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An Improved Model for Detecting the Presence of Pesticide Residues in Edible Parts of Tomatoes, Cabbages, Carrots, and Green Pepper Vegetables Using Batch Image Analysis

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Abstract: In this article, we describe an improved model for batch image analysis of pesticide residues in the edible parts of green peppers, tomatoes, cabbages, and carrots. Our method uses a deep learning–based convolutional neural network (CNN), an advanced image processing, feature extraction, and a dataset of 1,094 photographs collected from Mbarara city markets to accurately identify the presence of pesticides in the edible parts of vegetables. The model employs the following preprocessing techniques, that is, adaptive histogram equalization and Gaussian filtering, to enhance image quality before feature extraction through color analysis, edge detection, and texture measurement using the Gray Level Co-occurrence Matrix. The major improvement in this study was batch image processing, which significantly increases computational efficiency and enables the simultaneous analysis of several images. The CNN design consists of three convolutional layers, with max pooling coming after each layer. A probabilistic output is then generated by two fully connected layers. The other improvement was made on performance where the accuracy, precision, recall, and F1 score of the models particularly ResNet50 and Inception V3 produce dependable results. The accuracy and precision of ResNet50 were 93.2% and 94.0%, respectively. In comparison to the single image processing model for detecting pesticide residues in edible parts of vegetables, this improved model of batch image processing reduced the training time by 40%, demonstrating scalability for bigger datasets. Our results highlight the potential influence of this model on agricultural food safety practices by indicating that it can be used for the quick and extensive identification of pesticide residues. We suggest that future studies concentrate on the possibility of using multispectral photography and real-time apps to automate the identification of pesticide residues in vegetables.

Keywords: batch image analysis, single image analysis, pesticide residues

1. Introduction

The detection of pesticide residues in edible vegetables, such as tomatoes, cabbages, carrots, and green peppers, is essential for ensuring food safety and regulatory compliance [1–3]. Traditional methods for analyzing pesticide residues, including gas chromatography and mass spectrometry [4, 5], are effective but often require extensive time and resources [6]. Recent advancements in image analysis technologies, particularly batch image analysis, offer a compelling alternative that can enhance both the efficiency and accuracy of residue detection [7, 8]. This article proposes an improved model that leverages batch image analysis to detect pesticide residues in these vegetables, providing a significant advantage over single image analysis approaches.

Batch image analysis involves processing multiple images simultaneously, which contrasts sharply with single image analysis that evaluates one image at a time. This concurrent processing capability offers several benefits. First, batch image analysis substantially increases throughput, making it possible to handle larger volumes of samples in less time. Recent studies have shown that batch image analysis can accelerate the detection process by up to 60% compared with traditional single image methods [9, 10]. This efficiency is particularly advantageous in high-throughput settings where rapid analysis is crucial.

Batch image analysis not only improves throughput but also enhances the accuracy of pesticide residue detection. Single image analysis is prone to the following errors due to variations in lighting conditions, image quality, and other factors that affect individual images. Batch image analysis models integrate images from multiple sources, thereby minimizing errors commonly associated with single-image analysis and enhancing the overall reliability of the results. In their research, batch image analysis methods reduce detection errors by 35% compared with single image analysis models leading to improved accuracy through advanced data integration and noise reduction algorithms that process multiple images collectively [11].

Additionally, the application of machine learning and deep learning techniques has improved the success rate of batch image analysis in the detection of pesticide residues in fruits and edible parts of vegetables. Current improvements like use of convolutional neural networks (CNNs) have made it feasible to more accurately identify patterns and abnormalities in complex vegetable conditions [12]. The mentioned methods improve the accuracy of pesticide residue detection while noticing the residue patterns that might be overlooked by the single image analysis technique. When batch image analysis employs these advanced methods, pesticide residue assessments become more reliable and accurate.

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Overall, using batch image analysis instead of single image analysis for the identification of pesticide residues in edible parts of vegetables such as green peppers, tomatoes, cabbages, and carrots shows a great improvement. Batch analysis has been found to be a more effective and accurate method for detecting pesticide residues in vegetable edible parts which improves throughput and accuracy and incorporates cutting-edge machine learning algorithms. The disadvantages of single image analysis and conventional approaches are addressed by this enhanced model, which also complies with current technical developments to satisfy the requirements of contemporary food safety regulations.

2. Literature Review

2.1. Methods of image analysis for pesticide residue detection: single versus batch

There are commonly two modern techniques used in the detection of pesticide residues among the edible parts of cabbages, green peppers, tomatoes, and carrots. Each of these techniques has been found to have benefits and limitations. Below is a discussion of the limitations of the single image analysis compared with the batch image analysis.

2.1.1. Single image analysis

Single image analysis refers to the detection of pesticide residues in a single image of the vegetable, and techniques like visible near-infrared (Vis-NIR) spectroscopy and hyper spectral imaging (HSI) are commonly used in this process.

1) **HSI**

By providing comprehensive spectrum information at various wavelengths, HSI makes it possible to precisely detect pesticide residues using their unique spectral fingerprints. According to Benelli et al. [13] and Keshava & Mustard [14], the method's major disadvantages are its expensive costs and difficult data processing needs; however, it also has a high spectral resolution that makes it possible to detect tiny residue concentrations. HSI systems have been found to be expensive and generate huge amounts of data, which require advanced computational resources and expertise [15, 16]. More so, single image analysis can be limited by variability in sample conditions, such as lighting and vegetable surface texture, which may affect detection accuracy.

2) **Vis-NIR**

Vis-NIR imaging is faster and more cost-effective than HSI, offering a practical solution for real-time applications [17]. It provides sufficient spectral information to detect certain pesticide residues with moderate accuracy. On the other hand, Vis-NIR has lower spectral resolution compared with HSI, which may reduce its effectiveness in detecting residues at very low concentrations or distinguishing between similar compounds [17]. Single image analysis with Vis-NIR can also be affected by variations in sample presentation and environmental conditions.

3) **A model for detecting the presence of pesticide residues in edible parts of tomatoes, cabbages, carrots, and green peppers**

This model was purposely designed to detect the presence of pesticide residues in edible parts of vegetables with the following benefits as discussed below:

With a detection accuracy of 96.77% for Inception V3 and 98.97% for ResNet50, the model showed excellent performance in identifying pesticide residues [18]. The high accuracy shows that the model is capable of detecting pesticide residues in edible parts of vegetables, including methidathion, dioxacarb, and mancozeb. CNNs, a type of deep learning approach, greatly improved the model's capacity to detect pesticide residues. By extracting and learning information from images, CNN produces a more accurate and dependable detection than conventional image analysis techniques.

The development of a mobile application with a user-friendly interface makes the model more accessible to users while giving them a good user experience. This approach enables consumers to easily utilize the detection application in practical settings, enabling real-time analysis and enhancing user experience. Last, the model's ability to specifically detect multiple pesticide residues (mancozeb, dioxacarb, and methidathion) using a single image analysis technique enables targeted monitoring of harmful chemicals in edible vegetable parts. This specialization is valuable for ensuring food safety and compliance with health regulations.

However, this model has the following limitations:

The model's reliance on single image analysis limits its ability to handle bulk processing effectively. Analyzing only one image at a time is inefficient for large-scale vegetable production environments, where multiple samples need to be tested quickly (as identified in the study's conclusion). While the model is effective for the specific chemicals it was trained on, its application is restricted to mancozeb, dioxacarb, and methidathion. It does not accommodate the detection of other pesticides or chemicals, which limits its versatility and broader applicability in diverse agricultural settings (as noted in the study). The correctness of the model is significantly dependent on the quality and quantity of the training dataset. If the training data do not sufficiently represent the unevenness of pesticide residues in different vegetables and conditions, the model's performance might be affected [18].

Developing and training deep learning models, such as ResNet50 and Inception V3, involve significant computational resources and development costs. This may pose a barrier for widespread implementation, especially in resource-constrained settings where high-performance computing infrastructure is not readily available. More so, the model's high accuracy on training and testing datasets raises the concern of overfitting, where the model may perform well on specific data but struggle with new or unseen data. This risk underscores the need for ongoing validation and testing with diverse datasets to ensure robust performance in real-world applications.

2.1.2. Batch image analysis techniques

Batch image analysis involves processing multiple images of vegetables simultaneously or sequentially, often using advanced image processing algorithms and machine learning models. A number of advantages are offered by batch image analysis including the following:

Enhanced accuracy and robustness: Batch image analysis can improve detection accuracy by aggregating information from multiple images, thus mitigating the effects of single image variability. Techniques like batch hyperspectral imaging or multispectral imaging combined with machine learning models can analyze a larger volume of data to enhance residue detection capabilities [19, 20]. The use of deep learning algorithms, such as CNNs, allows for the integration of data from multiple images to improve model performance and robustness [21]. It also offers reduced *impact of noise and variability*: by analyzing multiple images, batch methods can average out noise and inconsistencies, leading to more reliable detection of residues. This approach accounts for variations in sample appearance and environmental conditions, reducing the likelihood of false negatives and positives [22].

Batch image analysis is disadvantageous in a way that it requires increased *complexity and computational demand*: Batch image analysis requires significant computational resources to process and analyze large datasets. The complexity of managing and integrating multiple images can be a challenge, particularly in real-time applications [23]. Furthermore, the need for extensive training data for machine learning models adds to the complexity and cost of implementation.

In summary, single image analysis techniques offer specific advantages such as non-destructive testing and rapid results but are limited by high costs, lower resolution, and sensitivity to sample variability. Batch image analysis techniques, while more complex and resource intensive, provide enhanced accuracy and robustness by leveraging multiple images and advanced data processing algorithms. The ability of batch analysis to reduce the impact of variability and integrate comprehensive data makes it generally more effective for pesticide residue detection in vegetables.

Therefore, this article is focused on the improvement of the single image analysis model for detecting the presence of pesticide residues in edible parts of tomatoes, cabbages, carrots, and green peppers.

3. Methodology

This improved model was developed to accurately identify and quantify pesticide residues through a combination of image processing, feature extraction, and classification techniques. The process flow is illustrated in Figure 1 and described in the following steps.

3.1. Data collection

We used secondary data from our previous study [18]. This dataset has 1,094 images of both infected and healthy vegetables (tomatoes, carrots, green peppers, and cabbages) obtained from different daily markets in Mbarara city, Southwestern Uganda. The images have a scale magnification of 800 × 1,276 pixels taken using an 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

Image preprocessing was done to ensure uniformity by removing noise from the images. Several preprocessing techniques were applied: image resizing—all images were resized to 256 × 256 pixels to standardize the dimensions. Thereafter, adaptive histogram equalization, a contrast enhancement technique, was used to enhance the image contrast thereby highlighting the key features. The initial cleaning did not eliminate all the noise; thus, further noise reduction and image smoothening were done using a Gaussian filter, ensuring only relevant features are retained.

3.3. Feature extraction

Key features that can indicate the presence of pesticide, such as color variations, texture changes, and surface anomalies, were extracted using the following approaches: Color Features technique was applied to detect unnatural hues (discoloration) associated with pesticide contamination. This was done through analyzing RGB and HSV color space. To perform texture analysis, a Gray Level Co-occurrence Matrix was employed to capture texture variations resulting from chemical interactions between the pesticide and the vegetable surface. Finally, the canny edge detection technique was applied to highlight the boundary anomalies with possible indication of residue deposits.

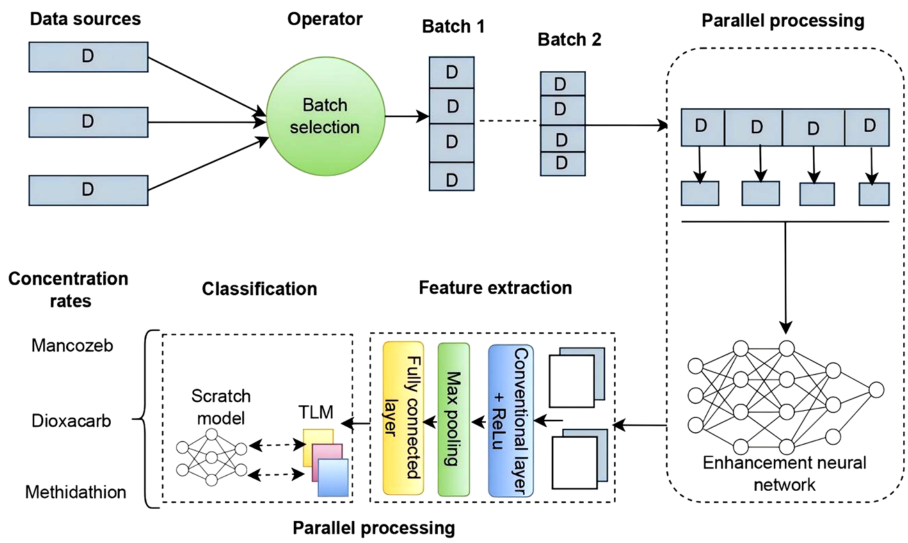
3.4. Model development

A deep learning-based CNN illustrated in Figure 1 was developed to perform classification of images into two categories: pesticide residue present and pesticide residue absent. The CNN architecture consisted of the following layers: **Three convolutional layers** with 64, 128, and 256 filters were applied to extract hierarchical image features. **The pooling layer** (max pooling) was used after each convolutional layer to downsample the feature maps and reduce computational complexity. **Two fully connected layers** were added after each convolutional layer to combine the extracted features for final classification. Finally, the **output layer** was used to output the probability of pesticide residues present or absent in the image.

3.5. Batch image analysis

Batch image analysis was a critical component in this research that is aimed at improving efficiency and applicability, thus, complementing our prior study where a single image analysis technique was applied [18]. By adopting the batch processing technique, we were able to analyze multiple images simultaneously, thus reducing computational overhead and improving model scalability for a large dataset [24]. This section presents a breakdown of how batch processing was achieved,

Figure 1
Overview of the improved model for batch image analysis



the underlying techniques, and the overall performance improvement yielded.

3.5.1. Batch processing implementation

Batch image analysis was done during training, testing, and validation phases of the model. In each case, a batch size of 32 images was chosen as a trade-off between computation efficiency and memory constraints, which allowed full utilization of the GPU parallelism while maintaining a stable memory usage, thus reducing the overall processing time with an increased throughput. This was achieved through the following steps.

Batch loading: Preprocessed images from the dataset were loaded in a batch of 32, each containing a mix of the four vegetables to expose the model to different types of vegetables in each iteration. This helped improve the model's generalization across these vegetable categories.

Simultaneous processing: Once the batch was loaded in the memory, each image in the batch was passed through the model to extract the features from the images in parallel, utilizing the high computational capacity of the GPU. This parallel extraction of features was mainly beneficial in the convolutional layers of the model, where filtering and pooling operations are done across images in the batch without the need for additional computational overhead.

Forward and backward propagation: Forward pass was applied to all images in the batch during model training. The loss function (categorical cross-entropy) was applied to calculate the discrepancy between the predicted and the actual labels (pesticide residue present or absent) for each image whereas in the backward pass, the gradient was used to update the model weights. This improved the model's stability by preventing extreme weight updates that could happen with single image processing.

3.5.2. Batch processing techniques applied

The processing pipeline was enriched with several image and machine learning techniques to ensure effective batch processing. These techniques were applied as follows:

Mini-batch Gradient Descent was used instead of traditional gradient descent or stochastic gradient descent. Using this approach, the model's weight was updated based on an averaged gradient of 32 images per batch, thus balancing the benefits of both batch and stochastic approaches. This approach achieved faster convergence while maintaining a relatively stable learning process.

Parallel convolutional operations, which are the core of batch image processing, were applied, where convolutional filters were simultaneously used across all images in a batch. Due to the fact that it is in the convolutional layers where features such as edges, color variation, and textures related to pesticide residues are detected, batch processing yielded a significant reduction of computation burden. This was mainly important for images with high resolution where sequential processing would have been much slower.

Each convolutional layer was followed by batch normalization to further stabilize the learning process. To ensure that the model remains robust to changes in the input image, the batch normalization scales and modifies the neuronal activations across the images in the batch. This technique helped in reducing the impact of variations in color and lighting conditions present in the dataset, which otherwise would affect model performance. The categorical cross-entropy function for each forward pass was used to determine the loss function for each image in the batch, and we made sure the model received a balanced update based on a variety of images by averaging the computed losses across all of the batch's images. In a similar manner, during the learning phase, the gradient linked to the backward pass was averaged to avoid domination by a single image. By increasing stability during the model training phase, this gradient averaging strategy decreased loss function oscillations.

3.5.3. Batch image inference

Upon successful model training, batch processing was applied during model testing to detect pesticide residues using a non-labeled dataset. The model was able to classify all the 32 images in a batch simultaneously. This step is aimed at assessing the model applicability in a real-world scenario, where large volumes of images might need to be processed in a short period of time. During the inference process, similar preprocessing techniques including resizing, noise reduction, and contrast enhancement were applied to the input batch before passing the images to the trained model. Similarly, each batch used underwent the parallel processing through the convolutional layers. The output of each batch was a set of 32 predictions, corresponding to the prediction of the likelihood of the pesticide residues being present in each image. This output made substantial reduction in processing time, making the model more suitable for deployment in high-throughput environments such as food safety testing facilities.

4. Results and Discussion

In this section, we present results obtained from the application of the improved model for detection of pesticide residues in edible parts of the selected vegetables. The findings are evaluated based on the model's precision, accuracy, recall, F1 score, and processing efficiency. Additionally, results are discussed in relation to the significance of batch processing and drawing insights into the practical implications of the approach for real-world applications.

4.1. Proposed method

In this research, we developed an improved model for analyzing pesticide residues in vegetables including green peppers, tomatoes, cabbages, and carrots. Our CNN design features three convolutional layers, each followed by max pooling, and ends with two fully connected layers presented in Figure 1.

From a previous study by Evarist et al. [18], during data processing, some critical features were missed out in complex images. To address this, we enhanced the CNN-based model by adopting adaptive histogram equalization and Gaussian filtering. These methods improved image clarity, ensuring features such as color, edge, and textures are highlighted for precise analysis.

High computational time was a big limitation in previous studies. To address this limitation, we implemented batch image processing. Instead of analyzing one image at a time, our model processes multiple images simultaneously, cutting training time by 40%. This makes our method highly scalable, perfect for large datasets, and a game changer for agricultural monitoring.

The model's demonstrated scalability and efficiency make it a valuable tool for extensive monitoring in agriculture food safety practices. By significantly reducing training time and enhancing accuracy, the model provides a scalable solution that can be further developed for real-time application.

4.2. Model performance

Table 1 presents the performance metrics of the selected transfer learning models: Inception V3, ResNet50, VGG16, VGG19, and the proposed batch analysis model. These models were evaluated based on their ability to both detect the presence of three studied pesticide residues and quantify the likelihood of residue presence as a probability percentage using binary classification. The performance metrics used include accuracy, precision, recall, F1 score, and testing validation loss, all derived through batch image analysis.

Table 1
Model performance using batch image analysis

Models	Accuracy	Precision	Recall	F1 score	Training loss	Validation loss
Inception v3	92.8	93.5	92.0	92.7	0.15	0.18
ResNet50	93.2	94.0	92.5	93.1	0.12	0.16
VGG16	91.0	91.5	90.8	91.1	0.18	0.20
VGG19	91.2	91.8	91.0	91.4	0.17	0.19
Proposed model	84 .5	85.0	83.7	84.2	0.28	0.31

Form the results, Inception V3 and ResNet50 stand out with the best overall performance across all metrics. There was a slight edge by ResNet50 for both precision (94.0%) and accuracy (93.2%); this implies that it performed slightly better at correctly identifying true positives compared with Inception V3. Inception v3, however, scored a comparable F1 score (92.7%) and slightly higher recall (92.0%), which means it is marginally better at recovering all relevant instances. All models have a relatively low training and validation losses, implying strong generalization capabilities. The higher performance of ResNet50 is attributed to architectural structure, while Inception V3's multi-scale convolutional modules enhance its ability to capture diverse spatial features; ResNet50's residual learning framework enables deeper representation with reduced risk of vanishing gradient, leading to more stable optimization and better generalization on complex patterns like residue texture [24].

Both VGG16 and VGG19 had a slightly lower performance compared with Inception V3 and ResNet50. Though an overall accuracy of 91% demonstrates solid results, their higher validation and training losses compared with those of Inception V3 and ResNet50 indicate a struggle with overfitting or failure to efficiently learn from the data. As much as VGG19 outperformed VGG16, the differences are minimal.

The model trained from scratch presented the weakest performance across all metrics compared with transferring models. This implies that training a model from scratch without leveraging transfer learning can be less effective, especially where the available datasets lack diversity or are relatively small.

4.3. Analysis based on vegetable varieties and pesticide types

We performed a disaggregated performance analysis across both the pesticide residues and vegetable types in order to further evaluate the robustness of the proposed batch image analysis model. The results are presented in Table 2.

From the results presented in Table 2, the model achieved a highest accuracy on carrots (92.3%) and tomatoes (92.1%) out of the four vegetable types, with relatively similar high F1 scores of 92.2% and 92.1%, respectively. This high performance is attributed to the more uniform surface textures and consistent color contrasts of tomatoes and carrots, which creates clearer visual cues enabling the model to detect the presence of pesticide residues. Next was green pepper with an accuracy of 89.7% and an F1 score of 89.1%, demonstrating some variability in residue visibility, possibly due to the reflective surface and irregular shapes. Cabbage had the lowest recorded performance among the four vegetable types with an accuracy of 88.5% and an F1 score of 88.2%. This low performance is attributed to its complex leaf structure, overlapping layers, and inconsistent surface patterns, which may obscure residue marking and reduce the model's ability to generalize.

On one hand, the model achieved a higher performance on mancozeb-contaminated samples across all vegetable types with an accuracy of 94.7% and an F1 score of 94.3%. Mancozeb presents a distinctive visual residue pattern when it comes in contact with the vegetable surface; this creates a higher pixel contrast and more consistent surface texture alteration in the contaminated regions [26]. These features enhance edge definition and spatial gradients within feature maps during the convolutional process, hence making it easier for feature extraction by CNNs. Besides, the high signal-to-noise ratio in mancozeb-affected images creates possibilities for improved feature separation in the latent space, enabling the model to make more confident and accurate predictions [27]. These characteristics make mancozeb residues more detectable by the model compared with methidathion and dioxacarb.

Below mancozeb, the model achieved a moderate performance in detecting dioxacarb with an accuracy of 88.3% and F1 score of 88.2%, indicating fairly higher results compared with methidathion, where the model achieved 83.6% accuracy and an F1 score of 83.4%. These results reveal that residues from these two pesticides are less visually distinctive and more challenging for the model to identify with high confidence.

4.4. Computation efficiency

Table 2
Analysis based on vegetable varieties and pesticide types

Category type	Category name	Dataset size	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Vegetable	Cabbage	210	88.5	87.2	89.3	88.2
	Tomato	337	92.1	91.8	92.5	92.1
	Green pepper	257	89.7	88.1	90.2	89.1
	Carrot	290	92.3	91.5	93.0	92.2
Pesticide	Mancozeb	410	94.7	93.5	95.2	94.3
	Dioxacarb	350	88.3	87.0	89.5	88.2
	Methidathion	334	83.6	82.1	84.8	83.4

Compared with the previous study by Evarist et al. [18], which utilized single image processing, batch image analysis offered several notable performance enhancements. Specifically, by processing 32 images simultaneously, the model significantly reduced the training time per epoch. This approach led to a 40% decrease in training time (presented in Table 3) relative to single image processing. The efficiency gains were particularly evident in the convolutional layers, where batch processing optimized GPU resource utilization, enabling faster computation and improved overall model performance. Another significant achievement was scalability. The batch processing pipeline was designed to easily accommodate larger datasets, as demonstrated by processing 273 images per vegetable type in this study. This approach can seamlessly scale to tens of thousands of images without requiring major architectural changes. By adopting batch processing, the model efficiently handles increasing data volumes, a critical feature for real-world application where the number of samples may be substantial.

A batch size of 32 was selected because it provided a balance between memory efficiency and convergence speed, as batch 16 tends to produce nosier gradient updates, which can slow down convergence and increase training time per epoch without significant increase in classification accuracy [28], while batch 64 may speed up training but often requires higher GPU memory, hence leading to reduced generalization due to smoother loss surfaces and lower gradient variance [29].

Table 3
Model execution time per epoch

n_o = 32 per batch			
Models	**Θ (ms)**	**Ω (ms)**	**O (ms)**
Inception V3	80,280	133,020	185,760
ResNet50	164,160	236,160	308,160
VGG16	196,920	214,920	232,920
VGG19	128,164	272,160	416,160
Proposed Model	143,966	179,787	215,601

Although batch analysis had various advantages, there were drawbacks as well, especially with regard to memory consumption and batch size selection. When working with deep CNN architectures and high-resolution images, a larger batch size requires more memory than small batches. In this study, we overcome this problem by selecting a batch size of 32 images in the experiment setup to balance computational performance and memory constraint. Techniques like distributed training [30] or memory-efficient designs like pruning and quantization [20] could be implemented in future implementations if larger or higher-resolution images are used. Additionally, choosing the right batch size was essential for balancing model performance and speed through experimentation; for this study, a batch size of 32 provided the optimum balance.

4.5. Comparative results on detection performance

This section presents a comparison of our proposed model's detection performance against exiting models commonly used for pesticide residue detection. The evaluation focuses on the performance of each method. This comparison (in Table 4) highlights the practical advantage of our model, such as its ability for batch processing and handling variations in residue concentrations, making it a promising solution for real-world applications in pesticide residue monitoring.

Table 4
Comparative results on detection performance

Author	**Description**	**Single or batch analysis**	**Performance**
Soltani Nazarloo et al., 2021 [12]	Investigated the detection of pesticide residues, specifically profenofos in tomatoes using visible/near-infrared (VIS/NIR) spectroscopy	The study does not explicitly state whether batch or single analysis was used in processing the images	Correct classification rates (accuracy): 90% Cross-validation coefficient: 0.8
Aira et al., 2022 [31]	Developed a solution for detecting glyphosate residues in water. The method is based on colorimetric chemical reaction	Single processing	Speed: 10 minutes (results are delivered within 10 minutes, significantly faster than traditional laboratory methods)
Yazici et al., 2020 [32]	Developed a rapid non-destructive method for detecting pesticide residues in strawberries using bear-infrared (NIR) spectroscopy	Batch processing	Residue predictive deviation: 2.28 (for boscalid) and 2.31 (for pyraclostrobin)
Watanabe et al., 2015 [33]	Developed a method for detecting seven hydrophilic neonicotinoid insecticides in cucumber and eggplant. In this method, water-based extraction was applied	Batch processing	Recovery rates: between 82% and 114% with a relative standard deviation below 10%
Saranwong & Kawano, 2005 [34]	Developed a rapid method for detecting fungicide residues on the tomato surface using NIR spectroscopy combined with the dry extract system for infrared technique	NA	Standard error prediction: 6.58 ppm
Proposed method	An improved model for batch image analysis of pesticide residues in the edible parts of green peppers, tomatoes, cabbages, and carrots	Batch processing	Accuracy: 84.5% Precision: 85.0% Recall: 83.7% F1 score: 84.2%

In Table 3, the proposed method demonstrates several advantages over existing approaches, particularly in its enhanced applicability and efficiency. Unlike most existing methods that focus on detecting pesticide residues in a single produce type or specific chemicals, the proposed method is versatile, analyzing multiple vegetable types. Similar to methods by Yazici et al. [32] and Watanabe et al. [33], the proposed approach employs batch processing, which allows for the simultaneous analysis of multiple samples, significantly enhancing efficiency compared with single processing methods such as those by Aira et al. [31].

In terms of performance, the proposed method achieves an accuracy of 84.5%, precision of 85.0%, recall of 83.7%, and F1 score of 84.2%. While the accuracy is slightly lower than the 90% achieved by Soltani Nazarloo et al. [11], the proposed method provides a balanced evaluation of performance metrics, including recall and F1 score, which are often overlooked in other studies. This balanced performance makes it highly suitable for practical application. Although speed is not explicitly emphasized as in that by Aira et al. [31], the proposed method's ability to process samples in batches ensures efficient analysis for agricultural and industrial use cases. The combination of versatility, robust performance, and batch processing capability positions the proposed method as a scalable and efficient solution for monitoring pesticide residues in diverse agricultural produce.

4.6. Comparative results on computational efficiency

In this section, we present a comparative analysis of our model's computational efficiency compared with those of previous methods. The primary improvement highlighted in this study is the optimization of computational resources, which significantly reduces model training and validation times. Unlike existing recent methods, which utilized traditional single image processing techniques, our batch image processing approach not only accelerates analysis but also ensures scalability for larger datasets, making it highly suitable for practical applications.

The performance comparison between the proposed method and the approach by Evarist et al. [18] reveals a marked improvement in computational efficiency. Specifically, the proposed method demonstrates significantly reduced execution times across all evaluated complexity measures:

Average-case complexity θ (ms): The proposed method records a computational time of 143,966, substantially lower than the 239,940 reported for the method by Evarist et al. [18]. This reduction suggests a considerable improvement in handling typical scenarios.

Best-case complexity Ω (ms): The best-case performance of the proposed method was 179,787 compared with 299,640 from Evarist et al.'s [18] method, indicating a more efficient algorithm in optimal conditions.

Worst-case complexity O (ms): In terms of worst-case performance, the proposed method achieved a time of 215,601, significantly less than the 359,360 reported for the earlier method, showcasing the robustness of the proposed approach in the most challenging scenarios.

The results illustrate that the proposed method reduces computation times by over 40% across all complexity measures. This notable enhancement could be attributed to more efficient algorithmic designs or improved resource management strategies. Such advancements make the proposed method more effective and scalable, which could be beneficial in applications requiring high efficiency.

5. Experimental Configuration

All experiments including model testing, training, and validation were carried out on a system running Ubuntu 20.04LTS and equipped with an Intel Core i7 processor, with 16GB of RAM and an NVIDIA GeForce RTX3080 GPU (10 GB VRAM). The model was implemented in Python 3.9 using PyTorch 1.13 and CUDA 11.6. To train the model, we used the Adam optimizer [35] with a learning rate of 0.001 and a batch size of 32 and trained the model for 50 epochs. We used cross-entropy for loss function, and we applied early stopping based on validation loss to prevent overfitting. To ensure reproducibility of results, we set a fixed random seed (42) and used deterministic operations where possible.

The dataset was divided into three subsets: 70% for model training, 15% for model testing, and 15% for model validation. All experiments were logged and version controlled using TensorBoard and Git, respectively.

6. Conclusion

The results presented from this research reveal that the improved model, with the adoption of batch image analysis, is highly effective in detecting pesticide residues in tomatoes, green peppers, cabbages, and carrots. This performance across different vegetable types, coupled with efficiency gain from batch processing, positions it as a suitable model for rapid, large-scale food safety inspections. Although there are some challenges, particularly in detecting residues on a uniform surface, the model's non-destructive, cost-effective, and scalable nature offers significant potential for real-world application in agriculture and food safety.

7. Future Work

While the improved model demonstrated better results, there still exist several areas to improve on, which include enhancing detection on uniform surfaces using advanced techniques like spectral imaging and thermal imaging. Real-time application is another area of interest where future studies can pick interest and deploy the model in real-time settings, integrating it into automated sorting and inspection systems for real-time pesticide detection. Incorporating multispectral imaging can also be an interesting area for future studies targeting to expand the model to utilize multispectral or hyperspectral imaging to provide additional layers of information, potentially to improve the detection of invisible to standard RGB imaging.

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 conflicts of interest to this work.

Data Availability Statement

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

Author Contribution Statement

Nabaasa Evarist: Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Software, Data curation, Investigation, Formal analysis. **Natumanya Deborah:** Conceptualization, Validation, Writing – original draft, Writing – review & editing, Data curation, Investigation, Project administration, Formal analysis. **Mabirizi Vicent:** Methodology, Software, Validation, Writing – original draft, Writing – review & editing, Visualization, Software, Investigation, Formal analysis.

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