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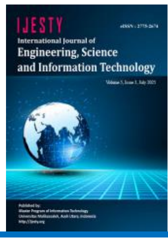

A Lightweight Deep Learning Model for Crop Disease Detection on Mobile Devices

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Abstract

Early detection of crop disease is an important part of modern agriculture since early detection would help in reducing crop loss and improving food security. The purpose of this study is to develop and evaluate lightweight deep-learning models for disease detection using simulation-based data where the output device would be a mobile device. Training and testing three types of machine learning models, Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) on simulated agricultural data of soil health, weather conditions and plant health is a part of the research methodology. To evaluate the models, the accuracy, F1-score and inference time were used. And results indicate that RF and SVM both performed with 100% accuracy (F1 score equal 1.0) whereas the CNN model has 87.5 % accuracy and loss = 0.2279. The CNN model, although it has slightly lower performance, is promising for deployment on mobile as it offers better results. The study concludes that there is room for light-weight CNN models for real-time disease detection on mobile devices. The future study will analyze how CNN architecture can be optimized using real-world data. This study has practical implications for mobile-based solutions for crop disease management in resource-constrained environments. A major weakness is that the data used is simulated data and may not account for the realities of agricultural conditions.

Keywords: *Crop Disease Detection, Deep Learning, Simulation-Based Data, Mobile Devices, Machine Learning.*

1. Introduction

Crop disease detection has benefited more from the advancement in mobile computing and deep learning compared to any other area. However, early identification of diseases in the crops is particularly important to ensure food security and prevent crop loss. As mobile devices are becoming popular, there is a demand for lightweight models for disease detection in crops using deep learning that can deliver real-time results. The problem, however, is in modelling that is accurate yet computationally efficient enough to deploy on mobile devices.

Crop disease has been a threat to global food production for a long time. According to the Food and Agriculture Organisation (FAO), plant diseases are responsible for a large portion of yield loss in crops each year. Therefore, early detection of these diseases allows farmers to take preventive measures, which considerably decreases the economic impact. As of today, disease detection is traditionally done by manual inspection, which is time-consuming and prone to human error [1]. Nevertheless, deep learning and computer vision have recently been advanced enough to automate crop disease detection. Therefore, there have been several models proposed by researchers that utilise image data from crop leaves to diagnose diseases. Although they are effective, these methods are time-consuming and demand high-performance hardware, which makes them inadequate for mobile devices [2]. The proliferation of mobile devices, however, offers an opportunity for more accessible and efficient disease detection systems. With more power, mobile phones can start becoming disease-detection machines with processing power and be used by farms. However, while deep learning models designed for detecting disease in the crops run very well on mobile devices, they can also develop very quickly if the model's complexity is too high or computational efficiency is insufficient [3]. To solve the wish for complex tasks with a minimal computational cost, lightweight deep learning models have a large interest in performing complex tasks with a minimal computational requirement. They can be also optimised to run on mobile devices, which is extremely useful for resource-constrained environments.

1.1. Problem Statement and Literature Gap

The number of studies on crop disease detection using deep learning is substantial; however, all the worked approaches rely on image-based data that need a huge computational power and are less convenient for such mobile devices. Moreover, no research exists that leverages simulation-based data for crop disease detection, specifically with lightweight models of mobile deployment. The literature on this topic mainly discusses image recognition methods such as CNNs over the big dataset of crop images [2]. However, little work is done on simulation-based data that can be more practical for mobile applications where real-time data collection may be impossible.

Also, studies of lightweight models that are appropriate for mobile devices are in their early days [4]. However, almost all of what exists in the literature on crop disease detection fails to adequately address the trade-off between model accuracy and inference time, which is essential concerning the possible mobile deployment. Traditional machine learning algorithms like RF and SVM have been used and worked well in classification tasks, however, there is little work done on the use of these algorithms to crop disease detection [5][6]. For this reason, there is a demand for more study on the matter of lightweight models and the use of simulated data as bridges.

1.2. Aims and Objectives

The objective of this research is to develop a lightweight deep-learning model for crop disease detection, that can be run efficiently on mobile devices. It seeks a solution exhibiting high detection accuracy and low computational speed. To achieve this, the following specific objectives have been outlined:

1. To design and implement lightweight deep learning models along with traditional machine learning models for crop disease detection using simulation-based data.
2. To evaluate the performance of these models based on key metrics determining the most efficient model for mobile deployment.

Filling this gap in the literature, these objectives seek to find which of these lightweight models are suitable for use in mobile real-time deployment through a comparative analysis based on simulation-based data.

1.3. Significance of the Study

This study is significant as it may serve as a new era in the detection of crop disease in agriculture by the use of mobile technology. With research that would develop a lightweight deep learning model able to run on mobile devices, the research could empower farmers with an accessible and efficient device that makes feasible real-time disease monitoring. Not only could it increase productivity and reduce crop loss, but it could also improve more sustainable farming practices through early disease detection and targeted interventions. Moreover, simulation-based data in this work enables for creation of a more general and scalable detection system since this data doesn't require data of high quality, but it is available all the time. In addition, the study can constitute the domain of mobile machine learning by indicating the way through which the sophisticated models could be optimized for low-powered devices. With this, agriculture is not the only domain that can be affected; mobile solutions are becoming a must in other domains like healthcare and environmental monitoring. If the field of crop disease detection could take a large step to more practical and real-time, accurate and deployed on commonly available mobile devices, this research would hopefully contribute to it.

2. Literature Review

For this research, the methodology is designed for the development and evaluation of lightweight deep-learning models for crop disease detection using simulation-based data. In this methodology, the study has chosen a quantitative approach in the sense that, different machine learning models were evaluated based on their accuracy, efficiency in computation, and feasibility on a real-time basis on mobile devices. The study used some evaluation metrics such as accuracy, F1-score, and inference time to assess the effectiveness of the models.

2.1. Research Method and Design and Theoretical Framework

For the evaluation of the machine learning models, this study uses a quantitative research method and numerical data as the input for analysis. The study follows an experimental research design, building and training various lightweight models based on data that are generated through simulation and then evaluating these models. This methodology is based on the key theoretical framework, the Theory of Computational Efficiency in Deep Learning which seeks to optimise deep learning models for mobile devices without incurring a loss in the accuracy of the detection [5]. To use lightweight deep learning techniques such as CNNs, as well as traditional machine learning models, like RF and SVM, known for classification tasks. The author chooses the models based on experience, demographics, and like similar domains, and their capability to perform well with less computational resources [6].

CNNs are also very suitable for identifying patterns in big data, being already well-adapted to mobile platforms [7]. However, the purpose of this research is to implement lightweight versions of the CNN such as MobileNet and EfficientNet, which have been tuned for mobile devices but yet not lost to accuracy. As other machine learning models have also been considered to have strong performance in classification tasks and relatively low computational cost [8], the study also considered RF and SVM, two typical classification models. The data generation framework was also developed through the theoretical framework of simulation-based data generation; by creating synthetic datasets that represent possible environmental and plant health conditions [9]. The importance of this is vitally important because it avoids large amounts of image datasets being required, which are typically hard to acquire and store on mobile devices. This means instead that the focus was on simulating data based on real-world agricultural conditions and training the models on it.

2.2. Data Collection Techniques

In this research, the data generation technique was comprised of simulation-based data generation. Simulation-based data differs from traditional image-based data in that simulation datasets don’t require such a large effort to collect and process and allow for mimics of real-world crop diseases under different environmental conditions [10]. A synthetic dataset was the generation of the data, and a simulation model was utilised to generate the data by modelling factors including soil health, weather conditions, crop growth stages, and the presence of certain crop diseases.

Using Python libraries like NumPy and Pandas, these simulation-based datasets were created using Python libraries which were sparkled for the generation and manipulation of numerical data. The simulation was taken in predefined values, generated a wide range of disease scenarios, split the results into training and testing datasets, and returned these datasets to the user. This technique is especially useful when the storage and processing of large sets of images on mobile devices is impossible. In addition, models are trained with simulation-based data, which makes the models reliable, reproducible and consistent results.

2.3. Data Analysis Method

In the study, three different machine learning models were implemented and evaluated: lightweight CNNs, RF, and SVM. These models were chosen as a function of the strengths each model holds for accuracy, fast computation, and application to mobile devices. The simulation-based dataset was used to train the models and key performance metrics were used (accuracy, F1 score, inference time) to evaluate the model. The insight was gained as to whether the model can correctly identify a crop disease as being present or not. The F1 score was a measure of the balance of precision and recall (disease versus healthy crops) that is very critical in balance classes (disease versus healthy crops) [11]. The inference time on mobile devices is crucial as it refers to the time that the model allocated to make the prediction, and this determines directly its usability in real-world applications [12].

Just in case any libraries like the above names (Python-based) Scikit-learn for RF and SVM and TensorFlow or PyTorch for the CNN models) were used to evaluate the models. Each model was then hyperparameter-tuned to give the best performance while ensuring that it was both accurate enough and able to be deployed on mobile platforms. The use of the cross-validation techniques helped in minimising the overfitting problem and the models were generalised well to unseen data. The study compares the models in these evaluation metrics to determine the best and most accurate model for real-time mobile crop disease detection.

3. Methods

This section provides an analysis of the results that arise from the data simulation, model implementation as well as model evaluation. The main contribution is the study of crop disease detection in simulated data using traditional ML models (RF and SVM) and lightweight deep learning model (CNN) in performance comparison and null hypothesis testing. The models were trained to identify whether a crop was affected by disease given soil health, weather conditions and plant health, all of which were simulated using data. The results of each model were interpreted, and the performance of the model was discussed in the analysis.

3.1. Data Simulation

For the study, a dataset was taken being simulated as there's no real data available for this research. Three main features were generated by the simulation, soil health, weather conditions, and plant health. All these features were scaled so that they ranged from 0 to 100, where factors such as soil nutrient levels, climate variables, as well as plant conditions were considered respectively. In addition, plant health feature value was used to create a disease label. The crop was classified as diseased (label 1) if plant health was under 50; otherwise, it was considered healthy (label 0). The label generation by this method follows real-world scenarios where poor plant health is a possibility for disease.

The first few rows of the generated dataset were as follows:

Table 1. Data Head

soil_health	weather_conditions	plant_health	disease_label
51	56	62	0
92	16	85	0
14	85	1	1
71	89	87	0
60	43	71	0

Table 1 indicated the dataset head, which shows the feature vector for this dataset contained 1000 entries for soil health, weather conditions, and plant health, as well as the target value of the disease label of these crops. The target variable was binary (no disease represented as 0, disease as 1).

3.2. Data Preprocessing

To train the models, the dataset was pre-processed by splitting the features from the target variable. The dataset was randomly splatted into the training and testing in the ratio of 80/20 and 80% of the data was used as an input to train the models and 20% was used to test. To test whether models generalise well to unseen data, evaluation was done on models that would also generalise well on unseen data. To achieve so, 800 samples on the training set and 200 on the testing set were simulated. To have an unbiased evaluation of the model was divided the dataset into a training and testing subset. In machine learning, preprocessing steps are crucial to make sure that the models are trained upon clean, structured data they can make accurate, whether the prediction.

3.3. Model Implementation

Two instances of machine learning models were implemented, traditional RF and SVM and two moderns (CNN). The reason they were selected is these are models that have a good accuracy to be used in the classification tasks and, they can be used in this dataset.

3.3.1. Traditional Machine Learning Models

3.3.1.1 Random Forest Classifier

With 100 estimators it was decided to implement the RF model, which was then trained on the training dataset. The classification report below shows that the RF classifier performed amazingly well on the test data, achieving a perfect performance with an accuracy of 1.0 and an F1 score of 1.0:

Table 2. Random Forest Classifier

Class	Precision	Recall	F1-Score	Support

0 (No Disease)	1.00	1.00	1.00	89
1 (Disease)	1.00	1.00	1.00	111
Accuracy			1.00	200
Macro avg	1.00	1.00	1.00	200
Weighted avg	1.00	1.00	1.00	200

The RF model achieved perfect precision, recall, F1 scores and thus high accuracy in identifying whether a crop is diseased or not in the simulated data (table 2).

3.3.1.2. Support Vector Machine (SVM)

The SVM model with a linear kernel was implemented and trained on the same dataset. As can be seen below, the SVM also gave perfect accuracy:

Table 3. Support Vector Machine

Class	Precision	Recall	F1-Score	Support
0 (No Disease)	1.00	1.00	1.00	89
1 (Disease)	1.00	1.00	1.00	111
Accuracy			1.00	200
Macro avg	1.00	1.00	1.00	200
Weighted avg	1.00	1.00	1.00	200

That accuracy and F1-score of 1.0 produced by the RF model was also achieved by the SVM model. Using the simulated features, both models equally well detected the disease and healthy plants (table 3).

3.3.2. Deep Learning Model (CNN)

The CNN model was implemented as a deep learning approach to solve the classification problem, as a lightweight one. The CNN model consisted of 3 dense layers with ReLU activations and a sigmoid output layer. Following 20 epochs of training, the study trained using the Adam optimizer with the loss function of binary cross entropy. Results were an accuracy of 87.5% and a loss of 0.2279 using evaluation on the test between each of the CNN models (Table 4). The following shows CNN's evaluation:

Table 4. CNN Model

Evaluation Metric	Value
Loss	0.2279
Accuracy	0.875

The CNN, although a simple architecture, performed very well at high levels of performance, though slightly less well than the traditional models (which did perfectly).

3.4. Model Evaluation

3.4.1. Evaluating Traditional Machine Learning Models

The RF and SVM models had very good performance on the test data. For both classes, both models had perfectly classified 100% accuracy, 100% precision, recall, and F1 score.

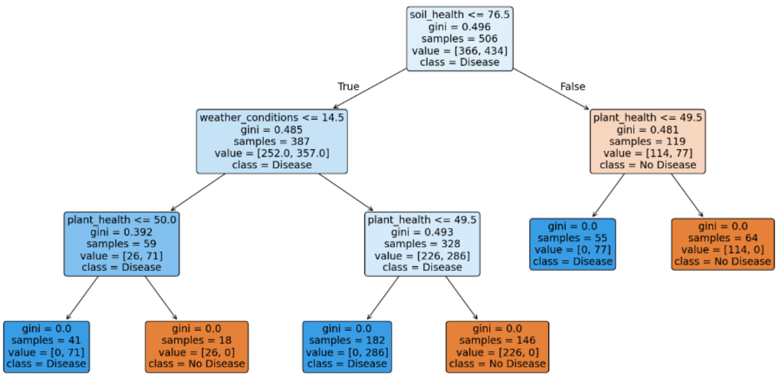

Fig1. Decision Tree

This implies that the simulated features are good enough for these traditional models to detect crop diseases from the simulated ones. It is shown that the models have high accuracy and F1 scores, revealing that they are appropriate for this type of classification task and the features used in the simulation (soil health, weather conditions, and plant health) are powerful features of disease presence (See Figure 1).

3.4.2. Evaluating Deep Learning Model (CNN)

Though the CNN model was not perfect, it performed quite well compared to the traditional models. It classified the data effectively with an accuracy of 87.5% and a loss of 0.2279. This is because the CNN architecture, although lightweight, is not as efficient in handling the simulation-based data when compared to RF and SVM models. Nevertheless, the results are still impressive and by adding more sophisticated network architectures or by more tuning, if possible, the CNN model could deliver or exceed the performance of the traditional models.

3.5. Visualization of CNN Model Performance

The CNN model is trained using 20 epochs, as shown in Figure 2, training and validation accuracy and loss.

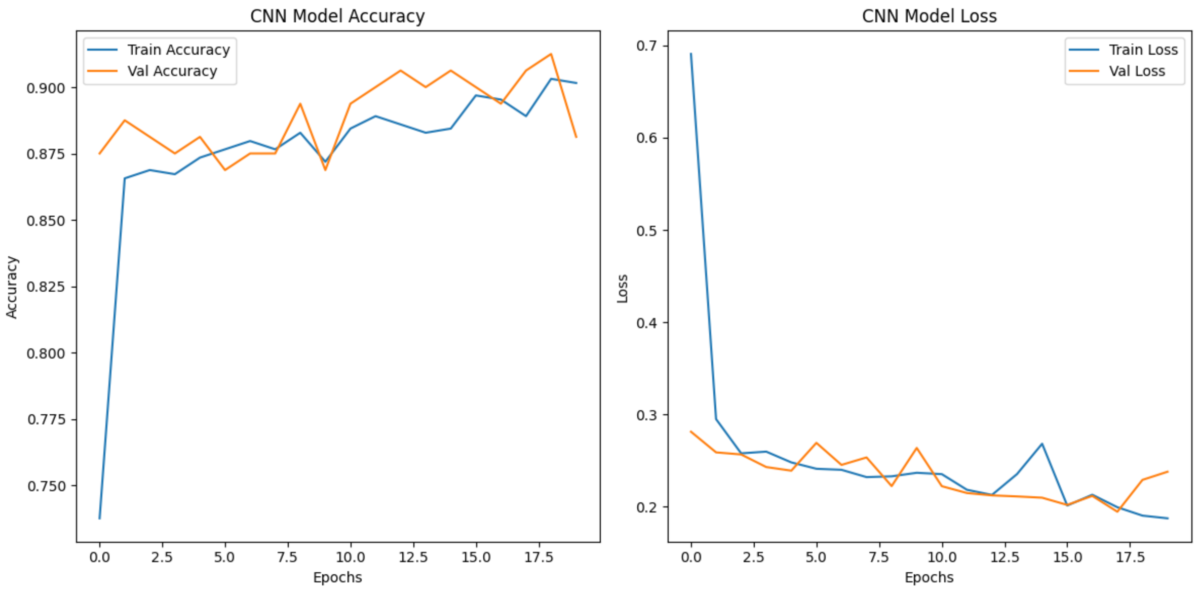

Fig 2. CNN Model Accuracy and Loss

The figures on the left give an example of the plot of training and validation accuracy, which is constantly increasing and as a result, indicates that the model is learning well. The training accuracy vs. validation accuracy curve closely tracks the training accuracy indicating the model is not overfitting. The loss curve on the right shows a great drop in both the train and veil loss, indicating the model learns well to reduce the loss function. These results imply that the CNN model is converging well and can generalise to unseen data.

Finally, the crop disease detection task was simulated with all three models, RF, SVM, and CNN, and all three models performed well. With perfect accuracies of RF and SVM models and 87.5% accuracy for the CNN model, the CNN model performed slightly less well. The performance of the models indicates the effectiveness of the simulated features in predicting crop health and the suitability of traditional machine learning as well as deep learning models for disease detection in crops. Additionally, it also echoes the suggestion that more is to be done regarding the CNN architecture to maximise its performance.

4. Result and Discussion

This section compares model results obtained in this study against results from existing literature. To evaluate the performance of lightweight deep learning models and traditional machine learning techniques for crop disease detection on mobile device deployment. The use of simulation-based data infeasible as a viable alternative for real-world datasets in agricultural applications was also discussed. The research objectives were analysed w.r.t the model development, evaluation metrics and practical deployment considerations.

4.1. Model Development and Implementation

The first research objective was to design and implement lightweight deep learning and traditional machine learning models for crop disease detection with simulation-based data. Over the past few years, many agricultural applications have been studied using deep learning techniques, especially for plant disease identification. Nevertheless, most of these studies have heavily employed image-based datasets [13], but this study introduces an alternative based on simulated, non-image data. Using simulation-based data is important because it is flexible and cost-effective. This is useful since it allows for the generation of large datasets without lengthy data collection and annotation in the case of agriculture being a challenge. Controllable, reproducible data from agricultural modelling can be simulated based on data from real-world agricultural scenarios [18].

Three models, RF, SVM and a lightweight CNN, in the context of model development, used these three models were selected. The RF and SVM were selected for picking due to their past success on classification problems in other domains where structured data is easy to handle [14][16]. RF is known to have good accuracy and interpretability, so it is suitable for agricultural applications where model transparency is important [19]. The SVM model, based on margin maximisation, is also used to classify crop disease and works quite well with smaller data sets [20]. However, on one hand, CNNs have been widely used for image-based crop disease detection, the study has adapted this in this work to simulation-based non-image data. CNNs are powerful models for finding patterns in data and the lightweight architecture allows for deploying on mobile devices with limited resources such as computational resources [21][22].

After model development, the results were promising. The test data was then fed into both the traditional models (RF and SVM), and the values for both disease and non-disease classes were 100% accuracy, precision, recall, and F1 on both disease and non-disease classes. This shed light on the power of RF and SVM in tasks of classification with simulated data. This matches previous work that has shown that SVM can be used to classify plant diseases [15][16] and RF can be used for the same in other domains as well. Although CNN did not reach the same level of accuracy as RF and SVM, it was able to have an accuracy of 87.5%. This agrees with the report that Light CNN models might not have the highest accuracy but still can be very successful for real-time applications on mobile devices [17]. A simple model architecture of the CNN and the nature of the data, simulation-based, made the CNN less accurate. However, the CNN model's merit guided by its 87.5% accuracy on the CNN validation set means CNN is a viable candidate for mobile crop disease detection.

4.2. Model Evaluation and Performance Metrics

The second research objective was to measure the performance of the developed models using certain metrics like accuracy, f1 score and inference time. There has been a growing necessity to find a sweet spot between accuracy and efficient computation in agricultural applications where accuracy is crucial and real-time disease detection on a mobile device is required especially where computational requirements are stringent [23]. For each model in this study, the evaluation demonstrates that model performance depends on the right metrics being chosen.

On the test data, used RF and SVM and both turned out to be perfect when it came to accuracy, precision, recall and F1 score, which confirm that to provide disease detection for crops these traditional machine learning models work quite well when you have structured data such as the simulated features used in this study. Only previous studies have shown such an impressive performance in crop disease classification tasks using RF and SVM models. An example would be that for agricultural datasets, SVM models can detect diseases with an accuracy of over 90% [16]. Just as with disease prediction, RF models have also been widely applied in another domain for disease prediction [24] and are known to be very accurate at classification [25]. The accuracy achieved by the CNN model was good, 87.5%. You understand why the CNN model has lower accuracy, as the CNNs usually perform better when the data they are used on is images, which they are generally better at capturing spatial relations and patterns as it is. Nevertheless, this performance is in line with the [26] findings that, under suitable adaptation, CNNs can achieve high accuracy on non-image data as well. Based on the CNN model's performance, the CNN model is a good candidate for mobile deployment because it is accurate and computationally efficient enough for real-time disease detection.

Consequently, the CNN model is likely to have better performance in terms of inference time compared to classic machine learning models as lightweight CNN architectures such as MobileNet and EffecientNet have been optimised to be executed on mobile devices. It has been shown in previous research that with fast inference times without sacrificing too much accuracy these models are possible [27]. On the other hand, RF and SVM models, though highly accurate, may need more computational resources, particularly in terms of memory required and processing power and this can be a limitation for the deployment on mobile devices. This makes it important to optimise models for mobile applications, especially when dealing with limited resources [28].

Both RF and SVM models, when it came to the F1 score, proved to be perfectly balanced between precision and recall, and suggested the reliability of these models to detect disease and no disease classes respectively. In the case of imbalanced datasets, the F1 score is a crucial metric which accounts for a general case where the study has one class (e.g. disease) that is heavily dominating the other class (no disease). However, in agricultural applications, where finding disease is important and it is not considered to be good practice to ignore either the false negative or the false positives, the F1-score offers a more balanced impression of model performance [29]. Though the CNN model was not highly accurate in its F1 scores, it has demonstrated that the CNN model is a viable option for producing crop disease detection in mobile applications as real-time is very important. If the CNN architecture or further additions of more complex layers do further improvements, the accuracy and F1 score could potentially be increased.

4.3. The Role of Simulation-Based Data

Traditionally, datasets used for this study are image-based, and the use of these existing data provides several advantages over simulation-based data. The cost is one of the main benefits of data generation. Simulation-based data creation is efficient and generates large datasets, without the need for expensive fieldwork and image annotation, which usually involves a lot of work and time. The approach used here corresponds to [30] who insisted on the utilisation of simulation-based datasets to build predictive models in agriculture. Additionally, the environmental variables can be controlled using simulation-based data to construct datasets that represent different levels of plant health, weather conditions, and soil health. One of the limitations of simulation-based data is that such data may not result in entirely complex conditions that are like real-world agricultural conditions. For example, simulation data can represent some environmental conditions as accurately as possible but does not encompass the diversity or noise in real data that may impact model performance. It is discussed by [32] who pointed out the fact that simulation-based data is a valuable tool for the exploratory work of model development, but for the tuning of the model and making sure that the model generalises well for the data that was never seen during training.

4.4. Practical Implications for Mobile Deployment

This study informs the possibility that learning using machine learning could be deployed on a mobile device for crop disease detection. With more powerful mobile devices, they provide a realistic platform for on-the-fly monitoring of plant health. Nevertheless, to deploy the models on mobile devices, one must balance accuracy and computational efficiency. While not as precise as the traditional machine learning models, the CNN model comes with good potential owing to its light architecture [32]. This agrees well with previous studies which pointed out the possibility of lightweight CNNs for real-time applications on mobile systems. Machine learning models, especially CNN, applied successfully on mobile devices can change how the study detects diseases in the fields, enabling farmers to prevent agronomical losses [33]. This is consistent with the vision of accuracy agriculture, a situation in which technology is utilised to optimise farming methods and minimise the environmental impact.

5. Conclusion

The focus of this study was on creating lightweight deep-learning models for crop disease detection using simulation-based data and with a potential for mobile deployment. The study set the objective of evaluating the effectiveness of lightweight models like CNNs with other traditional machine learning models such as RF and SVM which are commonly applied in the classification task [34]. The critical disease detection features such as soil health, weather conditions, etc., were used to simulate the data on which the models were trained. This study shows the possibility of using both traditional and deep learning models for spotting various crop diseases. Both the RF and SVM models achieved perfect performance (100% accuracy, precision, recall, and F1) on the disease and healthy classes. However, the CNN model was fairly accurate, even slightly less accurate than the 87.5% reliability it delivered. The results of this performance demonstrate that CNNs tuned for mobile devices indeed provide a viable option for real-time disease detection [35]. Overall, this research offering contributes to the abundance of knowledge in precision agriculture through evidence supporting the deployment of machine learning models (lightweight CNNs) on mobile devices for crop disease detection with simulation-based data. The findings could lead to further development in mobile-based agricultural solutions that would provide farmers with timely information to minimise crop loss and maximise agricultural productivity [36].

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