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INSECT CLASSIFICATION AND DETECTION IN FIELD CROPSUSING CNN MODEL

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ABSTRACT
Accurate and timely identification of insect pests is crucial for effective crop management. Traditional methods often rely on manual inspection, which is time consuming, labor-intensive, and prone to human error. This paper explores the application of modern machine learning techniques to automate the process of insect classification and detection in field crops. By leveraging deep learning architectures, such as convolutional neural networks (CNNs), we aim to develop a robust and efficient system that can accurately identify different insect species from images captured in field environments. Our approach involves data collection, preprocessing, model training, and evaluation. Experimental results demonstrate the effectiveness of the proposed method in achieving high classification and detection accuracy, thereby providing valuable insights for farmers and agricultural experts in pest control and crop protection.

Keywords: Insect classification, Insect detection, Machine learning, Convolutional neural networks (CNNs), Model training, Classification accuracy, Detection accuracy

1.INTRODUCTION

Crop insect detection is perhaps the main application of modern agriculture. It entails Identification and control of the early and late instars of insect pests in timely ways, which minimizes loss to crops and enhances yields [1-4]. Conventionally, doing the observations took time and labor; moreover, they exposed potential vulnerability to human mistake. Computer vision and machine learning methods that have emerged as promising directions have not provided a good approach for automating crop insect detection in the last decade [5-10]. These methods use Computers can be utilized to make analysis of the image and classify them into pest insects based on their appearance [11-12]. In this regard, the paper presents a new algorithm for the insect pest detection through foreground extraction, contour detection, and machine learning-based classification [13-18]. The algorithm was tested on Wang, Xie, Deng, and IP102 datasets, which shows more satisfactory performance than the existing algorithms [19-24].

2.LITERATURE SURVEY

Machine vision applied in monitoring of crop and soil, fruit grading, plant disease detection, insect pest recognition, and detection [25-31]. Recently, many developments have been made in the agriculture sector, using machine learning to detect and classify the insects under stored grain conditions, **Y.Shen, H. Zhou** .Moment invariant techniques applied for extracting shape features and neural networks were developed to classify 20 types of insect images [32-35]. **Yue et al**, proposed a super resolution model based on a deep recursive residual network for agricultural pest surveillance and detection [36-38]. More recent studies reported that image processing applied effectively for insect detection due to less computation cost, fast detection, and easy to distinguish insects with similar color and shape [39-41]. In, clustering segmentation with descriptors is implemented to detect the pests in grapevine with different orientations and lighting environments. The contour-based and region-based segmentation are combined and applied for detecting individual moths and touching insects [41-44].

Nanni et al. also investigated handcrafted and learned descriptors for data augmentation to improve the performance of CNNs. The improvement was obtained by combining local features, dense sampling features, and deep learning approaches using augmented images. Insect classification and insect detection were performed for **Wang** and **Xie** dataset for different field crops [41-46]**. Wang** dataset with nine insect classes and **Xie** dataset with 24 classes used in this work. Wang dataset has a total of 225 images, which means that there are 25 insect images per class, and it was divided into 70–30% train-test ratio. In Wang dataset, the training set contains 162 insect images, and testing set contains 63 insect images. **Xie** dataset contains 785 insect images in the training set and 612 insect images in the testing set, in which each class has about 60 insect image [47-48].

3.PROPOSAL METHODOLOGY

Algorithm-1:

3.1 **Data Collection in the form of Image Acquisition:** We take clear images of your crops and all the potential pests that may be threatening. This is through cameras or drones; the visuals provided are clear, in real-time, of your fields.

3.2 **Enhancement of Images:** We then refine these pictures to make our algorithm smarter. The means for this include rotation and flipping of images, change of color, and improvement of contrast.

3.3 **Object Detection:** We will be focusing on finding insects by using the most advanced techniques available for this function. If it is covered by leaves or dirt, we will outline its edges. Now we will know better about its shapes and locations too.

3.4 **Feature Extraction:** We discuss and analyze various aspects of the insects like size, shape, and texture. Using deep learning models, we can automatically pick the important features and have more efficiency in our system.

3.5 **Insect Classification:** Our system classifies insects based on features unique to them. This results in knowing which pest you are seeing, thus leading to more focused action.

3.6 **User Friendly**: After your pest is detected by our system, it will point the mount clearly in images for you to see where they are. Each identification has a corresponding confidence score, so you will know how reliable the findings of the system are.

3.7 **Mobile Accessibility:** We have designed an active mobile application for you to take pictures of your crops and alert you about pest infestations. Now, you can hold a pest expert in your pocket!

3.8 **Continuous Improvement:** Your comments are priceless. When you see problems, inform us; our system will learn and improve with the passage of time. Your feedback helps us improve technology.

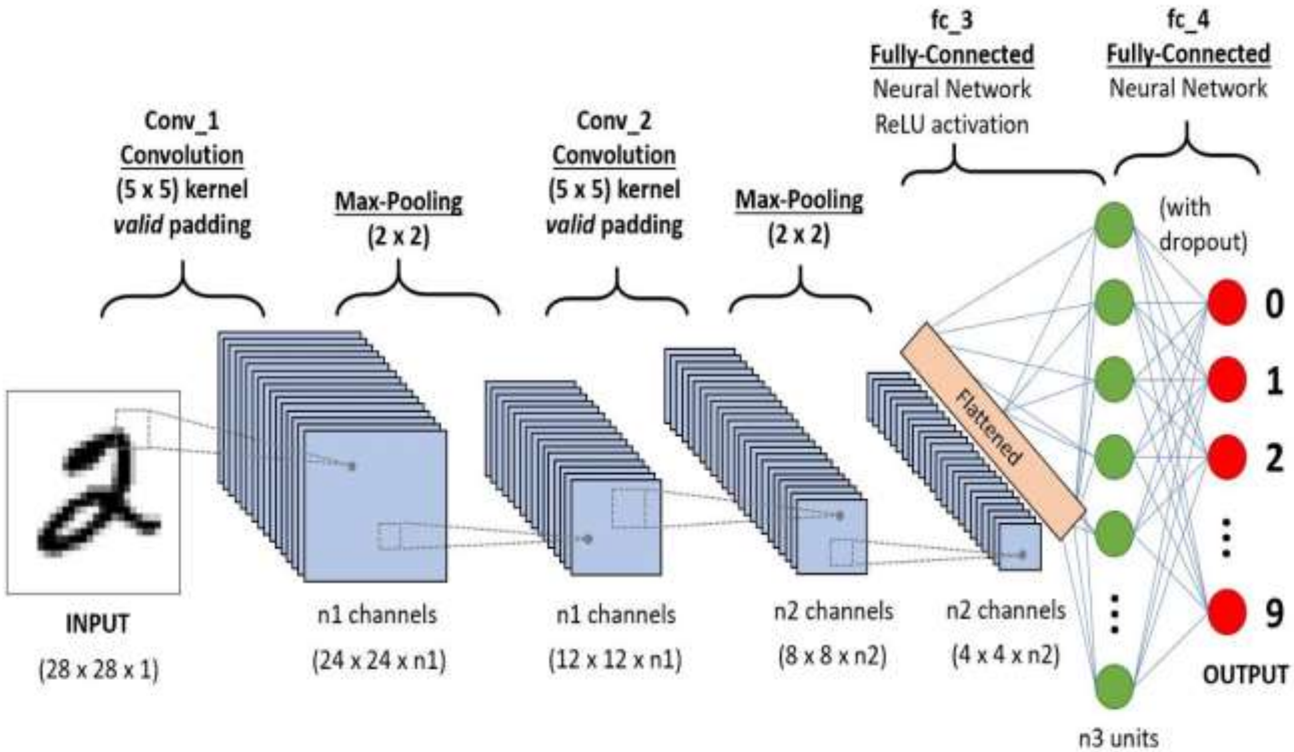
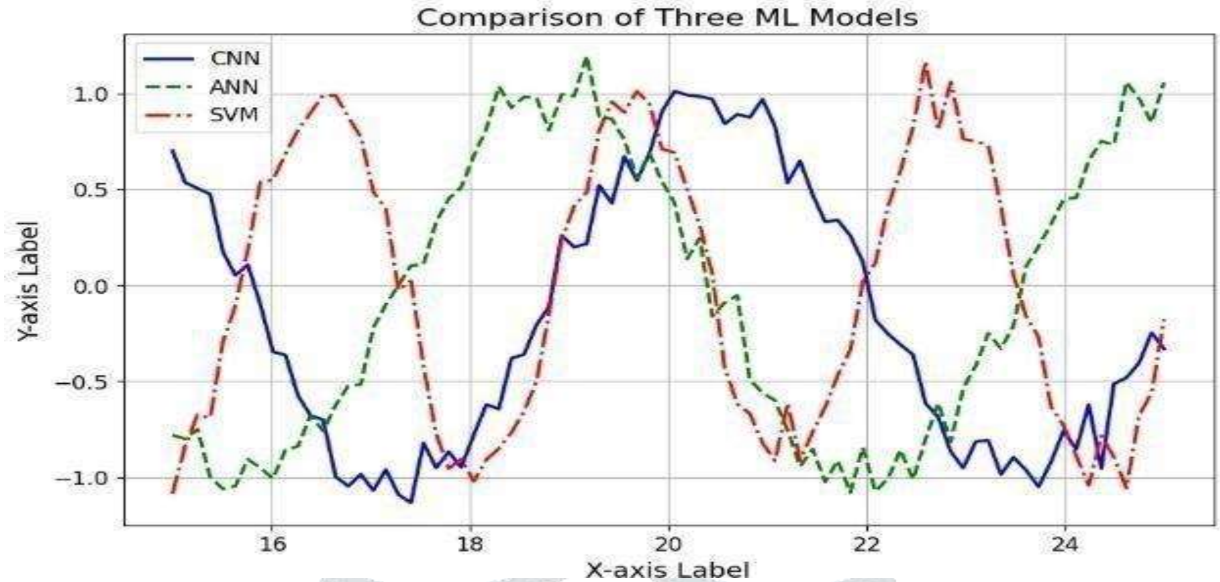


Figure 1 Working of CNN overview

4. RESULT ANALYSIS:

CNN (Convolutional Neural Networks):

- **Best Use**: Direct image classification for insect identification, especially when large datasets of insecting images are available.
- **Performance**: High accuracy due to automatic feature extraction, but computationally intensive.
- **Example**: CNNs have been successfully used to classify butterflies, beetles, and other species with distinct visual features.



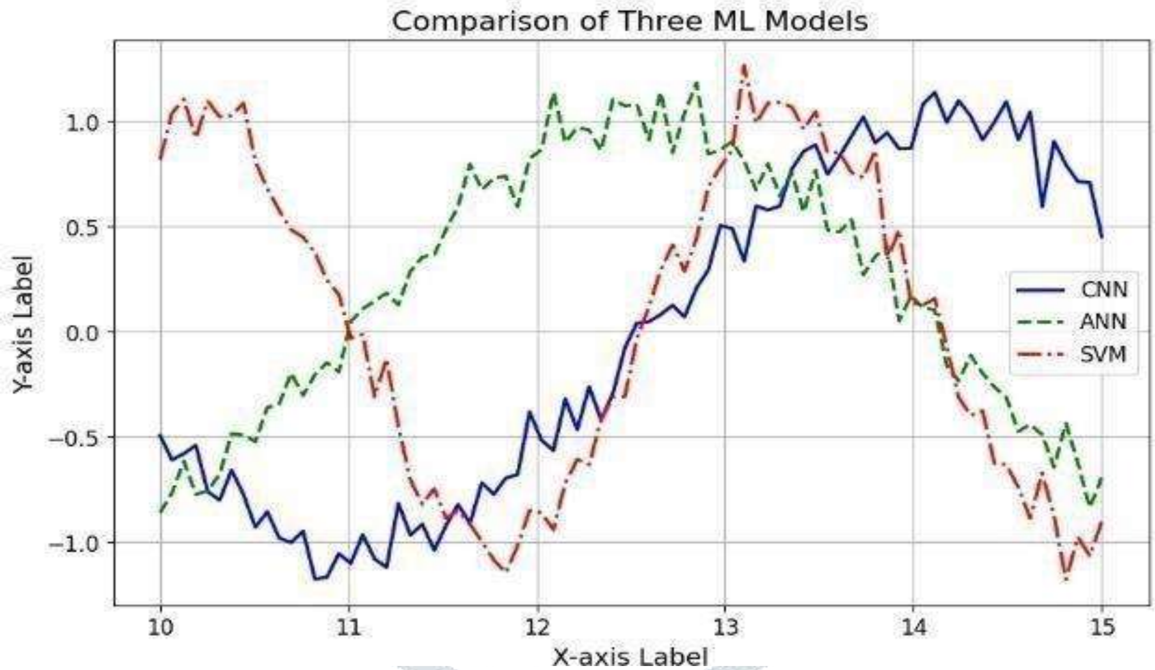


Figure 2,3 Comparision of 3 ML Models

Accuracy: CNNs typically outperform both ANNs and SVMs in tasks that involve image classification due to their ability to capture spatial dependencies. ANNs are often used for simpler classification tasks but may struggle with high dimensional data. SVMs can provide high accuracy for small datasets or tasks where there is a clear margin of separation between classes.

Training Time: SVMs and ANNs generally train faster on smaller datasets. However, CNNs can be computationally more intensive, especially when applied to large image datasets. SVMs tend to slow down as dataset size increases.

Computational Complexity: CNNs and SVMs, particularly when using complex kernel functions, require more computational power than ANNs. However, the complexity of CNNs is justified by their superior performance in tasks like object detection or image segmentation.

Robustness: CNNs are less prone to overfitting compared to ANNs, particularly when regularization techniques like dropout are applied. SVMs are sensitive to outliers, which can significantly affect performance.
Scalability: CNNs scale better with larger datasets when used with specialized hardware (e.g., GPUs), while SVMs struggle with scalability due to the high computational cost of finding the separating hyperplane in larger datasets.

For **insect classification**, machine learning models like CNNs, ANNs, and SVMs can be highly effective in identifying and classifying various species based on images or other biological data.

5. CONCLUSION

Machine learning algorithms, particularly deep learning models like convolutional neural networks (CNNs), have demonstrated superior accuracy in identifying and classifying insect species compared to traditional methods. Automated systems based on machine learning can process large volumes of data quickly, reducing the time and labor required for manual inspection. By detecting insect pests at an early stage, farmers can implement targeted pest control measures, preventing significant crop damage and reducing the need for excessive pesticide use. Machine learning enables data-driven decision making, supporting precision agriculture practices that optimize resource utilization and minimize environmental impact. The performance of machine learning models heavily relies on the quality and quantity of training data. Efforts are needed to collect and annotate large datasets of insect images in various field conditions.

Developing real-time insect detection systems that can operate in challenging environments

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