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Smart Pesticides Detector With Advanced Artificial Intelligence Technologies

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Abstract- The pest detection and classification in agricultural crops plays a significant role to ensure good productivity. The agricultural productivity is reduced due to the presence of pests and diseases. Various technology-based methodologies have been discussed in this paper. This is a review of existing technique which will be useful in deriving new techniques for detection and classification of pests.

Index Terms-
K-means Clustering, Support Vector Machine, Artificial Neural Network, Deep Learning,

I. Introduction

1.1 Role of Artificial Intelligence:

Artificial intelligence (AI) is increasingly common in electronic devices at home or work, in social media, video streaming services, electronic commerce, and in internet search engines. Now, AI is rapidly entering the farming scene. Growers using modern precision agriculture tools and techniques often face a barrage of high data volumes created by increasingly prolific, data-hungry electronic devices and services. Compare a smart phone's data needs with an old desktop phone. Or contrast an old-style paper map of your farm with today's digital geographic information system maps, showing multiple layers of every square inch of your fields, updated every week or month by automated aerial surveys with drones. Successful use of precision agriculture requires improved, smarter methods for managing, understanding and integrating all the "big data" being generated. Fortunately, AI implemented as machine learning may be able to help. Machine learning uses computer algorithms to parse data, learn from it and make determinations without Artificial intelligence for detecting citrus pests, diseases and disorders.

The complex interaction of natural product like soil, water, fertilizer etc. helps in providing agricultural by-products. So there is a requirement of good management of all these inputs to enhance the productivity.

The production yields are affected by biological parameters such as pest. Since in Pakistan, 75% of population depends on agriculture so the cultivation of agricultural by-product is needed to be highly technical to get optimum quality and quantity manufacture with low infestation. Research has been undergone commonly on biological parameters like pests. There is a requirement of careful monitoring and handling of crops in time to protect from heavy losses which is not feasible for all times. This needs continuous observation which is not practical for all the time. Integrated Pest Management method (IPM) is used with less environmental impacts. There are ongoing researches to control pests to control pest by non-chemical method instead of pesticide. As more use of pesticide is harmful to soil, air, water resources, crops and animals. Thus, crop yield is reduced. There exists several machine learning, image processing and internet of things methods applied in agricultural research for quality and quantity improvement of agricultural products. In this paper we have reviewed many research works based on pest detection and classification with object of getting an idea about the efficient and useful methods

II. BACKGROUND

AI is an emerging technology in the field of agriculture. AI-based equipment and machines, has taken today's agriculture system to a different level. This technology has enhanced crop production and improved real-time monitoring, harvesting, processing and marketing. The latest technologies of automated systems using agricultural robots and drones have made a tremendous contribution in the agro-based sector. Various hi-tech computer-based systems are designed to determine various important parameters like weed detection, yield detection and crop quality and many other techniques.

Considerable effort has been dedicated to the creation of more effective methods for pest detection and classification. Some techniques try to detect the associated damage instead of the pests themselves, but direct detection is the predominant approach. Many early studies tried to detect and identify insects by performing and acoustical analysis on the sounds emitted, but interest in this kind of approach seems to have faded in the last decade. Most studies nowadays use digital images for the task. While aerial images captured by means of unmanned aerial vehicles (UAV) are being increasingly explored, in most cases they not offer enough resolution for the detection of small specimens, and plant canopies may prevent proper detection. Thus, proximal images are still prevalent. Multispectral [14,15], hyperspectral, thermal and X-ray sensors are being explored, but conventional RGB (Red-Green-Blue) sensors still dominate due to their low price, portability and flexibility [19].

III. PROPOSED METHODOLOGIES

This article focuses on the combination of digital Red-Green-Blue (RGB) images with machine learning techniques for pest monitoring in the field. There are a few studies dedicated to pest detection in stored products [20–24], but those are not considered here. Also, although the majority of methods for pest monitoring using RGB images employs some kind of machine learning algorithm, there are a few studies that use only image processing techniques such as mathematical morphology, thresholding and template matching. While those methods fall a little outside the scope of this article, they are addressed in the text whenever deemed relevant.

The creation of an automatic system for pest monitoring can be roughly divided into four stages: data acquisition, model building, encapsulation in a usable tool, and practical use. The vast majority of the studies found in the literature focus on the second stage. In most cases, the first stage is usually only superficially addressed: a description of how the data was collected is usually provided, but a meaningful discussion on the efforts to make the data more representative and on the limitations of the database is rarely present. The third and fourth stages are often beyond the scope of the studies, as the final steps towards practical adoption of the technologies involve aspects that are more related to user experience, marketability, etc.

IV. Evaluation

This section is structured according to the task (detection or classification) addressed by the proposed methods. It is worth noting that a more logical structure in which the methods would be presented as they improved upon the weaknesses of their predecessors was considered. However, because most studies have as main goal to overcome the limitations associated to manual and visual monitoring, instead of targeting current research gaps, following a logical progressive sequence is largely unfeasible. This fact highlights one of the main issues detected in this study: many of the methods proposed in the literature employ similar classification strategies. In most cases, the only major distinction is the species of interest, resulting in studies with significant redundancy and limited novelty. This review identifies many of the research gaps that need to be addressed, which hopefully will serve as inspiration for future efforts.

- Observation:

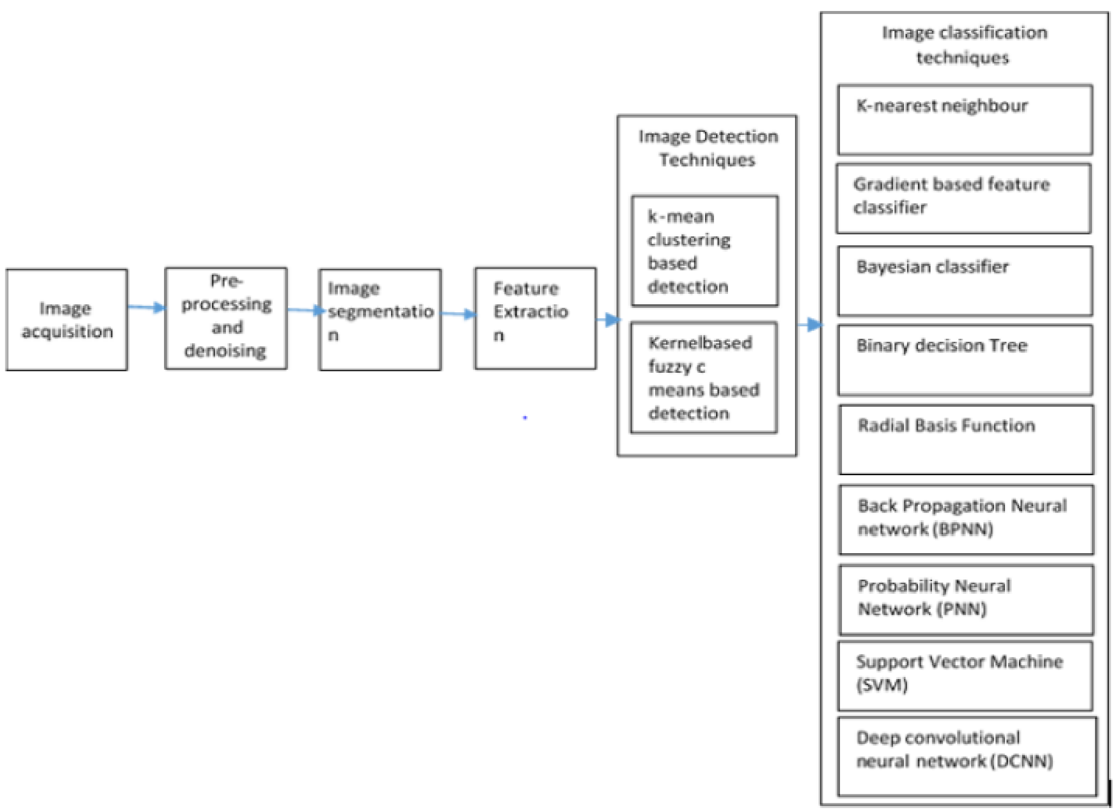

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Figure 1. shows several materials and methodology of pest detection and classification.

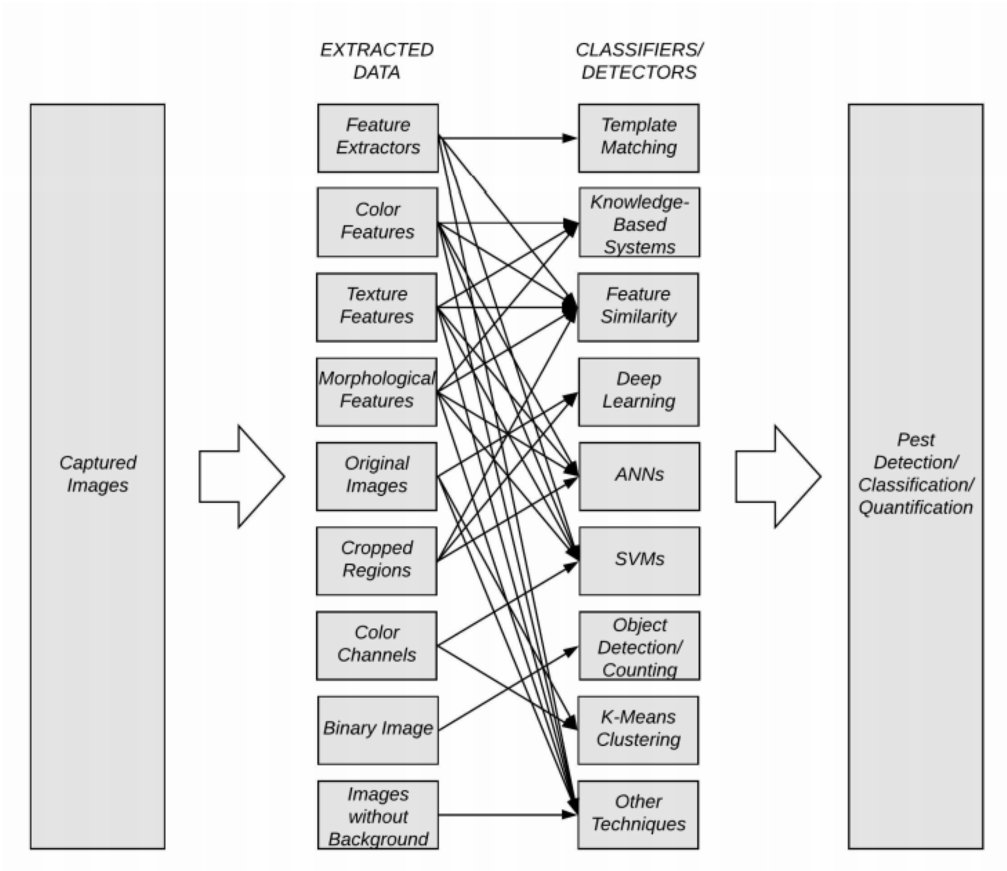

Figure 1. Diagram summarizing the types of data extracted from the original images and which of those are used as inputs to the classifiers and detectors.

4.1. Pest Detection Methods:

Detection methods are interested in distinguishing a certain target pest from the rest of the scene in an image. This is equivalent to a binary classification in which the classes are “target present” and “target absent”. The number of detected specimens is often tallied in order to provide a measurement for the degree of infestation.

4.1.1. K-means Clustering:

K-means clustering is a vector quantization technique that aims to group a certain number of observations into k clusters, or classes. The algorithm begins by dividing the image into 100 × 100 blocks. Both the RGB and L*a*b* color spaces are then used as basis for an algorithm that preselects potential cluster center, and then k-means clustering is applied to classify each pixel. Spurious objects are eliminated using ellipse eccentricity rules. The performance of three techniques, normalized cuts (NCuts), watershed and K-means clustering, applied to the separation of pest specimens in traps. NCuts with the optical flow angle as weight function achieved the most accurate results. K-means clustering was one of the classifiers tested in and it has also been used to enhance the results produced by deep learning models.

4.1.2. Support Vector Machine:

SVMs are among the most widely used machine learning classifiers. They are particularly suitable for binary classifications, as they try to find the hyperplane that best separates two classes. Researchers employed a three-layer detection strategy for the detection of rice planthoppers in crops. The first layer was an AdaBoost classifier based on Haar features; the second layer was a SVM classifier based on HOG features; the third layer used color and shape features to remove spurious objects detected in the first two steps. Four other machine learning classifiers were also tested: k-means clustering, Adaboost with Haar feature, and SVM with two different sets of features. Ebrahimi et al. [17] used the HSI (Hue, Saturation, Intensity) color channels as inputs to a SVM for detection of thrips in strawberry flowers.

4.1.3. ANN(Artificial Neural Networks):

Artificial neural networks (ANN) are models containing numerous nodes and connections, being loosely inspired by the way neurons are organized and interconnected in a brain. ANNs have been frequently used for the task of image classification. s. Vakilian and Massah combined image processing techniques with ANNs for the detection beet armyworms in images captured under controlled conditions. Potential pests were first segmented by means of a Canny edge detector, then seven morphological and texture features were extracted and used as input for the three-layer neural networks

4.2. **Difficulties:**

4.2.1. Related to the Insects Themselves:

Most methods are designed to detect adult insects. However, a complete picture about the infestation and how it is evolving may require the identification and counting of specimens at earlier stages of development. This may pose a significant challenge, because younger specimens may not only be smaller but also have quite different visual characteristics In some extreme cases, young nymphs may be semi-transparent, which makes them very difficult to be detected.

4.2.2. Related to the Imaging Equipment:

The cameras used for capturing the images may also have considerable impact on the ability of the model to detect the objects of interest. Optical quality plays an important role and, under low illumination conditions, camera settings may also be a relevant factor [29]. Building a dataset including samples captured with all kinds of sensors is impractical; instead, cameras expected to be prevalent in practice should be given priority.

4.2.3. Related to Model Learning:

A problem that is often overlooked is that many machine learning algorithms tend to overfit the data [5], especially with limited data. It is common to find studies reporting accuracies very close to 100%, which may not be realistic depending of the problem being addressed (this may also be caused by too homogeneous datasets).

V. CONCLUSION

Machine learning techniques, and deep learning in special, have been showing a remarkable ability to properly detect and classify pests, either in traps or natural images. Arguably, the main factor preventing a more widespread adoption of automatic pest monitoring systems is their lack of robustness to the vast variety of situations that can be found in practice. This, in turn, is the result of limitations on the datasets used to train the classification models. Building more comprehensive pest image databases is essential to close this gap. However, given the degree of variability associated to practical use, it is very unlikely that substantial progress in this regard will be achieved using conventional approaches. Future efforts could focus on creating mechanisms to facilitate and encourage the involvement of farmers and entomologists in the process of image collection and labelling.

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