



# IoT-Based Pesticide Detection in Fruits and Vegetables Using Hyperspectral Imaging and Deep Learning

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**Abstract.** Fruits and vegetables contain rich nutrients and vitamins. So that they are part of our daily diet. For proper cell growth and health, we need these nutrients. Today in most crops during their growth and post-harvesting preservation different kinds of pesticides were used. Normal usage of such pesticides not that much affects health. But the actual situation is beyond our control. From soil preparation to the post-harvesting stage, pesticides are being added at alarming rates. It affects our health in a harmful way and leads to major health issues. Various studies exist to detect the pesticide levels in fruits and vegetables. This article analyses different existing methods of pesticide detection and examines their features and problems. Through this study, it is understood that Hyperspectral Imaging (HSI) is a very good method, and with it, more accurate results can be obtained by Transfer Learning (few-shot learning). This paper proposes an architecture and algorithm based on HSI and few-shot learning. Future studies are needed in this area to convert an RGB image to a spectral image because the HSI device is very expensive.

**Keywords:** Pesticide detection · Hyperspectral imaging · Deep learning

## 1 Introduction

Fruits and vegetables are a major part of our daily diet. We can consume almost all fruits and vegetables without cooking. Due to the huge demand of fruits and vegetables, it is necessary to protect them from pests and insects. Different kinds of pesticides and insecticides are used to protect these crops. Recent studies show that there is no control to limit the usage of these pesticides. But what happened is that these fruits and vegetables themselves contain chemicals and pesticides. Today in most crops during their growth and post-harvesting preservation different kinds of pesticides were used. Normal usage of such pesticides not that much affects health. But the actual situation is beyond our control. From soil preparation to the post-harvesting stage, pesticides are being added at alarming rates. When we are consuming this, it leads to several dangerous diseases like

cancer, liver problems, etc. Fruits and vegetables with these chemicals affected our full body functioning and health. The pesticides present in it cannot be detected by the naked eye, smell, or imaging. Because they are present on the outer surface as well as the inner parts of fruits and vegetables and are able to change the chemical structure also. Therefore, detecting the presence and levels of these pesticides is a challenging task and requires tools and methods.

Hyperspectral imaging (HSI) is one of the growing fields today. In this imaging, we get a typical image spectrum of objects. What is special about this imaging method is that we can detect the presence of particles beyond our naked eyes through this image. It gives us multiple levels of the spectrum when normal images only give three like RGB (Red-Green-Blue). The HSI images wavelength ranges from 400 to 1100 nm, and our naked eye can only be visible from 380 to 700 nm. But the spectral camera is very expensive.

Compared with traditional machine learning methods deep learning (DL) models are very efficient and performance-wise also good. DL models can extract high-level features automatically using multiple layers. But it has some problems that they lead to overfitting if the dataset contains less number of samples. Transfer Learning (TL) is one of the solutions for that. This paper investigates and analyzes different methods and techniques that are used in the field of pesticide detection in fruits and vegetables by deep neural networks.

## 2 Related Works

A lot of work is going on in this area today. Devi et al. [1] suggested an IoT-based pesticide detection using different types of sensors. Here four sensors were used to detect gases, moisture, pH, and temperature. Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel and Convolutional Neural Network (CNN) with GoogleNet architecture are the models used here. This system outputs real-time values but there have some problems SVM gave fast results but the affected percentage is not mentioned and is less accurate. CNN performance is better than SVM but the training time is 6.5 min more.

Kandasamy Sellamuthu et al. [2] proposed a system that mainly uses a Q-learning-based Recurrent Neural Network (RNN) so that it can handle complex, high-volume, and fast-happening data. There is a Q-table associated with it, by using this table the system updates the next action. This model analyses the pesticide based on the data drawn from three sources, soil, vegetables, and fruits. From these datasets, three components of the pesticides were extracted. But the problem with this is that a full understanding of pesticide utilization is not possible. Also, it is not supported the real-time pesticide detection.

Bo Jiang et al. [3] implemented a CNN-based hyperspectral imaging system. Here a sample of Apple is considered for the detection, with AlexNet CNN architecture. The neural network had eight convolution and max-pooling layers for the feature extraction. Anise t al. [4] explained a deep learning-based plant disease identification method. Five types of Deep Neural Network (DNN) classification models and five types of corn leaves datasets were used here. The models

are Inception V3, ResNet-50, VGG- 16, DenseNet-169, and Xception. The main aim of this work is to find the best model and best dataset based on accuracy. The result shows that the DenseNet-169 is the best DNN model with 80.33 % accuracy.

A Visible-Near-infrared (Vis-NIR) and Near-infrared (NIR) hyperspectral imaging system is suggested by Weixin Ye [5]. This method takes three grapes varieties and sprayed them with three types of pesticides. Then analyze the result with SVM and ResNet models. Here also ResNet gives better results compared with SVM. Identification of pesticide residue in black tea leaves by fluorescence hyperspectral technology is proposed by Jie SU [6]. A 1D- CNN and Random forest ML models are used here. Tiago Domingues et al. [7] presented a survey of different feature extraction methods and ML models that are used in the field of disease and pest detection in tomato leaves. Commonly used models are SVM, Random Forest (RF), and Artificial Neural Network (ANN) models. This paper suggested new and emerging transfer learning methods to avoid the problems like overfitting.

Xiaoyan Tang et al. [8] proposed a sensor-based pesticide contamination detection called an electronic nose, in tea leaves. For that, three Portable Electronic Nose-3 (PEN -3) electronic metal oxide sensors and Back Propagation algorithms with three hidden layers were used. Applications of different nanosensors explained by Rabisa Zia [9]. In this paper, different nanosensors that are mainly used in the pesticide detection area and their characteristics are also described. A review paper by Lili Li [10] explained different datasets and DL models used for leaf image processing.

A system for the freshness of the chicken checking is proposed by Rajina R Mohamed [11]. An electronic nose with Back Propagation (BPP) algorithm and SVM is suggested here. When comparing the existing works some of them need laboratory situations to measure pesticide concentration and some can detect the presence real-timely. The laboratory measurements are time-consuming as well as need costly equipment. There does not exist a good and accurate method for real-time detection.

### 3 Technologies Used for Detecting the Presence of Pesticides

Most countries have crossed the limit of minimum usage of pesticides and chemicals in agricultural crops. There has a Maximum Residue Level (MRL) to control the usage of pesticides in crops. It is the highest residue level that is tolerated in food or food crops. But today it crosses the limit, for preventing from insects or to get a high yield. It leads to dangerous situations of health problems. There have different technologies and ML/DL models for real-time pesticide detection. The Table 1 shows the existing technologies and architectures used in this field with the available datasets.

In these related works, the experiments were done with varieties of fruits or agricultural items like Corn, Black tea, tomato leaves, etc. Some of the datasets

are already available in data repositories. But some datasets were created in the laboratory itself, by collecting different pesticides and crops.

**Table 1.** Summary of different technologies, DL-models, and dataset used for pesticide detection

Ref.	Fruit/Veg.	Technology	Architecture	Dataset
[1]	Any fruit	IoT with 4 sensors	SVM (RBF), CNN	Fruit dataset
[2]	Any fruit	Q-learning	RNN	soil, fertilizer plant village
[3]	Apple	HSI	AlexNet with 8 layers	Created dataset
[4]	Corn		Inception V3, Resnet 50, DenseNet-169	Plant Village
[5]	Grape	Vis-NIR & NIR HSI	CNN, ResNet	Created dataset
[6]	Black tea	Fluorescent HSI	1D CNN, RF	Plant Village, Plant Doc
[7]	Tomato leaves		SVM, RNN, TL	Flavia & Malayekew Leaf
[8]	Tea leaves	Electronic nose (PEN-3)	Back propagation	Created data
[10]	Leaves	HSI	GoogleNet, GAN, VGG-16	Plant village, Plant pathology challenge

For generating the dataset in a laboratory, first made pesticide solutions with different concentration levels. Then dip each of the crops separately. These data were used for the analysis with the above mentioned technologies. Sensor-based methods directly sense the presence of pesticides in fruits and vegetables and image-based methods detect chemicals by processing the images of crops that are captured by cameras.

Analysis of existing methods in pesticide detection in fruits and vegetables shows that Hyperspectral Imaging (HSI) gives better accuracy compared with other methods. HSI is not affected by environmental conditions and it can detect the presence of chemicals that present inside the crop. Convolutional Neural Networks (CNN) require a large number of data for the operation. But for created data, it is not possible to make a dataset with considerable samples. It leads to overfitting problems during convolution operation. Transfer learning or few-shot learning is a good deep neural network to avoid overfitting with a small dataset. Here proposing an IoT-based system that uses HSI and transfer learning for detecting the presence of pesticides.

### 3.1 Hyperspectral Imaging (HSI)

Hyperspectral imaging is an imaging method that is used to produce the spectrum of the image. Normally images that are taken by Digital Camera are in RGB format. But in HSI, different spectra of images are generated. Mainly two types of spectrum are available that are Near-infrared (NIR) and Visible-Near-infrared (Vis-NIR). NIR is a destructive type which means it makes defects in the material surface in which the image is taken. Vis-NIR is not a destructive method. The HSI is mainly concentrated on visible and near-infrared (400 nm–1000 nm) [10]. The output of HSI is not similar to the object, but it generates the color spectrum of the object.

### 3.2 Transfer Learning/Few-Shot Learning

Few-shot learning or transfer learning is a pre-trained model. The main advantage of this model is that it can avoid overfitting when working with less number of samples. It creates or transfers knowledge from a large data set, this is called pre-training. Then another model (a few-shot model) is trained with this knowledge and is used with a smaller dataset.

Figure 1 shows a typical example of transfer learning. DL model 1 is trained by using a large dataset. This knowledge is passed to DL model 2. In model 2 a small dataset and this pre-trained knowledge is used for its training. The overfitting problem is avoided in this way.

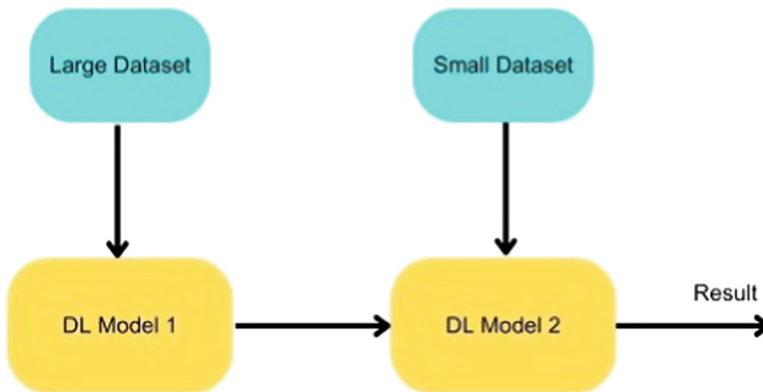


Fig. 1. Transfer Learning workflow diagram

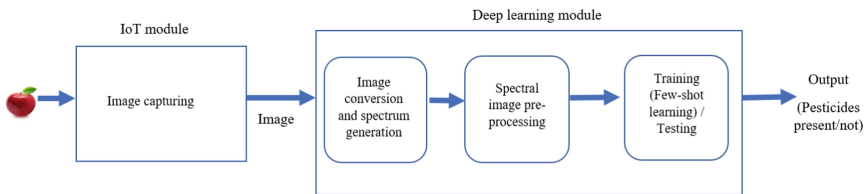
### 3.3 IoT-Based Pesticide Detection System Using HSI and Deep Learning

Real-time detection of pesticides is very essential in the current situation. IoT-based hyperspectral imaging helps a lot in the real-time detection of pesticides

and the conditions of the atmosphere and natural aroma do not affect it. A solution for overfitting with less number of samples is transfer learning or few-shot learning.

For example, markets and fruit processing industries handle different types of fruits and vegetables daily. Large amounts of pesticides are present in it, and consuming these fruits and vegetables leads to dangerous diseases. Only real-time as well as fast methods can detect and thereby control it. The proposed system can be used by Government authorities, consumers, or fruit-processing industries for the effective detection of pesticides.

During the training phase, we train the model using the dataset. Here the model that is used is few-shot learning. It has pre-trained knowledge by training with a large dataset. The dataset can download from any of the data repositories or by creating it in a laboratory environment. Figure 2 shows the block diagram of the proposed system. It has two modules IoT module and a deep learning module. In the IoT module, an image is captured by an HSI camera and this image is sent to the deep learning module.



**Fig. 2.** Block diagram of the proposed model

In the deep learning module, from the HSI image, the spectral vector or spectrum of the image is generated. After the spectral vector generation preprocessing of the image is carried out. In preprocessing remove noise and unwanted spectrum values. This processed image or spectral output is classified with the help of a CNN model.

Algorithm 1 takes two inputs, spectral images of the crops and a dataset that was created in the field. The output of the algorithm shows whether the pesticide is present in the particular crop or not. Let's see how this algorithm works. Processing of the dataset is done first. During the preprocessing step noise and unwanted values were removed. Training of this processed dataset is done by a transfer learning model. Using an HSI camera image of the particular crop is taken. Classification of this spectral image or vector is performed using a CNN model.

#### **Algorithm 1**

**Input:** *Spectral images of crops*

*Dataset: Dataset contains HSI images*

**Output:** *Pesticide present/ not*

**Procedure**

1. *Dataset preprocessing*
2. *Train DL model(few-shot learning) with dataset.*
3. *Spectral vector generation from the input image.*
4. *Fit the model with test data.*
5. *Classification with CNN model.*

## 4 Result and Discussion

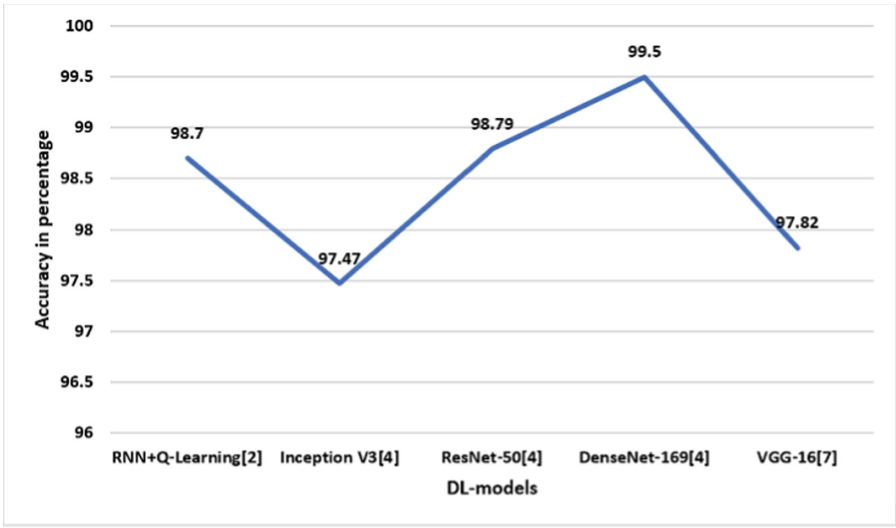
Pesticide detection in fruits and vegetables is one of the important areas that is most needed in today’s society. By analyzing the existing method, these systems have different features as well as problems. Table 2 explains the problems of existing methods or their future needs. From the table, it is understood that most of the sensors are affected by environmental situations and have some precision issues. Hyperspectral imaging is a good method, but the device is very costly, more than four lakhs. This is a complex system so we need an expert person to handle this equipment. To avoid these issues future research is needed in this area, to create an algorithm that can convert the normal RGB image to spectral image with high accuracy.

**Table 2.** Limitations of existing methods

Ref.	Problem/Features
[1]	CNN has better performance than SVM but takes more training and testing time
[2]	A complete understanding of pesticide utilization is not possible
[3]	Overfitting problem due to small dataset and need to improve extraction ability of the network
[5]	Need a large number of samples and deep transfer learning
[6]	Increase the number of samples and pesticide species. A real-time non-destructive identification system is essential
[7]	Lack of data leads to overfitting
[8]	The natural aroma of tea leaves interferes with containing pesticides. The system was susceptible to temperature, humidity & atmospheric pressure. The electronic nose test must perform immediately after spraying
[9]	Nanosensors have high sensitivity, specificity, and minimum response time but they are affected by the environmental condition
[10]	Real-time detection is difficult because of the complex background and small lesions
[11]	Odour must be cleared up each time and do not mix with previous samples. Need more samples

Each of the related works uses different kinds of image datasets for the detection of pesticides. Several systems are working with the PlantVillage dataset. It

is a publicly available dataset with 38 categories of species. Figure 3 shows the comparative results of the PlantVillage dataset with different deep-learning models in pesticide detection. All models show accuracy and performance above 95 percent with this dataset. DenseNet-169 gives better results than other models in terms of accuracy.



**Fig. 3.** Performance analysis of PlantVillage dataset with different DL-models

When comparing the architectures and technologies used in currently available pesticide detection systems understood that sensor-based methods and image-based systems have their own characteristics. Figure 4 shows a comparison graph of accuracies that are obtained with different existing systems that are based on image analysis. The graph easily infers that deep learning methods with more hidden layers give better accuracies compared with traditional machine learning as well as low-level deep learning models. Also, HSI images or spectral imaging methods give more results than normal RGB images.

Figure 5 shows a graphical analysis of the performance of the pesticide detection systems that are mainly based on sensors and IoT with various ML or DL models. It is an emerging area in the field of real-time pesticide detection. The sensors are easy to handle, deploy and analyze but it has some problems like being easily susceptible to environmental situations.

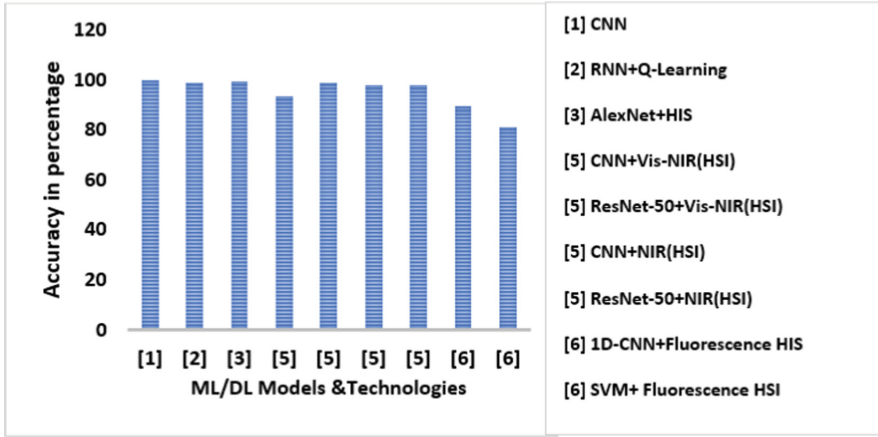


Fig. 4. Performance analysis of image-based systems

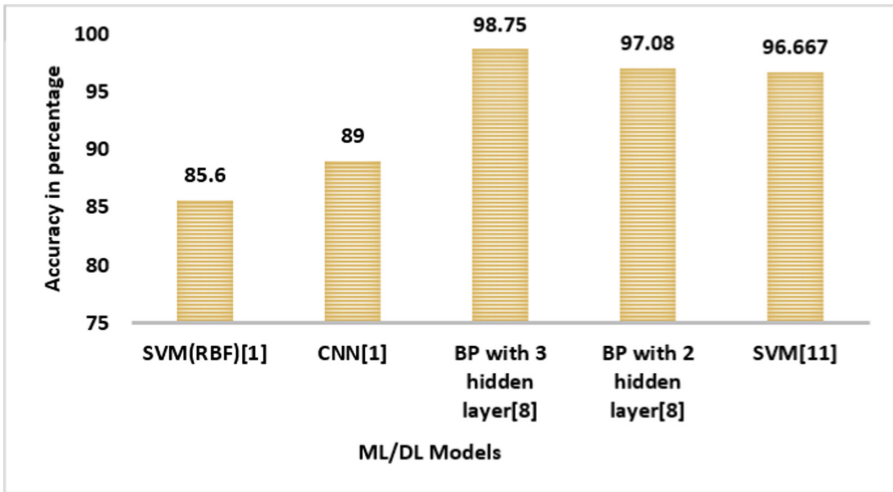


Fig. 5. Performance analysis of sensor-based systems

## 5 Conclusion

In this paper, we have presented different literature and existing works that address pesticide detection in fruits and vegetables using deep learning. DL models such as CNN, backpropagation, and transfer learning can be employed to accurately predict or detect the presence of dangerous pesticides that are present in the crops. These models have better performance than older machine-learning models based on manual feature extraction. However, deep-learning models need a large volume of data, which leads to the overfitting problem. Transfer learning (few-shot learning) has proven useful to tackle this issue. Hyperspectral imaging

(HSI) is a good solution for pesticide detection in terms of performance compared with standard image data.

This article aimed to provide a general overview of the different deep learning models, techniques, and dataset preparation in this area of research. And proposes a system that uses HSI and transfer learning to solve problems in this pesticide detection field. Further development in this area may help fill the current issues gap.

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