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A Model for Detecting the Presence of Pesticide Residues in Edible Parts of Tomatoes, Cabbages, Carrots, and Green Pepper Vegetables

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Abstract: With increased resistant pests and low crop yields, farmers especially in sub-Saharan Africa have greatly embraced usage of chemicals. These chemicals include pesticides used in gardens for better yields and also in the stalls for longer shelf life by sellers of farm products especially fresh perishables like tomatoes, cabbages, carrots, and green pepper vegetables. This, if not checked, may expose humans and animals to pesticide residues. In this research, a model for detecting the presence of pesticide residues in edible parts of vegetables (tomatoes, cabbages, carrots, and green pepper) was developed. A dataset consisting of 1094 images of both contaminated and uncontaminated vegetables including tomatoes, cabbages, carrots, and green pepper with a scale magnification of 800 × 1276 pixels taken using InfiRay P2 pro Night Vision Go Mini Infrared Thermal camera with a thermal module was taken from different daily markets in Mbarara city, South Western Uganda. Image preprocessing was done by noise removal and grayscale conversion. Both the neural network and median filter were applied on the images. A python script was used to cluster the dataset based on chemical concentrations rates of 0.1–0.8 mg/kg, 0.9–1.3 mg/kg, and 1.4–1.7 mg/kg, and this was done for both training and testing dataset. Feature extraction was done to detect the presence of mancozeb, dioxacarb, and methidathion residues from the cleaned images. To test the developed model, convolutional neural networks transfer learning models, Inception V3, VGG16, VGG19, ResNet50, and the scratch model were used. From the results obtained, Inception V3 achieved better performance compared to other transfer learning models with 96.77% followed by VGG16 at 86.98%, VGG19 at 87.56%, and ResNet50 at 82.11%, whereas the developed scratch model achieved 89.13% classification accuracy.

Keywords: pesticide residues, artificial intelligence and vegetables

1. Introduction

Agriculture is the backbone of Uganda's economy, employing 70% of the population and contributing half of Uganda's export earnings and a quarter of the country's gross domestic product [1]. Some of the agricultural products include coffee, maize, sugar, tea, and vegetables. Vegetables are one of the commonly produced and consumed food items on the Ugandan market with at least 90% of Ugandan households consuming tomatoes, green pepper, carrots, or cabbages on a daily basis [2, 3]. These vegetables contribute to national development through local and foreign exchange earnings (mainly from neighboring countries like South Sudan, Democratic Republic of Congo – DRC, Rwanda, Kenya, and Tanzania) but also in achieving sustainable development goals 2030 (SDG 2 on achieving food security, improving nutrition, and promoting sustainable agriculture, and SDG 3 on ensuring healthy lives and promoting well-being for all at all ages) and the parish development model (PDM 1 on production, storage, processing, and marketing). Vegetables are among the top priority commodities supported under the National Development Plan III that is prioritizing agriculture for inclusive economic development. However, these vegetables are prone to chemical contamination, which may affect the health of farmers and vegetable consumers through direct exposure to pesticides and eating of contaminated vegetables [3, 4].

In Uganda, there is inadequate monitoring and support on the usage and management of chemical residues in vegetables. Ugandan farmers tend to rely on colleagues for measurements of doses, with the major focus being preservation of the vegetables while neglecting the effects of the chemicals used [5, 6]. The commonly used chemicals in vegetables include mancozeb, dioxacarb, methidathion, and quinalphos [7]. Consumers of these vegetables tend to avoid the side effects of the chemical residues by washing the vegetables clean before consumption, but this does not guarantee complete removal of the chemical residues, some of the consumers and farmers are unaware of the damage the chemicals may cause to their health, thus consuming contaminated vegetables

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[8, 9]. This paper presents a more accurate artificial intelligent model that uses infrared technology in the detection of chemical residues in vegetables.

2. Literature Review

This section discusses the different methods and technologies used in the detection of chemical residues in vegetables. These methods and techniques can be categorized into three, i.e., traditional, laboratory, and advanced.

2.1. Traditional methods

Consumers have been using age-old techniques to check for pesticides on fruits before eating them ever since farmers began applying them on fruits and vegetables. Consumers do not utilize any tools; instead, they just use their eyes to detect the presence of pesticides on any fruits or vegetables. Pesticides are then removed by hand or rinsed with water when they are seen by the human eye. These techniques are by no means the greatest for eliminating pesticides. To remove up to 70% of pesticide residue, consumers also utilize washing, scrubbing, baking soda and water, and saltwater with vinegar [10, 11].

2.2. Laboratory methods

Chromatography (C), spectroscopy (S), and enzyme inhibition (EI) are now the methods used most often to detect chemical residues. High-performance liquid chromatography, gas chromatography-mass spectrometry, and supercritical fluid chromatography are the most frequently used techniques [12]. The major advantages of chromatographic techniques are their very high sensitivity and enhanced accuracy. They can also carry out multiple detections in a sample, which makes them suitable for the analysis of complex chemical residues [13]. However these laboratory methods are time consuming, quite costly with each analet costing about 100,000 Uganda shillings ($28.5), and unavailable to consumers and sellers [4, 14, 15].

2.3. Advanced methods

There are quite a number of advanced techniques used in detecting chemical residues in vegetables, though these are not popular in developing countries like Uganda due to their cost of operation. In order to identify the kind and concentration of pesticides, advanced approaches employ sensors, automation, artificial intelligence, and machine learning algorithms.

Among these is the fluorescence spectroscopy approach, which uses light wavelength measurement to identify a certain pesticide kind. The sample's molecules' electrons are excited by the laser beam, causing them to release light. A back propagation neural network then analyzes the light that was emitted [14, 16].

In contrast to laboratory procedures, surface-enhanced Raman scattering technology detects chemical residues significantly more quickly and inexpensively [17, 18]. When electrons are energized and vibrate, we may see a shift in their energy state, which is what causes the Raman effect [19].

The need for a more precise model to identify chemical residues in vegetables stems from the fact that, although these modern approaches are quick, they still contain errors because of their quick response times and smaller sample sizes for analysis, making them less accurate than laboratory methods.

3. Methodology

3.1. Data collection

The dataset used for this study consists of 1,094 images of both infected and healthy vegetables (tomatoes, carrots, green pepper, and cabbages) obtained from different daily markets in Mbarara city, South Western Uganda. The images have a scale magnification of 800 × 1276 pixels taken using InfiRay P2 pro Night Vision Go Mini Infrared Thermal camera with a thermal module. The dataset was collected in a balanced number of the three categories of vegetables including fresh vegetables – those that were collected from the garden on the day their images were taken, old vegetables – those that had spent some days in stock, and rotten vegetables – those that had gone bad.

3.2. Image preprocessing

In order to improve the image quality to facilitate further steps, image preprocessing was undertaken on the collected dataset. This step does not alter the image default composition; only two basic tasks were done including noise removal and grayscale conversion. The image is then exposed to Keras (enhancement neural network) – a deep learning application programming interface written in Python running on top TensorFlow library. This was used to standardize the input image with a fixed resolution (resizing) and eliminate non-vegetable images. An advanced image filtering techniques – median filter is also applied at this stage for further de-noising. Furthermore, healthy images, i.e., images which do not contain any of the chemicals under investigation, are eliminated at this step.

To facilitate easy model training and testing, a python script was used to cluster the dataset based on chemical concentration rates including 0.1 – 0.8 mg/kg, 0.9 – 1.3 mg/kg, and 1.4 – 1.7 mg/kg. This was done for both training and testing dataset. Considering the training subset, a total of 193 images had chemical concentration between 0.1 mg/kg and 0.8 mg/kg, 463 images between 0.9 mg/kg and 1.3 mg/kg while 194 images were followed under 1.4–1.7 mg/kg cluster. The same process was done for testing dataset where 49 images had between 0.1 and 0.8 mg/kg concentrations, 146 had between 0.9 mg/kg and 1.3 mg/kg concentration rate, and 49 images followed between 1.4 mg/kg and 1.7 mg/kg concentration.

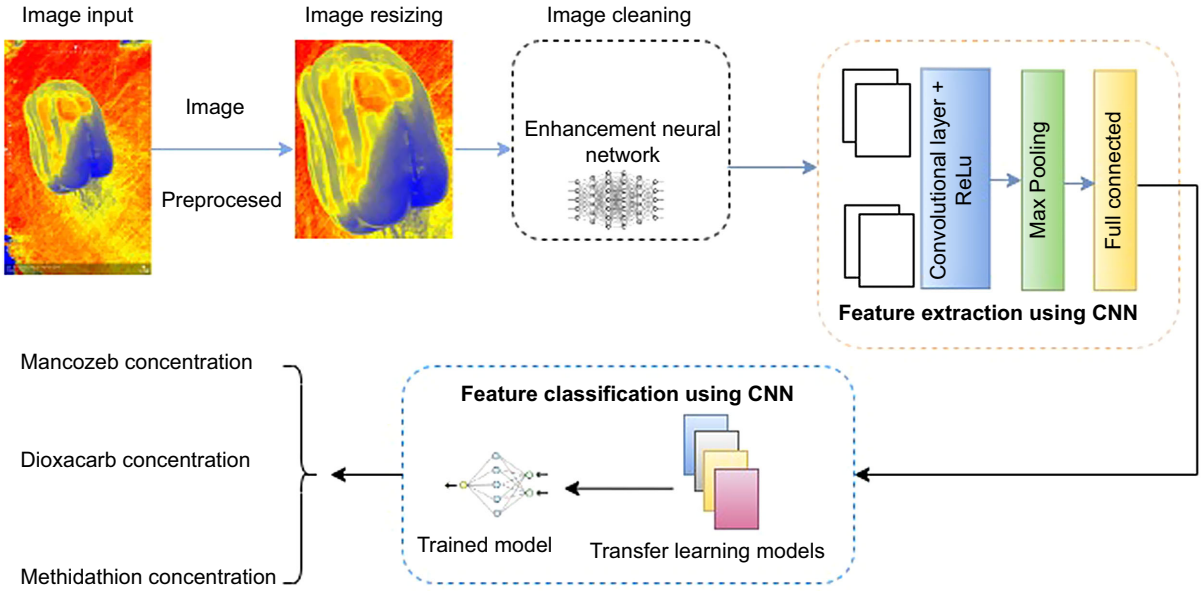
3.3. Feature extraction

This step aims at recovering parameters/features used in detection of mancozeb, dioxacarb, and methidathion chemicals from the cleaned image. To achieve this, the cleaned images in the training subset of the dataset were subjected to a segmentation neural network with three layers: convolutional layer with rectified linear unit (ReLu), max pooling layer, and full connected layer presented in Figure 1.

The convolutional layer has a total of 32 filters (kernels) each with a 3 × 3 dimension. The layers receive the cleaned image and apply the layers to perform feature extraction. Due to many obstacles created by filters, ReLu function is applied to improve feature extraction accuracy.

The initial image dimensions were 800 × 1276 pixels, this affected the model performance in extraction of trainable parameters; hence, the formed image from the convolutional layer was subjected to a 2 × 2 max pooling layer with a 2 pixel stride to reduce the image size to 64 × 64 pixel. This was done to improve

Figure 1
Overview of the proposed model



model performance in extracting trainable parameters while maintaining image quality. Additionally, data augmentation techniques like rotation, translation, zooming, and flip were applied to the dataset to diversify the training dataset while reducing overfitting. Furthermore, hyper parameter tuning which involved systematically adjusting of hyper parameters i.e. learning rate, batch size, loss function, and the optimizer were performed to find the optimal configuration that maximized the model's performance.

The output from the pooling layer is then exposed to a fully connected layer to accomplish flattering operations, which helps in converting the 2D matrix created by the pooling layer into a vector of features, which is then fed into the classification model. Thus, full connected layer is responsible for feeding the fluttered vectors into the classifier.

3.4. Feature classification

The objective of this step is to find out the percentage concentration of each chemical from the image. To achieve this, we applied convolutional neural network (CNN)-based transfer learning method considering four pre-trained models: Inception V3, ResNet50, VGG16, and VGG19. Besides, we trained a model from scratch that was later compared to transferring models using four performance metrics: accuracy, precision, recall, and F1-score. These were calculated using Equations (1–4). The output of the step is classification metrics indicating mancozeb, dioxacarb, and methidathion concentration measured in milligrams per kilogram (mg/kg) of a particular vegetable. Figure 1 describes the actual steps that were followed after subjecting the dataset to the model.

From Figure 1, an image in its original format is subjected to the model at image input phase; preprocessing techniques for resizing and cleaning are applied to eliminate the undesired parts and grayscale conversion, respectively. At the future extraction phase, the convolutional layer, ReLu, max pooling, and full connected layers are enclosed in a single phase, which perform feature extraction collectively as discussed in Section 3.3. The extracted features are utilized to establish chemical composition for mancozeb, dioxacarb, and methidathion.

In regard to this study:

Accuracy is the percentage of the suggested model that is correctly detected i.e. the proportion of the training and testing dataset that the suggested model was able to identify as having the chemicals in question, and it is represented by the equation:

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \tag{1}$$

Precision is a measure of the accuracy of positive prediction, i.e., the percentage of accuracy prediction the model is able to classify as the chemicals present in their correct concentration rate measured in milligram per kilogram (mg/kg) and is denoted by the equation:

$$Precision = \frac{Tp}{Tp + Fp} \tag{2}$$

Recall is the percentage of data samples the proposed model correctly identifies as belonging to a class of interest. In this case, the class of interest is detecting the presence of mancozeb, dioxacarb, and methidathion in vegetables and is denoted by the equation:

$$Recall = \frac{Tp}{Tp + Fn} \tag{3}$$

F1-score is the learning evaluation metric that measures the proposed model's accuracy by combining both precision and recall of the model and is denoted by the equation:

$$F1 - score = 2\left(\frac{Precision * Recall}{Precision + Recall}\right) \tag{4}$$

where

Tp is the true positive value, Tn is the true negative value, Fp is the false positive value, and Fn is the false negative value.

4. Results and Discussion

The proposed model was trained and tested on a dataset containing 1,094 images, of these images 210 were for cabbages, 337 for tomatoes, 257 for green pepper, and 290 for carrots. Model architecture was inspired by CNNs transfer learning models and scratch method approaches as presented in Figure 1.

From Figure 1, the model accepts input image in its original format, resized, and then subjected to the enhancement neural network for denoising and other preprocessing operations. The cleaned image is then exposed to the feature extraction phase containing three different layers: the convolutional layer, max pooling, and full contented layer, which perform feature extraction operations as discussed in the Section 3. At this step, the image is studied to confirm whether it is healthy or contains any of the chemicals under investigation (infected). A healthy image is discarded at this level (demonstrated in Figure 1), whereas an infected one is maintained and subjected to classification phase to establish the percentage of concentration for each image. A summary of model performance on both training and testing dataset is presented in Tables 1 and 2 while the subsequent Figures 2, 3, 4, 5, and 6 demonstrate visualization of model performance using transfer learning models and scratch method, respectively.

From Table 1, among transfer learning models, ResNet50 achieved the highest performance (98.97%) on testing the dataset as compared to other transfer learning and scratch models, followed by Inception V3 (96.81%), VGG16 (90.09%), and VGG16 (89.45%). The good performance achieved using ResNet50 is attributed to augmentation techniques that were to manipulate the dataset size. ResNet requires much more dataset than any other traditional learning models, thus increasing the volume of dataset improved model performance. Compared to other models used, VGG19 registered the worst performance and this is attributed to a big number of layers presented by VGG19, which paused much abstraction to input data hence affecting feature extraction. The proposed scratch model achieved 90.73% accuracy on training dataset, which is a better performance compared to VGG16 and VGG19 transfer models.

Table 1
Model performance on training dataset

Models	Precision	Recall	F1-score	Accuracy	Training loss
Inception V3	0.9681	0.9523	0.9601	0.9681	0.2123
ResNet50	0.9897	0.9838	0.9867	0.9897	0.1891
VGG16	0.9009	0.9010	0.9009	0.9009	0.3129
VGG19	0.8945	0.8943	0.8944	0.8945	0.3213
Scratch	0.9073	0.9067	0.9070	0.9073	0.2123

Table 2
Model performance on testing dataset

Models	Precision	Recall	F1-score	Accuracy	Testing loss
Inception V3	0.9577	0.9576	0.9576	0.9577	0.2211
ResNet50	0.8212	0.8212	0.8211	0.8211	0.1791
VGG16	0.8698	0.8697	0.8698	0.8598	0.2341
VGG19	0.8756	0.8756	0.8756	0.8756	0.3321
Scratch	0.8913	0.8912	0.8913	0.8912	0.1914

From Table 2, Inception V3 performed better (96.77%) as compared to other transfer learning models and the scratch model, followed by VGG16 (86.98%), VGG19 (87.56%), and ResNet50 (82.11%). The training dataset ResNet50 achieved a poor performance, this is because only 20% of the dataset was used for training the model and thus it affected ResNet50 performance due to its architecture that requires much more dataset. Thus, increasing the volume of validation dataset would improve model performance.

Blocks in the Inception V3 can convolve an input tensor using several filters, which improves feature extraction and enhances model performance [20]. Therefore, Inception V3's superior performance in both training and testing scenarios is attributable to its blocks' effortless extraction of detection parameters. The small dataset employed in this study and the fact that ResNet50's

Figure 2
Model performance using Inception V3

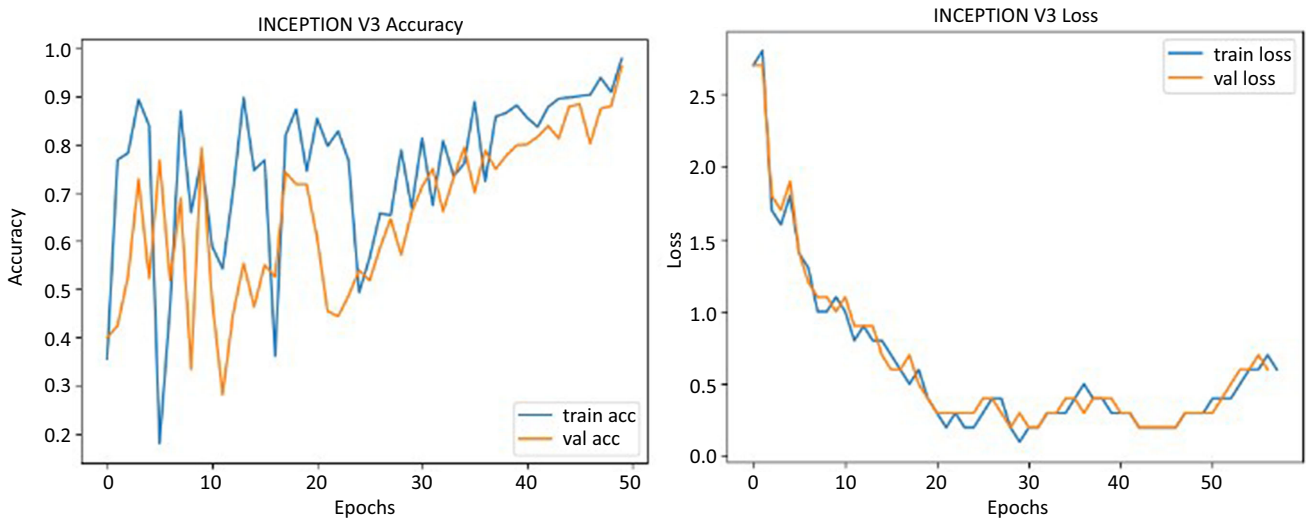


Figure 3
Model performance using ResNet50

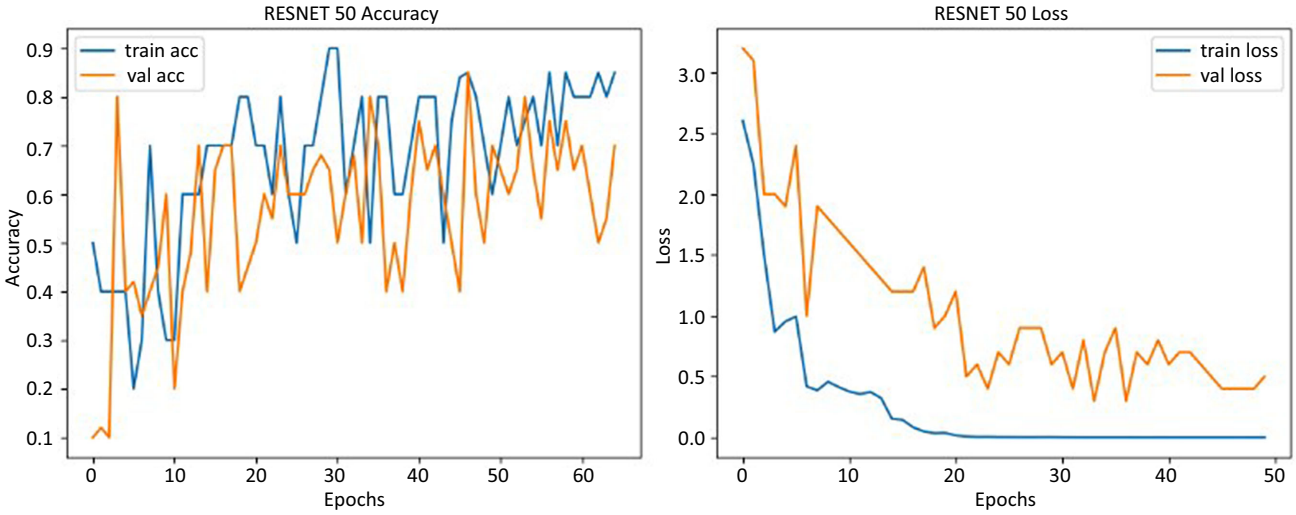


Figure 4
Model performance using VGG16

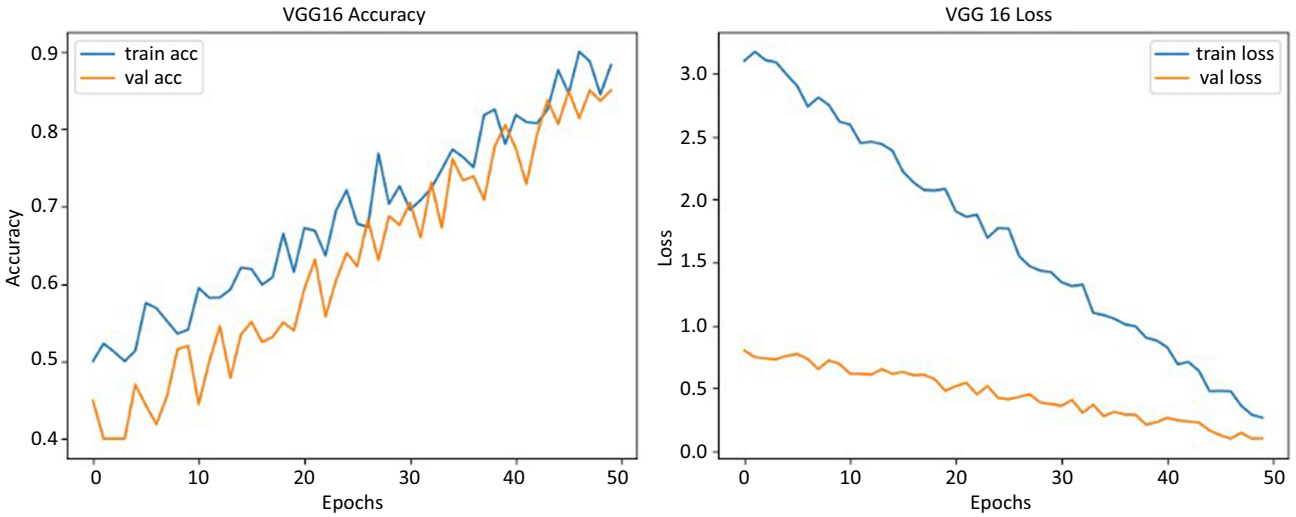


Figure 5
Model performance using VGG19

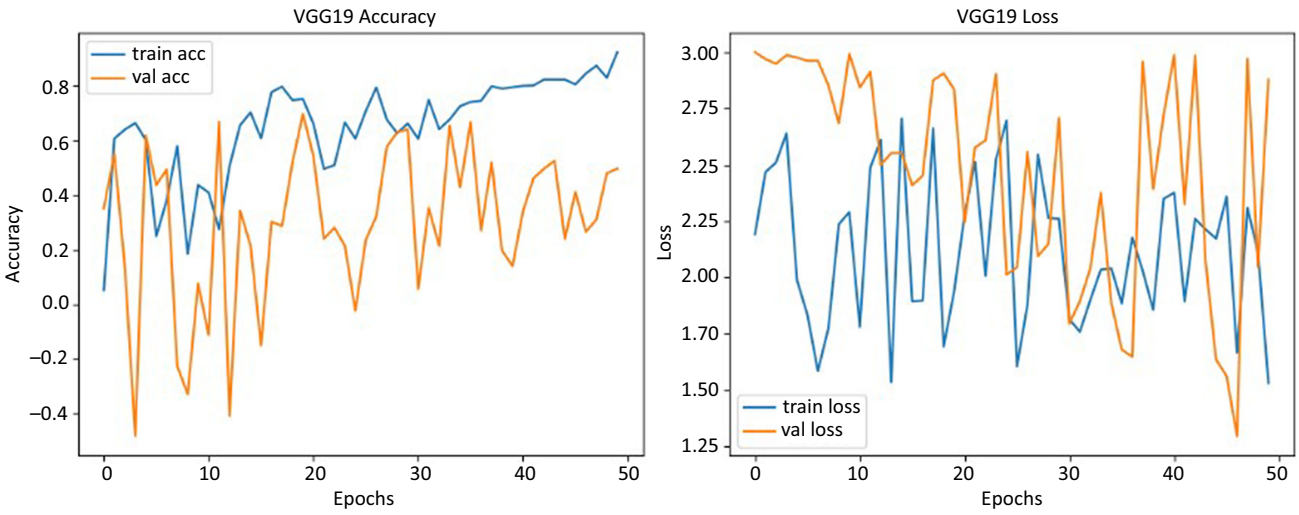
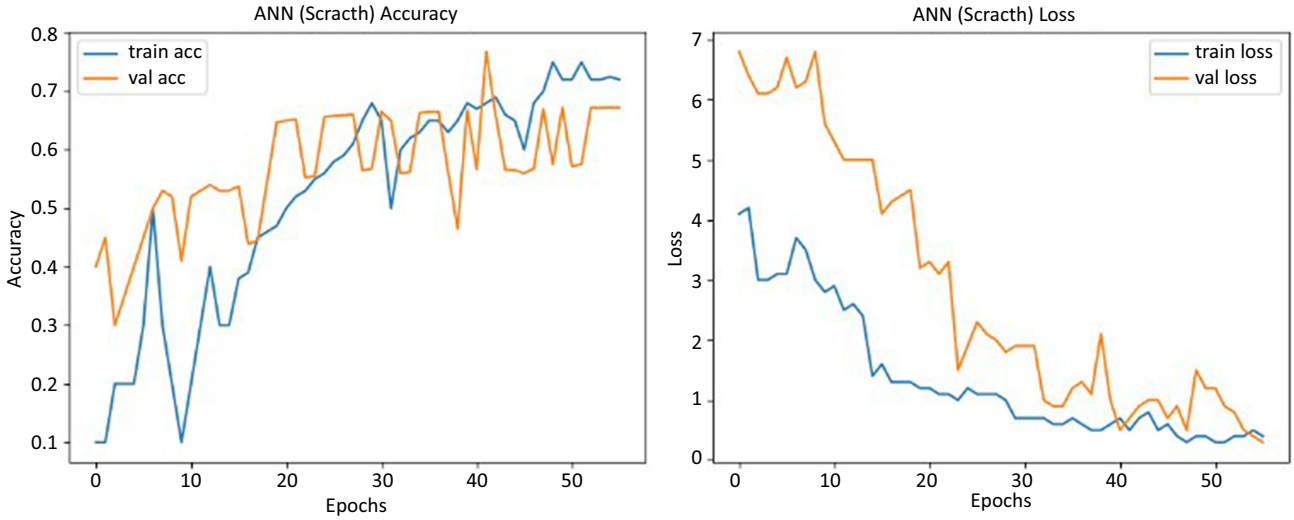


Figure 6
Scratch model performance on both training and testing dataset



architecture contains 50 layers, which presents additional learning challenges for the model, are the main causes of the model's low performance on both training and testing data. A significantly larger dataset is needed to lessen this effect. Taking into account Visual Geometry Group (VGG) models, the architecture of VGG19 is three layers heavier than that of VGG16. This explains the differences in performance between the two models; in particular, VGG16 would require more dataset and training time to improve its performance; alternatively, VGG16 performance would call for reducing filters which reduces obstacles to feature extraction. The more the weight layer, the faster the training; hence, less time and dataset are needed to improve model performance.

Several studies have been carried out in the field of agriculture especially to detect crop diseases, for example, a banana plant disease classification model based on hybrid CNN was developed [21], in this study, the concept of transfer learning was applied to test and train the model using ResNet model. A method for determining mancozeb deposition benchmark values on apple leaves to support management of venturia inaequalis was proposed [22]. In this method, the study images taken using infrared enabled camera were used and TIRI benchmark model was applied to validate the proposed model and a method for determining mancozeb residues in vegetables using head space Fourier transform infrared spectroscopy [23].

Although the above studies demonstrated a better performance and the potential to improve techniques for chemical and disease detection in crops/vegetables, their scope is either limited to a single transfer learning model or a single crop/vegetable species. In this study, we trained and tested the proposed model on four different vegetable species using four different transfer learning models and a scratch model, hence covering a wider range of deep learning techniques used in detecting chemical residues in vegetables.

5. Computation Complexity

The training and testing of the proposed model for the detection of mancozeb, dioxacarb, and methidathion concentration in vegetables were developed using PYTHON scripting language running in Jupiter notebook environment on an I7 processor with 8 GB RAM equipped with RTX 4070Ti 6GB AMD GPUs from NVIDIA.

The computation complexity of the proposed model is presented in terms of space and time required for execution. In regard to this study, time complexity describes the amount of memory required by the model in terms of the amount of input to the model, whereas space complexity is the number of elementary objects required by the model to store during its execution. These were computed asymptotically by analyzing the best, average, and worst case scenarios of each model computed using Equations (5), (6), and (7), respectively.

$$\text{Best case}(\theta) = f(n) \geq cg(n), \text{for } n \geq n0 \quad (5)$$

$$\text{Average case}(\Omega) = c'g(n) \leq f(n) \leq c''g(n), \text{for } n \geq n0 \quad (6)$$

$$\text{Worst case}(O) = f(n) \geq cg(n), \text{for } n \geq n0 \quad (7)$$

where *n0* is the initial number (positive integer) of data input, *n* is increase in *n0,* and *c* is a constant value.

The proposed model was trained and tested in Jupiter notebook environment running on an i7 processor with 8 GB RAM equipped with RTX 4070Ti 6 GB AMD GPUs from NVIDIA. During model testing, 100 datasets were used for each epoch and performance results for each model are presented in Table 3.

From Table 3, Inception V3 registered the best performance in all cases (best, average, and worst), followed by VGG19 with 213600 milliseconds although its worst case score diverted from

Table 3
Model execution time per epoch

$n_{0=100}$ par epoch			
Models	θ(ms)	Ω(ms)	O(ms)
Inception V3	133800	221700	309600
ResNet50	273600	393600	513600
VGG16	328200	358200	388200
VGG19	213600	453600	693600
Scratch	239940	299640	359340

the exhibited a better best case, the corresponding worst case diverted from the constant. ResNet50 and VGG16 consumed more computation resources during execution compared to other transfer learning models used. The proposed scratch model best case, worst case, and average execution time was 239940 ms, 359340 ms, and 299640 ms for 100 images per epoch, respectively.

Although the proposed model was run in an environment with higher specifications, a laptop/desktop computer that is GPU enabled with at least 4 GB RAM, 2.3 GHz speed plus 120 GB storage will be capable of running each of the models used in this study with at most 100 datasets per epoch. However, the need for more computing resources arises with an increase in the size of the dataset, i.e., the bigger the dataset the more computing resources required and execution time.

6. Conclusion and Future Works

Vegetable farming is one of the quick income generating agriculture schemes practiced by farmers in Uganda. There are over 30 vegetable types grown in Uganda both on a large and small scale. The fact that they can be planted in the same garden, a farmer can plant varieties and these have ready markets especially in urban settings. Although vegetable production has gained momentum, the chemicals used to improve production put a health threat to the consumers. To reduce consumer exposure to the chemicals, computerized methods have been proposed to assist consumers in detecting the presence of chemicals in vegetables; however, these methods have been limited to detection of a single chemical while others are trained on one model, which limits application scope of these methods. To mitigate these limitations, in this study a model for detecting mancozeb, dioxacarb, and methidathion using image processing techniques has been proposed. To achieve the research objectives, deep learning CNNs and scratch method were applied to train and test the proposed model. From results obtained using training dataset, ResNet50 achieved a better performance in detecting the chemicals in question with 98.97% accuracy, whereas Inception V3 performed better on testing compared to other models with 96.77% detection accuracy and excellent F1-score, precision, and recall values, hence demonstrating the suitability of the proposed model in detecting mancozeb, dioxacarb, and methidathion chemicals in vegetables. To ease model accessibility and usability, a mobile application was developed with friendly user interfaces that support a better user experience with the model.

To complement study findings, future work should focus on implementing a multi-tasking module of the proposed model to support batch image analysis instead of analyzing a single image. This will improve model suitability for bulk processing to support detection of mancozeb, dioxacarb, and methidathion chemicals in multiple images in a short period.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in vegetable chemical residue detection dataset at https://www.kaggle.com/datasets/vegetabledataset/mancozeb-and-other-chemical-residue.

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