural practices. The current study aims to develop models for identifying maize leaf diseases using RGB-based images at a sub-field scale with deep learning techniques, specifically CNN and ResNet50. The objectives of the study are; 1) collecting RGB-based images of maize leaves exhibiting various disease symptoms, 2) identifying maize disease from the collected maize leave sample in the laboratory and 3) exploring the feasibility of deploying the developed CNN and ResNet50 models in real-world scenarios for early detection multiple maize leaf diseases. The trained models enable disease detection in the field through images captured by a smartphone camera or the application camera where the disease name can be identified. By automating disease identification through image analysis, this study sought to contribute in enhancing food security and improving the livelihoods of the farmers in maize-producing regions.

2. Study area

The study was conducted in Mopani District, Limpopo Province of South Africa (Fig. 1). Mopani District is located in the northeast of Polokwane, the provincial capital city. The District has a subtropical climate, with hot and wet summers and mild and dry winters. The average annual rainfall is about 500 mm, mostly occurring from October to March [21]. The mean annual temperature is 21.5 °C, ranging from 16.9 °C in July to 25.2 °C in January. Mopani District is situated in the Lowveld region, which is characterized by low-lying plains with an elevation of 400–600 m above sea level [23]. The dominant soil types are sandy loams and clay loams, derived from granite and gneiss parent materials [24].

3. Methods

3.1. Maize disease data collection

Images of diseased maize for this study were collected from mid-May to early June 2023, in Mopani District, Limpopo, South Africa. A total of 1500 training and 358 testing maize leaf images were captured (Fig. 2), using a handheld Digital Optical Camera Zoom 8x camera with 50 Mega Pixels resolution (Huizhou Qing Teng Electron Technology Co., Ltd, China). The camera was equipped with advanced imaging features including a high-resolution lens and a polarizing filter, to ensure clear and detailed images of the leaf surface. The testing leaves were detached from the plant with petioles removed, and placed in a bag and sent for laboratory analysis. Each class comprised of 50 images based on their symptoms, where eight leaves were destroyed before the analysis. All seven classes were confirmed in the laboratory. Maize leaf dataset comprised of healthy, nutrient -deficient and diseased maize leaves, representing various disease types including northern corn leaf blight (NCLB), southern corn leaf blight (SCLB), maize streak, phosphorus deficiency, nitrogen deficiency and potassium deficiency. This diverse dataset was essential for effectively training and testing the CNN and ResNet50 models for accurate classification of maize leaf diseases. Fig. 3 shows the respective sampled maize leaves classes.

3.2. Data pre-processing and augmentation

The images collected from the camera underwent a series of pre-processing steps to eliminate background noise, resize and enhance the leaf features. Pre-processing techniques included image smoothing, utilizing a Gaussian filter to reduce the pixel intensity variations, and background subtraction, employing the thresholding method to isolate the leaf from its background. Given that multiple leaves with various diseases might be in a single photograph, an online tool (Clipping Magic) was used to clip the leaf of interest. Each image was then resized to a resolution of 64 x 64 per pixels, to ensure uniformity across the dataset and reduce computational load. A subset of images with known disease labels was extracted from the image dataset to create a validation dataset. The validation set comprised of 358 images, representing seven different maize diseases. It was essential for testing the accuracy and reliability of the CNN and ResNet50 models in disease detection. Serving as a ground truth, the validation set allowed for comparative evaluation

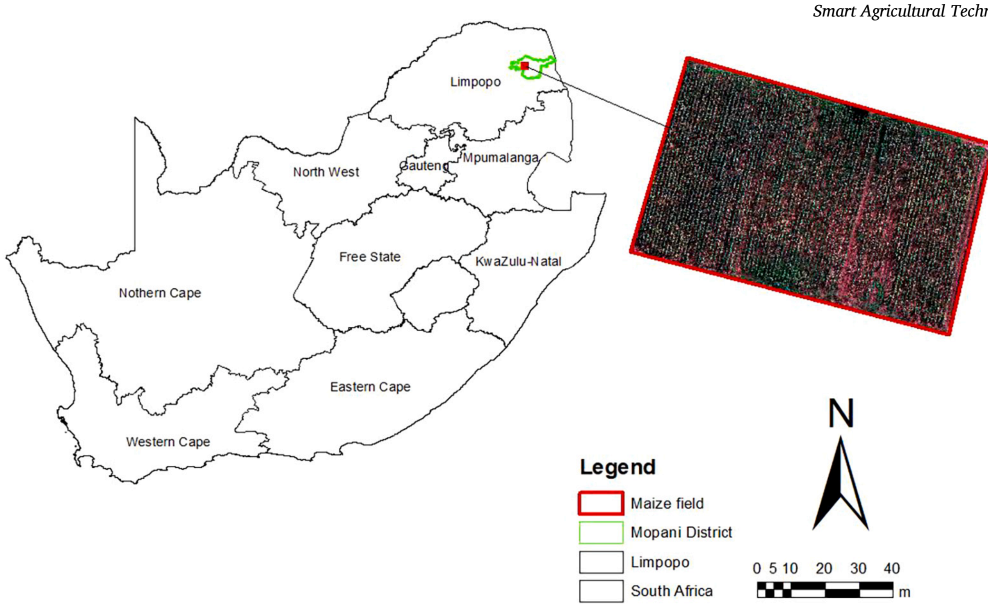

Fig. 1. The study area map of maize field in Mopani District, Limpopo, South Africa

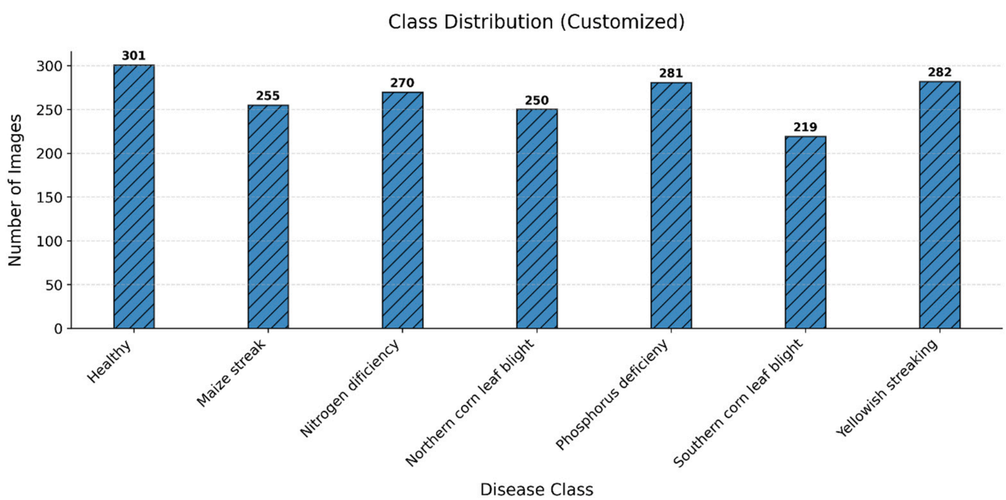

Fig. 2. A bar chart showing the number of samples per disease class.

of the predictions made by both models. Each image in the validation set was carefully labelled, to ensure the quality and validity of the evaluation process. Training CNNs requires a substantial amount of data to capture a wide range of features. Since the original leaf dataset collected for this study was not sufficient, it became necessary to expand the dataset using various methods to differentiate between the different disease classes. Fig. 4 presents the augmentation process of one leaf image into multiple images from different angles. After, initializing the original versions were created by converting the images into a numpy array. The expanded dataset helps reduce over-fitting during the training stage [13]. Once the data set was divided using the sklearn train-test-split function to separate the dataset into testing and training sets, 80% of the dataset was allocated for training the model, while the remaining 20% was used for validation.

3.3. Deep learning model development

3.3.1. Convolutional neural network model selection

A suitable CNN architecture was selected for the image classification task. CNN is currently one of the most common models and has shown outstanding performances in image classification in the agricultural field. In this study, the CNN model architecture was applied to handle the complexity and diversity of the maize leaf images and diseases (Fig. 5). The CNN architecture consisted of several convolutional, pooling, and fully connected layers, which were able to extract and learn the relevant features from the images [17]. The convolutional layer can be considered as a filter to extract features from the maize images, followed by the pooling layer, which helps the model to focus on important features while making the model more robust. It performs down sampling and retains the most important information of the maize images. It is noted that the pooling layer not only reduces the space size of the representation and the number of parameters, but also prevents over-fitting, thus making the model more effective [7,28]. The CNN architecture was also flexible and adaptable, allowing for fine-tuning and optimization of the model parameters. The last layer of CNN is the fully connected layers. It applies the Softmax activation function to classify the high-level features obtained from the images into various categories with labels.

3.3.2. Residual network model selection

ResNet50 is widely used pre-trained CNNs. It is a deep convolutional neural network architecture introduced by Microsoft Research in 2015 [14]. It has been applied in various computer vision tasks, including im-

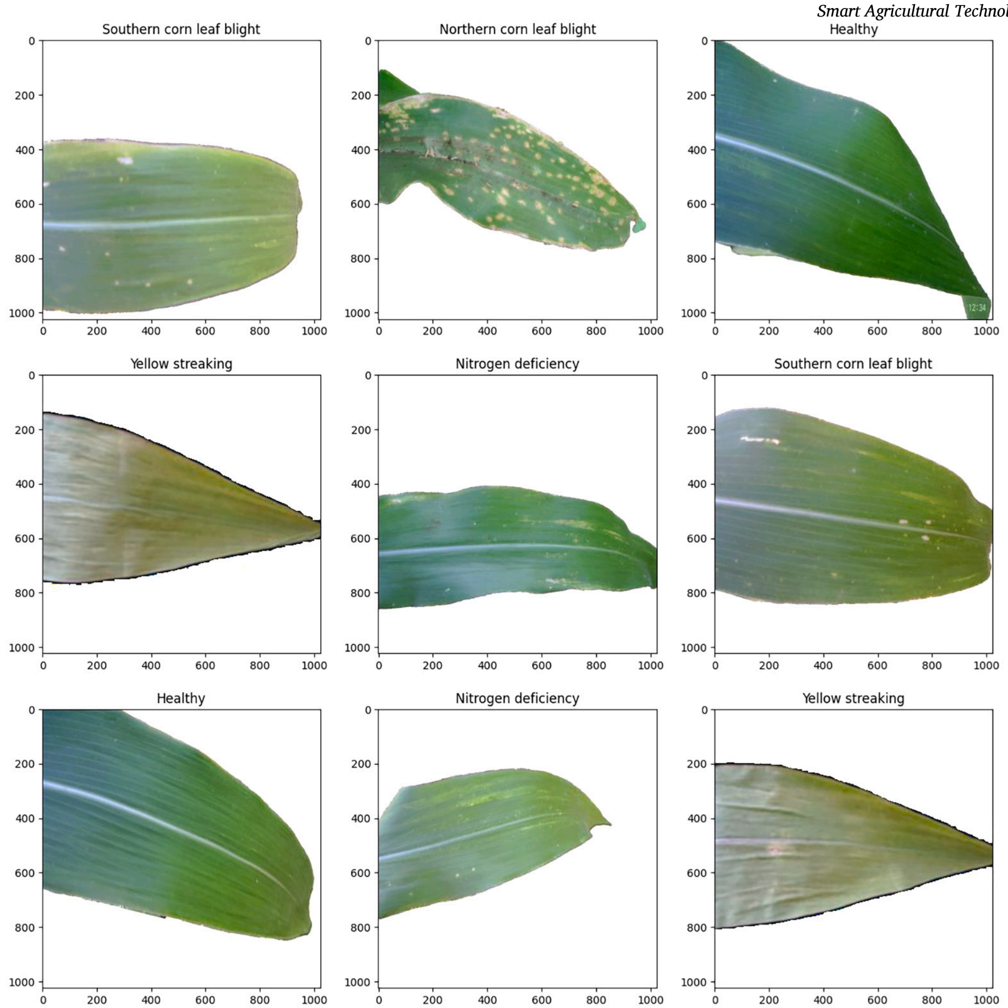

Fig. 3. Maize leaves samples with different diseases symptoms at a sub-field level in Mopani District, Limpopo, South Africa.

age classification object recognition, and image segmentation [31]. The "50" in ResNet50 indicates the number of layers within the network, comprising convolutional layers, fully connected layers, and shortcut connections [16]. These shortcuts connections allow information to bypass certain layers, facilitating more efficient training and enabling the model to learn deeper representations. Fig. 6 represents the layers within the ResNet50 model.

Table 1
CNN and ResNet50 model parameters and augmentation details.

Parameter	CNN Model	ResNet50 Model
Input Shape	(256, 256, 3)	(256, 256, 3)
Batch Size	64	64
Learning Rate	0.001	0.001
Optimizer	Adam	Adam
Epochs	100	100
Number of Layers	4 (2 Conv, 2 Dense)	50+ (Residual blocks)
Total Parameters	15,000	23.5 million
Training Time	6 hours	48 hours
Loss Function	Categorical Crossentropy	Categorical Crossentropy
Metrics	Accuracy	Accuracy

3.3.3. Model fitting and evaluation

Both CNN and ResNet50 models were trained over 100 epochs with a batch size of 64 to assess their accuracy (Table 1). Each image underwent 100 steps per epoch, producing a batch of 64 augmented images. Consequently, a total of 64000 images were augmented during each epoch. To evaluate the model, validation data were employed to check accuracy by utilizing the predict function for feature extraction. Images were reviewed to confirm disease detection once satisfactory validation results were obtained. Finally, characteristics were analysed to determine if the leaves were infected. Model performance was evaluated based on accuracy, precision, recall and F1-Score, using the models to predict labels for the testing dataset (Fig. 7).

4. Results

4.1. Model training for convolutional neural network and residual network models

In deep learning algorithms, learning curves illustrate the model's progression throughout the dataset training process in an incremental trend. CNN and ResNet50 models were trained based on the architectures shown in Fig. 8. The learning rate adhered to a specific annealing schedule, starting from 0.01 and increasing 100 epochs for both ResNet50 (Fig. 8a) and CNN (Fig. 8b). Model performance was evaluated on the testing set of each model's effectiveness in handling the dataset.

4.1.1. Maize disease classification with residual network50 and convolutional neural network models

The confusion matrix for the ResNet50 model presents the classification performance across seven classes: healthy, maize Streak, nitrogen deficiency, northern corn leaf blight, phosphorus deficiency, southern corn leaf blight, and potassium deficiency (Fig. 9). The model achieved an overall accuracy of 78.76%. It performed the highest in identifying

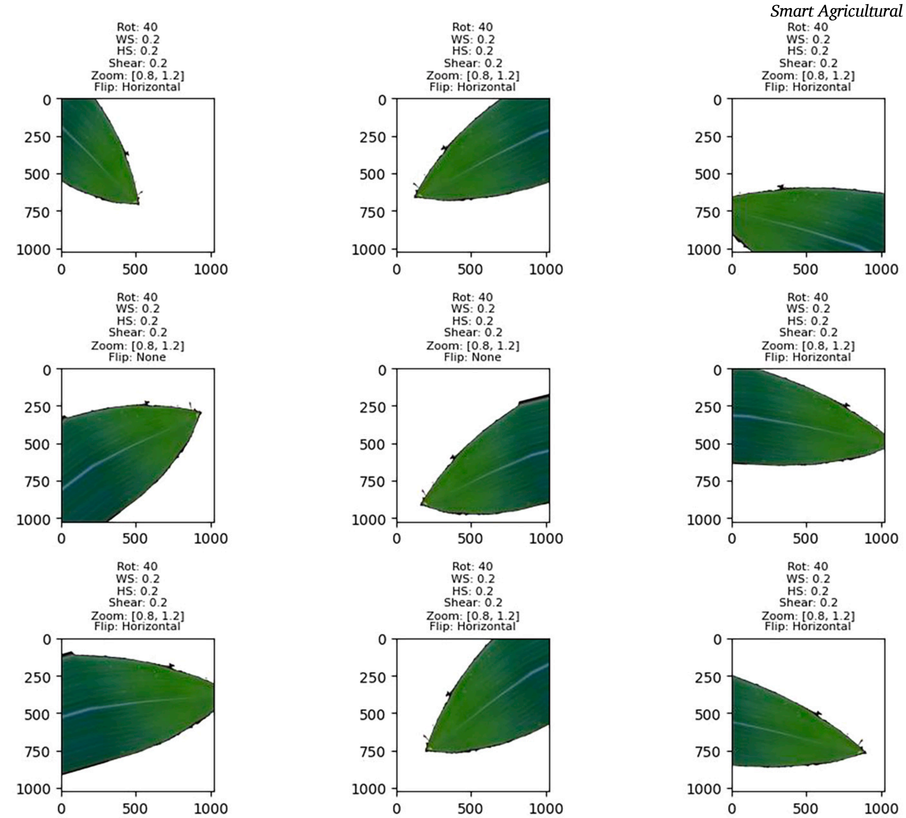

Fig. 4. Image augmentation of maize leaves showing one leaf image into multiple images from different angles.

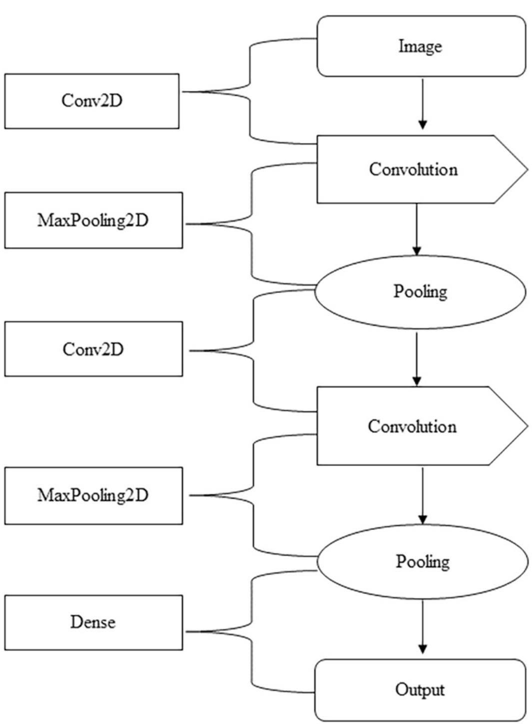

Fig. 5. Convolutional Neural Network (CNN) model architecture that was used to classify maize leaf diseases in the sub-field level in Mopani district, Limpopo.

healthy leaves, with phosphorus deficiency, achieving user's accuracy of 83.17% and producer's accuracy of 82.34%. However, its performance was lowest for maize streak and nitrogen deficiency; with user accuracies of 72.17% and 75.17%, respectively in contrast, the model showed better results for northern corn leaf blight and southern corn leaf blight, with user's accuracies of 73% and 78.33% and producer accuracies of 76.84% and 76.67%, respectively. For potassium deficiency, the model achieved a user's accuracy of 77.83% and a producer accuracy of 73.78%. For the CNN model, an overall accuracy of 71.01% was achieved (Fig. 10). The "Healthy" class recorded the highest user's accuracy of 82% and producer's accuracy of 76.76% %, while those of the phosphorus deficiency class were 74.67% and 80.43% respectively. Maize streak achieved user and producer accuracies of 72% and 64%, respectively. The lowest performance was recorded for nitrogen deficiency, with user and producer accuracies of 57.50% and 62.61%, respectively. Northern corn leaf blight and southern corn leaf blight achieved user's accuracies of 73.5% and 64.67% with producer user's accuracies of 77.10% and 64.56% respectively. The CNN and ResNet50's performance was assessed using accuracy, precision, recall, and F1-score, all of which were provided with a 95% confidence interval (CI) (Table 2). ResNet50 architecture is more resilient and reliable than regular CNN in detecting and categorizing maize leaf states using RGB photos. The ResNet50 model outperformed the CNN model on every metric. The model has the greatest accuracy of 0.788 ± 0.03, successfully classifying around 79% of samples on average. In contrast, the typical CNN model achieved a lower accuracy of 0.710 ± 0.04. ResNet50 has a precision of 0.77 ± 0.04, compared to CNN's 0.70 ± 0.05. This shows that ResNet50 was more effective at reducing false positives. ResNet50 had higher recall (0.76 ± 0.04) than CNN (0.69 ± 0.06), indicating greater accuracy in capturing actual cases. ResNet50 outperformed CNN in terms of precision and recall, with an F1-score of 0.76 ± 0.04 vs. 0.69 ± 0.05, indicating a better balanced performance.

5. Discussion

Deep learning models are recognized for their ability to capture multi-scale features, making them particularly effective for tasks that involve complex and diverse patterns, such as detecting maize leaf dis-

Table 2
The test set model performance using 1000 bootstrap samples to compute 95% confidence intervals (CIs).

Model	Accuracy (95% CI)	Precision (95% CI)	Recall (95% CI)	F1-Score (95% CI)
CNN	0.710 ± 0.04	0.70 ± 0.05	0.69 ± 0.06	0.69 ± 0.05
ResNet50	0.788 ± 0.03	0.77 ± 0.04	0.76 ± 0.04	0.76 ± 0.04

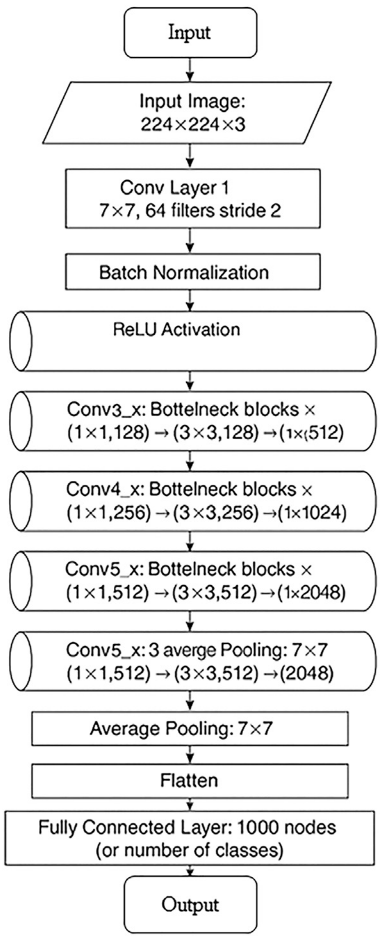

Fig. 6. Residual network (ResNet50) model architecture that was used to classify maize leaf diseases in the sub-field level in Mopani district, Limpopo.

- **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:**

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-Score:**

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP, TN, FP, FN denote true/false positives/negatives.

Fig. 7. Mathematica equations for Accuracy, Precision, Recall and F1-Score.

ease [9,19]. This study aimed to develop two deep learning models-ResNet50 and a standard Convolutional Neural Network (CNN)-for detecting maize leaf diseases at the sub-field level using RGB-based images. The Resnet50 model was selected for its balance between representational power and computational efficiency, allowing it to adapt its architecture to the specific challenges posed by maize leaf disease detection [33]. The CNN model was employed to provide a comparative baseline for assessing the performance of ResNet50. The results demonstrated the effectiveness of both CNN and ResNet50 models in classifying and detecting various maize leaf diseases. Notably, the deeper architecture of ResNet50 outperformed the CNN model highlighting the advantages of using more complex models in tackling intricate classification. The findings add to the body of evidence demonstrating the advancement and the effectiveness of deep learning techniques for automated crop leaf disease detection. The results indicate that both models performed well, however, some categories were misclassified. However, misclassification might have occurred from the computationally intensive models, which can limit their effectiveness in handling complex data. Both models excelled at classifying healthy maize leaves, but there was greater confusion when identifying maize nutrient deficiencies and common diseases. The superior performance of the ResNet50 model can largely be attributed to its deeper architecture, which allows the network to learn features that are more complex while mitigating the vanishing gradient problem often encountered in deep networks [14]. This model's skip connections allowed for better gradient flow and reduced overfitting, making it more stable and accurate in complex classification tasks. The high classification accuracy of the ResNet50 model further reinforces its suitability for plant disease detection tasks [34], who applied ResNet variants to rice disease detection and achieved high classification accuracies. The CNN model also demonstrated strong performance, but its classification accuracy was notably lower than that of the ResNet50 Model. The CNN's reduced effectiveness, particularly in detecting nitrogen deficiency, may be due to its limitation in capturing subtle distinctions between diseases that exhibit visually similar symptoms. This observation aligns with the findings of Mohanty et al. [22], who noted that, while CNN models are powerful for crop disease classification, they often necessitate extensive parameter tuning to attain high accuracy. These results are also consistent with the previous studies by Ferentinos [9], which confirm that Convolutional Neural Networks (CNNs) can accurately identify disease patterns in leaf images under varying lighting and background conditions. However, the deeper CNNs, on the other hand, often experience challenges such as vanishing gradient and overfitting, particularly when the data is complex. Researchers have looked into Residual Networks (ResNets), specifically ResNet-50, which uses skip connections to make it easier to train very deep networks. Thus, in this study, ResNet50 outperformed the CNN. These results are consistent with the previous study by Zhang et al. [35] who used ResNet-50 to detect tomato leaf disease and reported higher accuracy and robustness than standard CNNs. Although, the highest classification performance was observed in the healthy and phosphorus deficient maize leaves in both models, this could have been the results of distinct visual characteristics which may exhibit more consistent colour texture, and spatial patterns, making them easier for the model to learn and differentiate from other classes [36]. A comparative summary of model performance from this and related studies is shown in Table 3. The performance of the two deep learning models has proven to be a transformative alternative, leveraging their inherent architecture to effectively analyse the structure of image data. This allows them to automatically identify complex patterns and features that traditional diseases detection methods

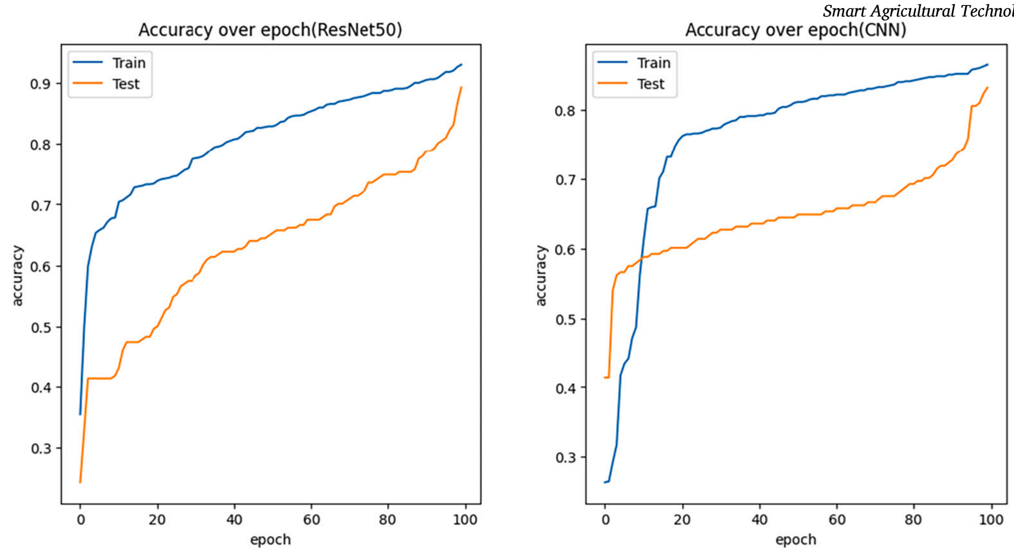

Fig. 8. Performance of the models showing the trends of training and testing accuracy (a) residual network50 model and (b) convolutional neural network model.

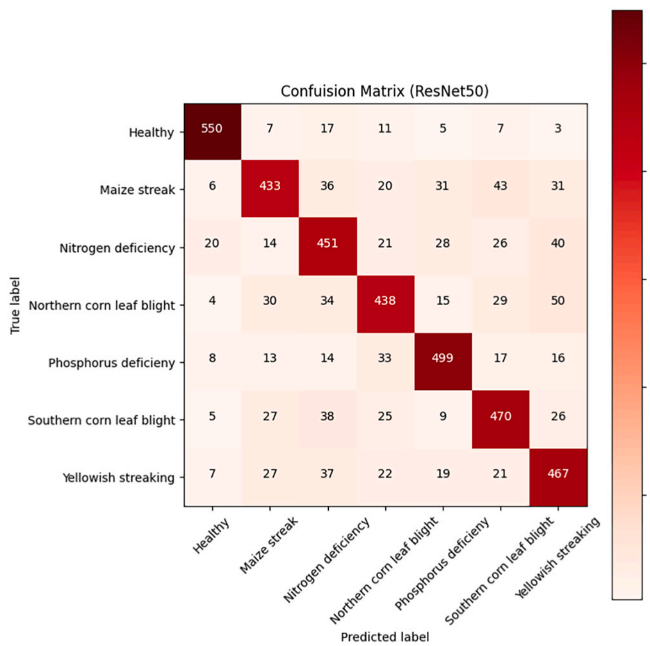

Fig. 9. Confusion matrix of the proposed residual network50 model on the testing set for classifying maize leaf diseases.

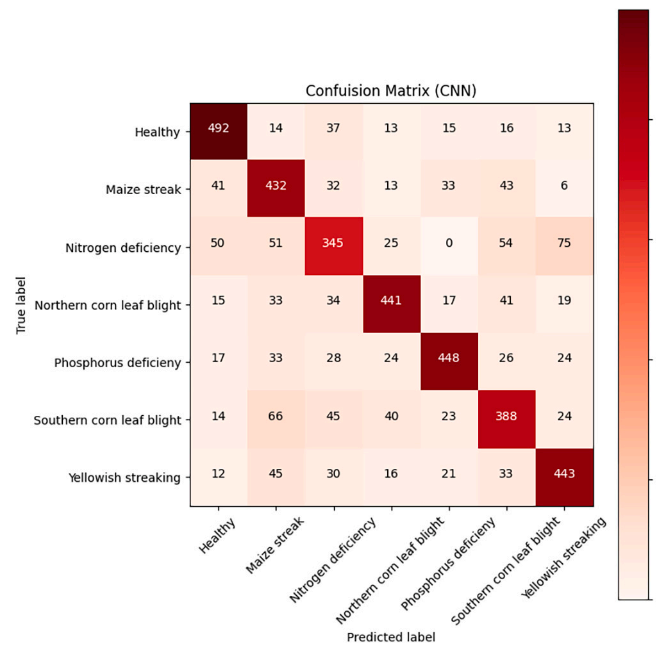

Fig. 10. Confusion matrix of the proposed convolutional neural network model on the testing set for classifying maize leaf diseases.

Table 3
A comparative summary of model performance from this study and related studies.

Study	Crop	DL Model	Accuracy	Notable findings
This study	Maize	ResNet50	78.76%	High performance, best in disease detection.
This study	Maize	CNN	71.01%	Lower performance than the ResNest50 in disease detection.
Ferentinos [9]	Multiple	CNN	99% (controlled)	High accuracy under lab conditions.
Zhang et al. [35]	Tomato	ResNet50	96%	Better than CNN in field conditions.
Wang et al. [34]	Rice	ResNet50	> 93%	Robust across lighting/texture variations

may overlook thereby enhancing the effectiveness of disease recognition Khan et al. [37]. The use of high-resolution images further benefits the adaptability of deep learning approaches. Both the CNN and ResNet50 models processed wide range of data inputs, making them particularly well-suited e for datasets a rich visual context images, such as those comprising plant disease images [5]. However, the use of high-resolution images under field control has a disadvantage on famers who are likely to use smartphones with variable image quality, lighting, and angles. These differences could affect model performance. Thus, it is critical to incorporate data augmentation techniques during training (e.g., varying brightness, rotations, and noise), which can simulate the diversity of smartphone-acquired images [4]. Furthermore, the process of detecting the diseases in the field should be integrated into a user-friendly mobile application that instruct farmers on how to capture clear leaf images and provides immediate feedback. The app should be used with device inference to ensure usability in remote areas with limited connectivity. Future research should incorporate smartphone image datasets or transfer learning from high-resolution to smartphone images to improve field applicability [3], as well as investigating model compression and edge computing techniques to make deep learning models more accessible for smallholder farmers with limited resources.

6. Conclusions

The study employed deep learning models to identify and classify maize leaf diseases using RGB-based images at a sub-field level in Mopani District. The findings demonstrated that both ResNet50 and CNN models effectively detected maize leaf diseases, with the ResNet50 model outperforming the CNN model. This superior performance can be attributed to ResNet50's deeper architecture, allowing it to learn more complex feature and reduce misclassification. Its ability to distinguish between various disease classes underscores its suitability for crop disease detection. The lower accuracy observed with the CNN model highlights the need for further tuning and optimizing deep learning architectures for improved disease recognition. Overall, the study reinforces the transformative potential of deep learning in advancing agricultural practices, serving as a vital tool for early crop disease detection and contributing to food security in maize-producing regions, more particularly smallholder farms.

CRediT authorship contribution statement

Basani Lammy Nkuna: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Khaled Abutaleb:** Writing – review & editing, Validation, Software, Resources, Methodology, Formal analysis. **Johannes George Chirima:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **Solomon W. Newete:** Writing – review & editing, Validation, Supervision, Project administration. **Adriaan Johannes van der Walt:** Writing – original draft, Validation, Supervision, Project administration. **Adolph Nyamugama:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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