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RESEARCH ARTICLE

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 paper 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 800x1276 pixels taken using InfiRay P2 pro Night Vision Go Mini Infrared Thermal camera with a thermal module were taken from different daily markets in Mbarara city, South Western Uganda. Image preprocessing was done by noise removal and gray scale 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 0.1-0.8mg/kg, 0.9-1.3mg/kg and 1.4-1.7mg/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 (CNN) 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 (The World Bank, 2019). 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 (Dijkxhoorn et al., 2019; Ssemugabo, et al., 2022). 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 wellbeing 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 (Ngabirano & Birungi, 2022; Ssemugabo et al., 2022).

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 (Mergia, et al., 2021; Sarkar, et al., 2021). The commonly used chemicals in vegetables include mancozeb, dioxacarb, methidathion and quinalphos (Kaye, et al., 2015). Consumers of these vegetables tend to avoid the side effects of the chemical residues by washing the vegetables clean before consumption but this doesn't 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 (Sekabojja, et al., 2021; Yang et al., 2022). This paper presents a more accurate Artificial Intelligent model that uses Infrared technology in the detection of chemical residues in vegetables.

2. Literature

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 don't 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 (Sonic Soak, 2019; Anderson, 2022).

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 (HPLC), gas chromatography-mass spectrometry (GC/MS), and supercritical fluid chromatography (SFC) are the most frequently used techniques (Jansson, et al., 2004). 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 (Issaka, et al., 2023). 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 (Ngabirano & Birungi, 2022; Thorat, et al., 2023; Violet, et al., 2022).

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 (Liang et al., 2022; Thorat, et al., 2023).

In contrast to laboratory procedures, Surface-enhanced Raman Scattering (SERS) technology detects chemical residues significantly more quickly and inexpensively (Pang, et al., 2016; Wang, et al., 2021). When electrons are energized and vibrate, we may see a shift in their energy state, which is what causes the Raman Effect (Xu, et al., 2017).

There is a need for a more precise model for the detection of chemical residues detected in vegetables arises from the fact that, despite these modern approaches being quick, they still include errors owing to rapid response and a smaller sample size for analysis, they are less accurate than laboratory procedures.

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 paper and cabbages) obtained from different daily markets in Mbarara city, South Western Uganda. The images have a scale magnification of 800x1276 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 doesn't alter the image default composition; only two basic tasks were done including noise removal and gray scale conversion. The image is then exposed to Keras (enhancement neural network) – a deep learning application programming interface (API) written in Python running on top TensorFlow library. This was used to standardize the input image with a fixed resolution (resizing) and eliminated non vegetable images, 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 0.1-0.8mg/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 figures 2.

The convolutional layer has a total of 32 filters (kernels) each with a 3x3 dimension. The layers receive the cleaned image and apply the layers to perform feature extraction. Due to many obstacles created by filters, Rectified Linear Unit (ReLu) function is applied to improve feature extraction accuracy.

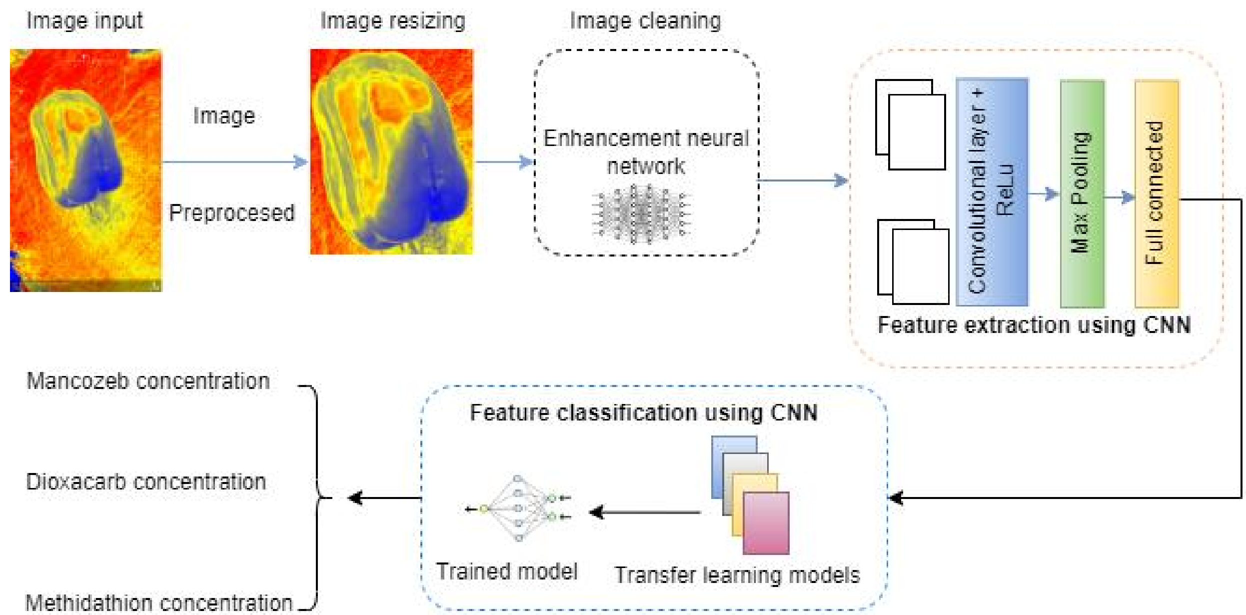
The initial image dimensions were 800x1276 pixels, this affected the model performance in extraction of trainable parameters hence the formed image from the convolutional layer was subjected to a 2x2 max pooling layer with a 2 pixel stride to reduce the image size to 64x64 pixel. This was done to improve 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 hyper parameters; 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 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 the 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 2 below describes the actual steps that were followed after subjecting the dataset to the model.

Figure 1
Overview of the proposed model



From Figure 1, an image in its original format is subjected to the model at image input phase, pre-processing techniques for resizing and cleaning are applied to eliminate the undesired parts and gray scale conversion respectively. At 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 regards to this study;

Accuracy is the fraction of detection the proposed model got right i.e. the percentage of the training and testing dataset which the proposed model was able to detect presence of chemicals in question and is donated by the equation:

$$\text{Accuracy} = \frac{\text{Tp+Tn}}{\text{Tp+Tn+Fp+Fn}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

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

$$\text{Precision} = \frac{\text{Tp}}{\text{Tp+Fp}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

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 donated by the equation:

$$\text{Recall} = \frac{\text{Tp}}{\text{Tp+Fn}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

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

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

Where;

Tp is true positive value, Tn is true negative value, Fp is false positive value, Fn is 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 paper and 290 for carrots. Model architecture was inspired by convolutional neural networks (CNNs) transfer learning models and scratch method approaches as presented in figures 1 and 2.

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 methodology section. 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 (3-7) demonstrate visualization of model performance using transfer learning models and scratch method respectively.

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

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 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 thus, and 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 (Simon, et al., 2023). 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 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 is 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 convolutional neural network was developed (Narayanan, et al., 2022), 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 (Rebel et al., 2020). 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 (Liu, 2022).

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.

Figure 3
Model performance using Inception V3

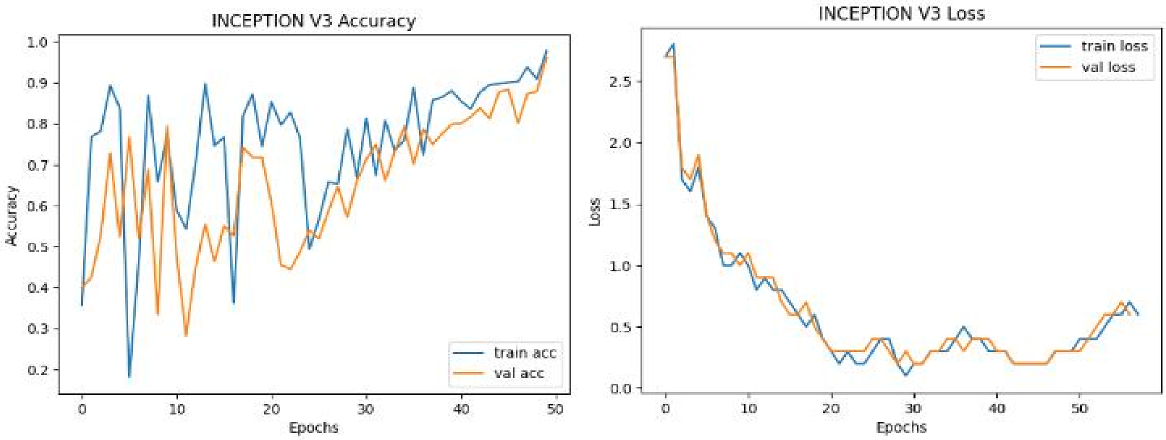


Figure 4
Model performance using ResNet50

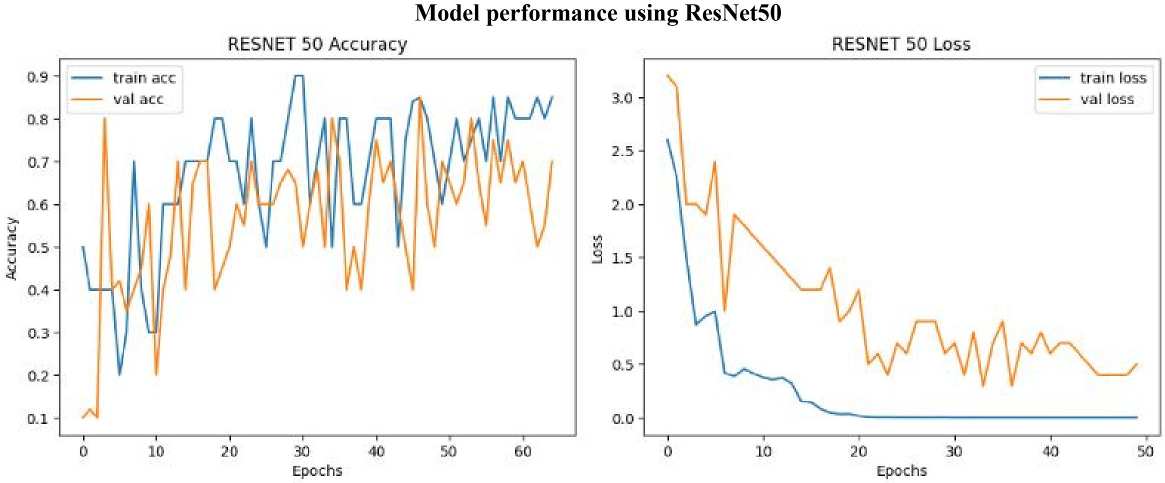


Figure 5
Model performance using VGG16

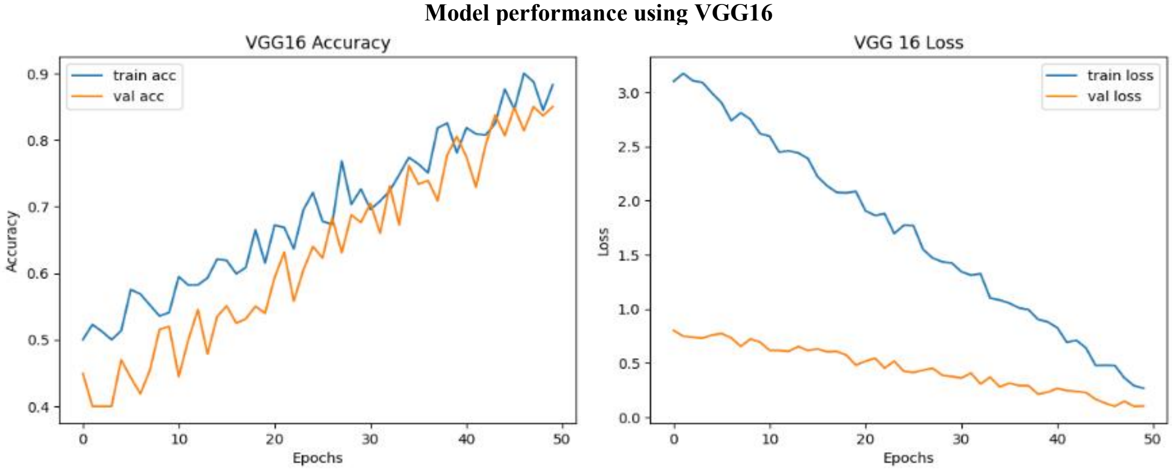


Figure 6
Model performance using VGG19

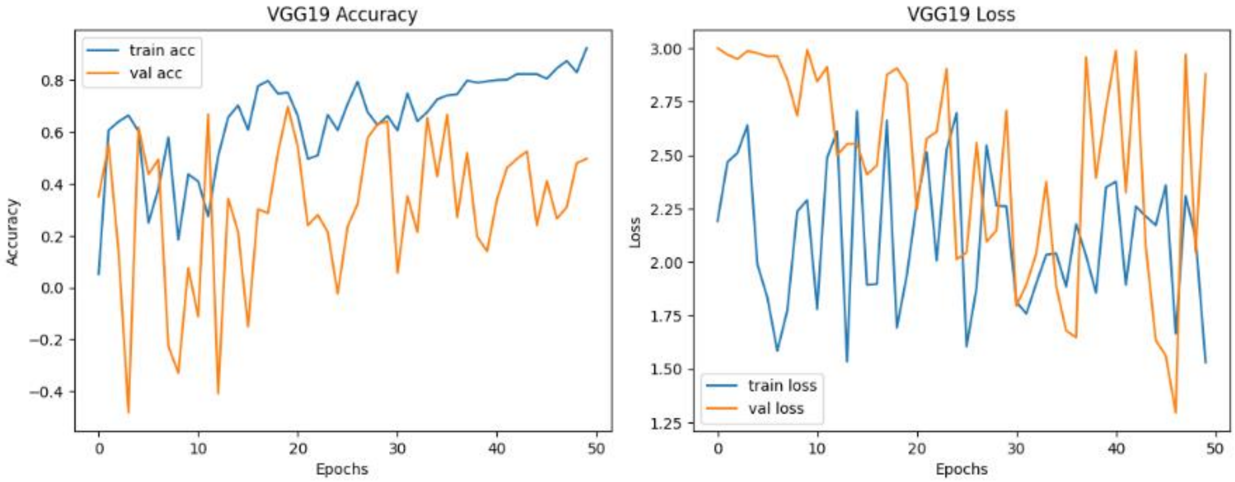
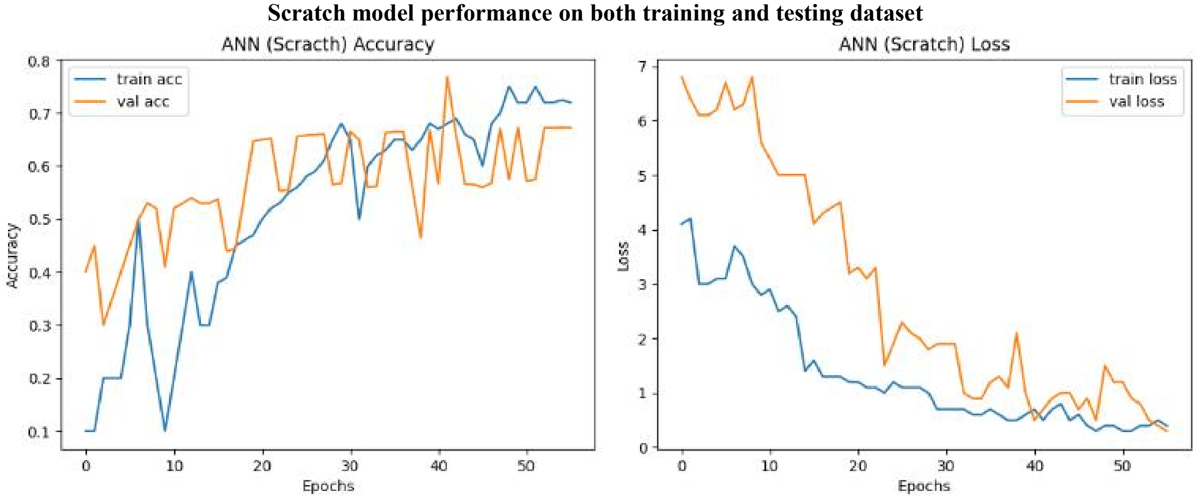


Figure 7
Scratch model performance on both training and testing dataset



5. Computation Complexity

The training and testing of the proposed model for the detection of mancozeb, dioxacarb and methidathion concentration in vegetables was developed using PYTHON scripting language running in Jupiter notebook environment on an I7 processor with 8GB 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 regards 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 the equations 5, 6 and 7 respectively.

Best case (θ) = $f(n) \geq cg(n)$, for $n \geq n0$ 5

Average case (Ω) = $c'g(n) \leq f(n) \leq c''g(n)$, for $n \geq n0$ 6

Worst case (O) = $f(n) \geq cg(n)$, for $n \geq n0$...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 8GB RAM equipped with RTX 4070Ti 6GB AMD GPUs from NVIDIA. During model testing, 100 dataset were used for each epoch and performance results for each model are presented in Table 3.

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

From Table 3, Inception V3 registered the best performance in both cases (best, average and worst), followed by VGG19 with 213600 milliseconds although its worst case score diverted from 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 239940ms, 359340ms and 299640ms 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 4GB RAM, 2.3GHz speed plus 120GB storage will be capable of running each of the models used in this study with at most 100 dataset per epoch. However, the need for more computing resources arises with increase in the size of the dataset i.e. the bigger dataset the more computing resources required and execution time.

Human behavior is complex. The relationship between behavior and attitude has been a topic of interest within the field of human psychology, Ifegbesan (2010). Since then many theories within this subject evolved in order to understand and predict attitudinal influences on behavior and response. The most widely used theory in environmental behavior researches is the Theory of Reasoned Action [TRA] and its extension, Theory of Planned Behavior [TPB] postulated and popularized by (Ajzen & Fishbein, 1980). The theory is based on a premise that individual behavior and intentions are directly related to their attitudes. Interestingly, many studies on knowledge and attitudes have found to have a positive and often statistically significant relationship between the behavior and intentions. TPB framework can thus provide guidance to design inter mediation strategies to support maintain positive behavior or bring in changes (Ifegbesan, 2010). The TPB has been widely used to predict a person's intentions to participate in a specific behavior related to environmental behavioral research (Ifegbesan, 2010). Ajzen (1991) mentions about three conceptually independent determinants of intention in the TPB. They are attitudes towards the behavior, subjective norm, and perceived behavioral control. However, these three independent elements intention in TPB varies depending on contexts and behavior (Ajzen, 1991). Figure 2 shows the TPB model as conceived by Ajzen.

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 convolutional neural networks 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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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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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