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A Deep Learning Approach for Detecting Pesticide Residues on Brinjal

[1]Sweta G. Phegade, [2]Monali Y. Khachane

[1]KCES's Institute of Management and Research, Jalgaon

[2]A.G. D. Bendale Mahiala Mahavidyalaya, Jalgaon

Email: [1]shwetafegade@imr.ac.in, [2]monalikhachane@agdbmmjal.ac.in

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Abstract

Pesticide residue classification is an essential task that involves finding and classifying pesticide levels built on hyperspectral image data. This process is extensively used in the field of agricultural quality review and food security monitoring. The proposed system covers three key phases, preparation of data, feature extraction, and classification. A modified deep learning neural network architecture, HSI-SpaClassNet, is used to categorize pesticide remains on Brinjal. To attain precise classification, the proposed system uses spatial features extracted from hyperspectral images as inputs to the model. Proposed approach provides better performance as compared to existing models such as MobileNet, EfficientNet, and DenseNet on the Brinjal dataset. Proposed model gives accuracy 98.58% while others deep learning models gives accuracy 97.25% for MobileNet, 96.15% for EfficientNetB0 and 91.86% for DenseNet Model. This paper presents a detailed comparison between the proposed architecture and existing algorithms highlighting the model's effectiveness for rapid and precise pesticide residue detection.

Introduction

Pesticides residues are a common finding in the Indian vegetables and monitoring studies have found that the same applies in Maharashtra as well. Vegetables such as Brinjal, okra and spinach tend to contain the traces of pesticides particularly insecticides like Chlorpyrifos and Coragen. The agricultural and food safety fields have been generating a large volume of data because of a high number of pesticide residues in vegetables being monitored. As such data may be complicated and high-dimensional, it is necessary to categorize it in the most effective way possible so that human contaminants could be detected more quickly and correctly. Our interests in work narrow down to chlorantraniliprole (Coragen) detection on Brinjal. The existence of pesticide remnants in the Brinjal vegetable can be detected using spectral information that is obtained through high spectral imaging of the vegetable. This hyperspectral information is processed on a computer by the transformation into an appropriate image format that can nevertheless be reviewed with deep learning.

Deep neural networks are used in this research since there are limitations in using traditional machine learning methods on massive image data. The deep learning models can extract spectral and spatial information of the hyperspectral images automatically and it follows by the classification of the pesticide residues on Brinjal, which is accurate and efficient. Hyperspectral imaging has taken place as a successful non-destructive technique of analyzing traces of pesticides in fruits and vegetables. Gao et al. [5] used both fluorescence and spectral characteristics as well as HSI and the analysis of chemo metrics to identify pesticide residues on tomato leaves and obtained high sensitivity. The authors used the convolutional smoothing algorithms, transformation of standard normal variables, multiplicative scatter correction algorithms and baseline calibration algorithms to process the spectral data. They obtained a high classification accuracy which indicated the validity of their method when it comes to detection of traces of pesticides. Dan [6] used spectral properties of HSI combined with convolutional neural networks (CNNs) in case of detecting the presence of residues in broccoli that showed that deep learning could enhance high-dimensional classification. The model was found to have recognition accuracies of 94.29, 95.71, 94.29 and 97.14 of high-efficiency cypermethrin, chlorpyrifos, imidacloprid, and water respectively, compared to traditional support retribution machine learning models Kaushik et al. [7] found that High-resolution hyperspectral detection combined with machine learning can distinguish between organic and conventional vegetable crops (Brinjal and red spinach) at 85-95 accuracy, although at the expense Organic crops will have different spectral characteristics facilitating successful regional mapping of crops. Li et al. [8] created a filter-array HSI device with spectral features and regression analysis to create a portable device that is capable of allowing quick field detection of pesticide residues with high correlation to the traditional chemical analyses. The authors of Phegade S. G. et al. [9] adopted hyperspectral imaging (4001000 nm) and Gray Level Co-occurrence Matrix (GLCM) attributes to identify the presence of chlorpyrifos residues on the spinach leaves. The KNN algorithm, SVM, and the Random Forest were trained to create machine learning models, with the last being the most accurate (86.39). Semyalo et al. [10] proposed an approach that used a short wavelength infrared hyperspectral technology in conjunction with spectral unmixing technology to measure pesticide deposits on perilla leaf edibles. Their classification accuracy was above 90 percent with the t-distribution honey badger algorithm-extreme learning machine (tHBA-ELM), which reflects the potential of the given method to detect pesticide residues without destroying anything.

He et al. [11] transformed spectral and spatial characteristics along with machine learning, and revealed that spatial information can be used to boost intelligent residue detection of fruits and vegetables. Research by Kasampalis et al. [12] compared the visible and near-infrared (vis/NIR) spectroscopy to differentiate between pesticides tainted and untainted baby leaf lettuce in production and after harvest. Key wavelengths throughout the near-infrared section were mostly discovered using PLS-DA alongside feature selection (GA and VIP scores). The technique gave 94-99% classification success, meaning that the vis/NIR spectroscopy is fast, dependable and non-destructive, method of identifying the presence of pesticides in lettuce. In a deep learning-based IoT-based pesticide detection, Augustin and Kiliroor [13] used spectral-spatial to reveal that networks are able to identify residues well in real-time. In their study Lee et al. [14] applied microfluorescence HSI to recover spectral-spatial fusion features to qualitatively detect chemical remains in Hami melon demonstrating that spatial features contribute greatly to improving residue classification. Liu et al. [15] used HSI to predict the anthocyanin concentration in whole eggplant peel non-destructively and proved that HSI can be used to detect small biochemical changes in crops. Mandrapa, B et al. [16] employed hyperspectral imaging method and machine learning to identify infestation of two-spotted spider mites on cucumber leaves. The feature selection methods were used to pick key wavelengths and three supervised algorithms that were used to classify healthy leaves and infested leaves. Even with a less variety of wavelengths all methods realized more than 80% accuracy indicating that machine learning can work effectively in real-time and fast spider mite identification. The article by Zhang et al. [17] used HSI in the identification of pesticide deposit in tobacco and it was revealed that hyperspectral information with the help of sophisticated analytical models can find reliably the amount of pesticide deposit. The SVM model which followed the preprocessing via WT-TC-CARS and parameter optimization via GSA exhibited doing of very well in this study. It showed a mean test accuracy of 91.8 that has a precision of 90.3, recall 90.3 and F1-score 0.9, approximately 8% higher than the original model. Microfluorescence hyperspectral imaging (MF-HSI) was utilized in the study and combined with machine learning [18] to identify insecticide residue in Hami melons. Some of the most important spectral and colour characteristics have been chosen and combined, and the SPA-PLS-DA model was attaining 93.48% accuracy on the validation dataset, which reveals that MF-HSI can be used effectively to detect pesticides as quickly and precisely as possible.

Liu et al. [19] used SWIR hyperspectral imaging in conjunction with tHBA-ELM which reported a high accuracy of 93.5% and high precision and sensitivity thus becoming an effective technique of detecting pesticide residues remnants on Hami melon and is a fast-employing non-destructive method of detection. According to

Vignati et al. [20], many submissions of spectral-spatial HSI have been reported in fruit and vegetable worth and safety assessment, which validates the universal use of this method. Hu et al. [21] also revealed VNIR and SWIR hyperspectral imaging to be able to detect the dissimilar pesticide residual on Hami melon without destruction. The model was based on information fusion and using a multi-branch 1D-CNN with attention, which has 94% accuracy, precision, and recall, and compared to the traditional machine learning models (KNN and RF). There were the highest classification effectiveness results by SWIR and fused spectra, which can be used to refer to the remains of pesticides on other thick-skinned fruit. The previous research, including Ye et al. [22], showed that HSI with machine learning could be used to detect pesticide traces in grapes, Vis-NIR, and NIR hyperspectral imaging were both effective to detect pesticides in grapes, and NIR gave better results. Deep learning networks (ResNet, CNN) were found to be superior to traditional models, reaching a maximum of 97 percent accuracy, resulting in hyperspectral imaging being seen as a quick, dependable detection instrument as well as Srivastava et al. [23] used hyperspectral remote sensing to identify the disease in Brinjal, by revealing spectral imaging as a multitasking tool. Previous background research, as in the multi-residue detection of pesticides on broccoli [24] and spectral-texture-based early disease detection on eggplant [25], is yet another confirmation that HSI coupled with sophisticated feature extraction and machine learning could be useful in classifying contaminants. The analysis [25] employed the method of hyperspectral imaging and texture to identify early blight on eggplant leaves. KNN and AdaBoost were used to analyze spectral and GLCM-based texture in RGB, HSV, and HLS images and attained over 88% classification accuracy showing that a combination of spectrum and texture measures are an effective method of identifying the disease. Hyperspectral imaging and machine learning on Brinjal pesticides were employed by Satthayabama B et al. [26]. The range of proposed 3D SERSN was 94 percent accuracy when separating two classes and 98 percent when separating four classes, which is higher than the conventional ML models such as SVM (89 percent) and KNN (78 percent).

The suggested model is aimed at categorizing pesticide residues on vegetables, which is based on the pesticide application phases. These experiments affirm the hypothesis that the hybridization of the spatial features and the deep learning models are effective in the rapid, non-destructive and accurate classification of residues. The paper is structured in the following way: Section 2 includes the description of the framework of proposed system. Section 3 deals with the results and analysis and its comparison with the existing methods. Lastly, Section 4 completes the paper summarizing the results and implications.

Framework of the Proposed System

The construction of the proposed framework is to enhance examining and describing hyperspectral pictures used in farm and environmental categories. Its primary aim is to have an accurate detection and differentiation of minute changes in the spatial information that can be used to indicate contamination, crops health, or pesticide residues. The framework will seek to offer an effective and accurate solution to real-time tracking and decision-making processes in precision agriculture by combining the use of advanced processes and classifications. The given algorithm design has a partial similarity to a conventional Deep Neural Network, but it still has several differences that form several important points which are used to highlight the exclusivity of the design and the way it functions. The proposed model has a framework as in figure 1.

The proposed architecture lays off with the gathering of hyperspectral photographs of vegetables and fruits by a permitted hyperspectral camera. These images are highly spectral and spatial in nature and one can identify the presence of pesticide residual on the food item surface. During the pre-processing phase, the process of data cleaning is conducted to eliminate the presence of noisy data or corrupted data, and spatial domain operations, including rotations, flips, scaling, etc., are used to augment the data. The process enhances the diversity of the datasets and assists in making the neural network resilient to the fluctuations in the input samples.

After pre-processing, balancing of the datasets is carried out in order to tackle the issue of unequal distribution of classes where each of the four categories of residues (High, Medium, Low, and Pure) is well represented. The balanced dataset is further cut into two sub sets; 80% to train and 20% to test. The parameters of the proposed neural network are optimized using the training subset and the testing subset that is not used during the training process is used to measure the generalization performance of the trained model. These data controls ensure an unbiased learning and equitable model consideration.

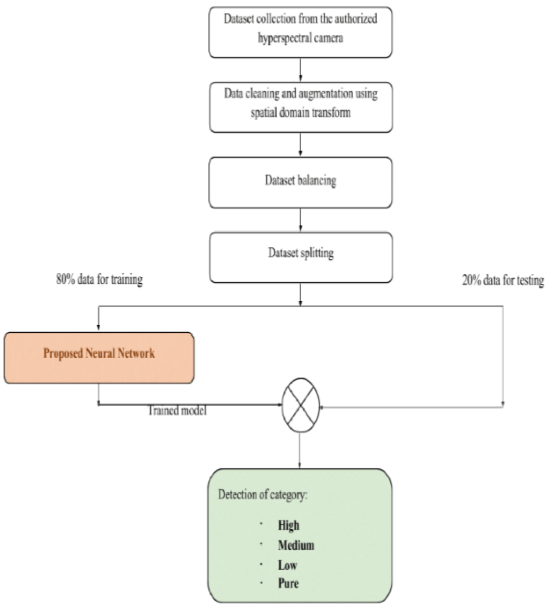

Figure 1. Framework for Proposed HIS-SpaClassNet Model

The HSI-SpaClassNet model is a specially a modified deep learning model used for classifying hyperspectral images by integrating spatial information.

Proposed Algorithm: HSI-SpaClassNet Model

Input: Training data X, labels Y, test data Xtest
Output: Trained model, predicted labels Ytest

Step 1: Start base model- Load model without final layer; hyperspectral input set.
Step 2: Freeze base layers - Don't update learned feature extraction layers.
Step 3: Add classification head -apply batch normalization, fully connected ReLU, dropout, and final softmax layer.
Step 4: Compile model - configure optimizer, loss function and evaluation metrics.
Step 5: Train model Feed minibatches, forward propagate, loss, back propagate gradient on head layers, update weights.
Step 6: Predict - Use the test data to predict, calculate the probability of each class, and give the highest probability class to output.

Once the model building is created, it is compiled by setting the optimizer, the loss function such as categorical cross-entropy and measuring assessment metrics such as accuracy, precision and F1-score. In the training stage, the data is separated into small batches which pass through the linkage in a process known as forward propagation. The model does predictions and the difference between the predictions and the actual labels is computed as the loss. The model minimizes this loss in backpropagation by updating the weights of the new layers added, and leaving the base model the same. Such a process repeats across a few epochs until the accuracy of the model and the performance it produces becomes stable and satisfactory. The model is tested with previously unfamiliar to the model hyperspectral images after training phase. The network is used to pass each test sample and the probability of every class is calculated by the Softmax layer. As the final prediction, a choice of the class with the largest probability is made. By so doing, the HSI-SpaClassNet model integrates the benefits of the ready-made deep learning networks with the other layers structured to work on hyperspectral images. ReLU activation function assists the model to learn significant features, dropout layer prevents overfitting and softmax layer performs good classification of pesticide residues.
This ensures that the model is highly applicable to real-life operations like the pesticide residues threats or the quality and status of agricultural products by using the hyperspectral imaging feature.

Result and Discussion

The data that has been used in this research was acquired in the department of Electronics and Communication
Engineering, Thiagarajar College of Engineering, Madurai. The data set was ready with four various levels Coragen pesticide residues, which were Low, High, Medium and Pure concentration levels. The Low concentration was made by using 0.3 ml pesticide per liter of water, the medium concentration was 3 ml per liter of water and preparation of the High concentration was 6 ml per liter of water. Pure class has samples that were not treated with pesticides. The experiments were conducted with the use of this dataset used to test the performance of the proposed model. On the recommended algorithm, the Brinjal Dataset consisting of a total number of 36000 images under each class is tested. Means in all there are a total of 1,44,000 images in all in that 80% images (1,15,200 images) are in training and 20% images (28,800 images) of testing.
According to the confusion matrix presented in Fig. 2, the majority of the values fall in the main diagonal indicating that the samples were classified correctly by the model. It is also demonstrative that the suggested approach HSI-SpaClassNet eliminates false classifications significantly.

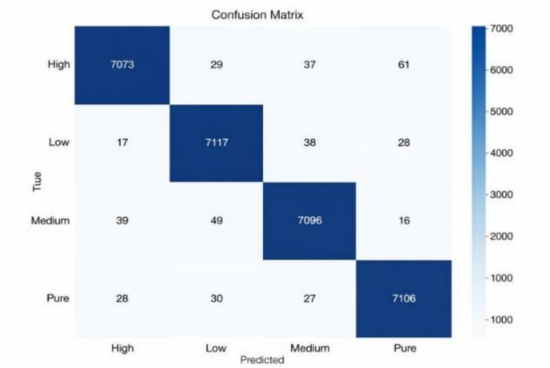

Figure 2. Confusion Matrix for Proposed Algorithm on Brinjal Dataset

The confusion matrix was used to find different performance measures. Using simple formulas, accuracy, precision, recall, and F1-score were calculated [27] which is given below and values shown in Table 1.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$Precision = TP / (TP + FP) \quad (2)$$

$$Recall = TP / (TP + FN) \quad (3)$$

$$F1\text{-}score = 2 \times (Precision \times Recall) / (Precision + Recall) \quad (4)$$

Table 1. Performance Parameters for Proposed Algorithm

Class	Accuracy	Precision	Recall	F1-Score
High	98.83	98.83	98.24	98.53
Low	98.38	98.38	98.85	98.61
Medium	98.58	98.58	98.56	98.57
Pure	98.54	98.54	98.69	98.62

It is evident in Table 1 that the classification of the highly concentrated samples is highest and the rest of the classes are similar in classification. The overall accuracy of the classification results is close to 98% and all the classes have the accuracy indicating the effectiveness and credibility of the proposed HSI-SpaClassNet algorithm. Moreover, the value of the precision, recall, and the F1-score is equally large proving that the model is always good at the correct recognition of various sets. These findings reveal that the suggested framework HSI-SpaClassNet is dependable, robust and applicable in real-life scenarios of targeting and classifying the target samples. Figure 3 has the following plot showing the values of performance parameters associated to each class.

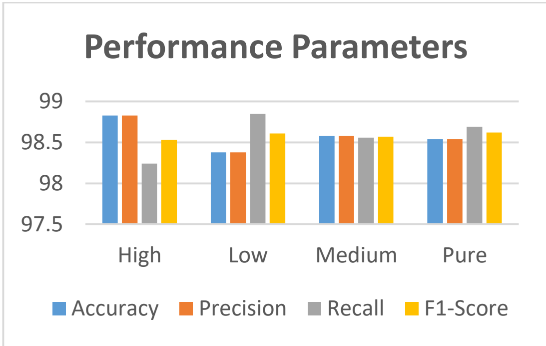

Figure 3. Performance comparison of the proposed algorithm on the Brinjal dataset

The proposed HSI-SpaClassNet architecture was evaluated on the Brinjal pesticide dataset and compared with existing architectures, including DenseNet, MobileNet and EfficientNet. The classification accuracies for detecting different pesticide residues are presented in Table 2. It shows the accuracy of classification on Brinjal Dataset for Proposed algorithm and traditional Neural network models.

Table 2. Accuracy of classification of pesticides residue on Brinjal Dataset using different Neural Network

Class	Proposed Model	MobileNet	Efficient Net	DenseNet
High	98.83	97.38	95.66	90.83
Low	98.38	96.56	95.69	91.93
Medium	98.58	97.14	96.37	93.59
Pure	98.54	97.93	96.90	91.09

Figure 4 illustrates the classification accuracy for each pesticide class in the Brinjal dataset, providing a comparison between the proposed model HSI-SpaClassNet and existing architectures. The results show that the proposed model consistently achieves higher accuracy for all pesticide categories compared to MobileNet, EfficeintNet and DenseNet. This indicates its enhanced ability to capture subtle differences in pesticide residue patterns, ensuring reliable differentiation between classes. The superior performance across every class highlights the robustness and effectiveness of the proposed architecture for accurate pesticide classification in Brinjal. This visual comparison makes it easy to see which algorithm performs best for each class. It is clear that the proposed model achieves the highest accuracy across all pesticide categories.

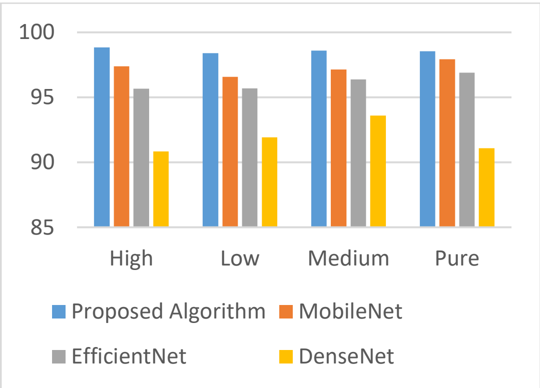

Figure 4. Performance comparison of the proposed algorithm with Traditional Neural Network Models

Conclusion

In this study, a deep learning model has been created to identify pesticide residues on Brinjal basing on its spatial and spectral characteristics of images. It is also able to reproduce a classification of unknown images. The suggested architecture was named HSI-SpaClassNet and was outperforming the other architectures, including MobileNet, EfficientNet, and DenseNet. On the Brinjal dataset, it obtained an average accuracy of 98.58% whereas MobileNet, EfficientNet, and DenseNet had 97.25, 96.15, and 91.86, respectively. The offered system also demonstrated high precision, recall and F1-score of approximately 98 percent, which is more than the current models. HW performance CPUs based on various processors (i3 to i5) and 8 GB RAM almost had the same processing time which was around 0.28 seconds. Nonetheless, the processing time with the help of the GPU (NVIDIA K80) was much shorter about 0.003 seconds and it was much faster. In general, the suggested system was precise, quick and will be efficient in identifying pesticide remains on Brinjal.

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