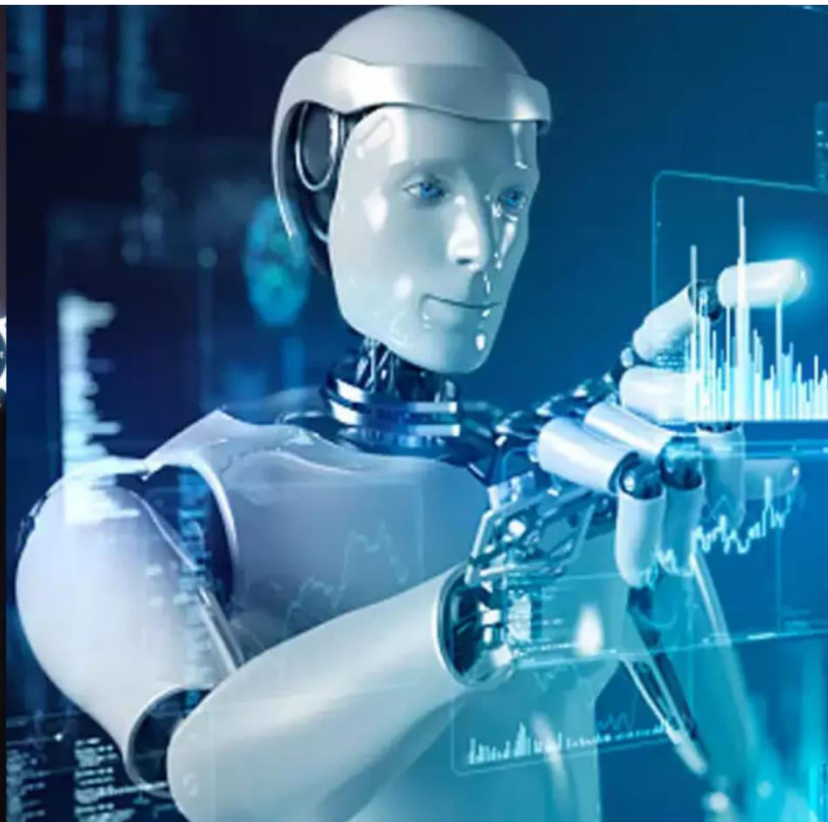




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# **Automated Pest Classification and Pesticide Suggestion using Deep Learning Algorithm**

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**ABSTRACT:** The correct and real-time identification of crop pests in agricultural environments is vital for precision farming and effective pest management. This paper introduces an Attention-Based Compound Convolutional Neural Network (ABCCNN) model to improve the recognition of pests in complex field conditions. The proposed model integrates a Parallel Attention Mechanism (PAM) module with Residual Blocks (RBs) to improve feature extraction, localization, and classification. The PAM module focuses on the relevant pest features while suppressing the background noise so that the system can recognize the objects reliably in cluttered environments. The residual blocks facilitate better gradient propagation and convergence, thus making the network deeper and efficient. The proposed ABCCNN framework achieves accuracy and real-time performance better than state-of-the-art deep models with an optimum trade-off in computational efficiency as well as accuracy. Extensive experiments on pest datasets from reality demonstrate that classification accuracy, inference speed, as well as environmental variation robustness, such as lighting, occlusion, or complex backgrounds for conventional CNNs, are always superior to other existing models. Further, with the proposed model, the generalization of CNN-based pest recognition frameworks boosts up and enhances the possibility of large-scale deployment in smart agricultural systems. ABCCNN also contributes to early pest intervention strategies by providing fast, accurate pest detection, avoiding higher crop losses, and achieving sustainable agricultural practices. The model is planned to be further integrated into the edge AI devices in real-time on-field pest detection and decision support systems.

**KEYWORDS:** Crop Pest Detection, Attention Module, Parallel Mechanism, Residual Blocks, Agricultural Monitoring and Precision Farming.

## **I. INTRODUCTION**

The growing need to adequately manage crop pests has been of increased importance to modern agriculture. As global food demand increases, the health and productivity of crops will be critical to sustainable farming practices [1]. Pest infestations are one of the most significant threats to crop yield and lead to great losses in the production of agricultural sectors. As a response, the prominence of technology in agriculture through precision farming continues to gain much attention. Precision farming incorporates advanced technologies such as sensors, drones, and artificial intelligence for optimizing crop management through the better monitoring and control of pests [2].

However, accurate and real-time identification of crop pests in dynamic and complex field conditions remains a significant challenge as environmental variables like lighting, occlusion, and cluttered backgrounds can hinder their detection. Traditional methods of pest management rely on human inspection or basic image processing, which are very time-consuming and labor-intensive with a high tendency to make errors. These methods also lack scalability, especially in large agricultural fields, where timely intervention is only possible through real-time monitoring [3]. As a result, there has been a major shift towards utilizing ML and DL techniques to overcome the limitations of traditional pest recognition systems. Among them, Convolutional Neural Networks (CNNs) have become very popular for image-based pest classification because of the possibility to learn directly the spatial hierarchy of features for the purpose of recognising objects. However, despite successes in many domains, models based on CNN are often difficult to deploy directly into real-world agricultural environments.

These environments are usually messy with different kinds of lighting conditions, occlusions, and varying backgrounds that make the task of accurate pest detection more challenging [4,5]. Such challenges have been addressed by advanced deep learning techniques, including attention mechanisms and residual networks, incorporated in the CNN models. The model, using its attentions, pays more attention to such crucial features as pests while making fewer contributions from irrelevant background information. Similar to residual blocks, they help in training deeper networks by improving gradient propagation, thus enhancing feature extraction capabilities.



- The proposed Attention-Based Compound Convolutional Neural Network (ABCCNN) employs a Parallel Attention Mechanism to emphasize significant pest features while reducing background noise, improving pest detection in complex agricultural environments where lighting changes, occlusions, and diverse backgrounds prevail.
- Residual Blocks are incorporated into the model to enhance feature learning and gradient propagation. This will lead to better convergence and real-time performance, even on resource-constrained devices for edge AI deployment.
- Experiments validate the superiority of the proposed model ABCCNN, which indeed demonstrates higher accuracy compared to popular models like ResNet, DenseNet, and Efficient Net and high speed robustness. Its application in scalable smart agricultural systems ensures real-time detection of pests with support to sustainable farming.

## II. LITERATURE SURVEY

The detection and management of pests in agriculture is a critical aspect of precision farming, where automation and real-time interventions are pivotal. Recent advancements have demonstrated the potential of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) to address the challenges posed by pest control in large-scale agricultural environments. This section will outline the related literature survey about the innovative frameworks in pest detection by focusing on integrating heterogeneous features, deep learning, IoT, and other related technologies for developing an effective strategy of pest management.

Ali et al. (2024) proposed a system for pest detection, prevention, and control using IoT and pest sound analytics. Their approach combines heterogeneous features such as sound data with deep learning models to build a strong peeling framework, capable of being applied in large agricultural systems. It underlines the efficiency in bringing IoT and AI together so that the environmental or acoustic data can be collected in real time and analyzed for the identification of correct pests. With deep learning networks, the system is able to monitor vast areas with IoT infrastructure. This hybrid system is scalable and can be used for pest control. It also provides precision and real-time capability, which is necessary in large-scale farming operations [6].

Similarly, Rahman et al. (2024) have proposed an automated framework for the detection of harmful insects in agriculture by combining IoT, machine learning, and blockchain technologies. This smart framework combines real-time data collection from IoT devices with machine learning algorithms to identify pests. Blockchain is used for secure data sharing and to ensure the integrity of pest-related data, making it possible to have transparent and efficient decision-making processes. Their work emphasizes the advantages of combining AI and blockchain to develop a reliable and scalable pest management system that ensures transparency and efficiency in large agricultural setups. This automation helps to minimize the intervention of man, ensuring sustainability and accuracy in pest control [7].

Reshmy et al. (2024) proposed an effective framework on deep learning for crop pest classification. Their approach involves classifying various types of pests using a deep learning architecture that classifies the infestation of pests found in the crops through high-resolution images. The proposed framework leverages the power of convolutional neural networks (CNNs), which are well-suited for image recognition tasks, to classify pests accurately based on visual features. The study demonstrates that CNNs can outperform traditional pest detection methods by providing higher accuracy, especially in environments where visual features are key to pest identification. The real-time classification of pests by the model allows for timely intervention, which leads to crop damage reduction and enhances productivity in general [8].

Kariyanna and Sowjanya (2024) explored the use of artificial intelligence in the management of insect pests in agriculture. Their research offered a summary of AI technologies, including machine learning algorithms and deep learning, increasingly being used to detect and control insect pests. The authors discuss the potential of AI to revolutionize pest management by automating the detection process and offering decision support for pest control strategies. The focus on insect pests highlights the importance of accurate species identification, and AI techniques such as deep learning and computer vision can substantially improve detection accuracy in challenging field environments. The study further focuses on the integration of various approaches to pest management, ranging from prevention, monitoring, and control, within a single system that can be applied in diverse agricultural settings using AI [9].

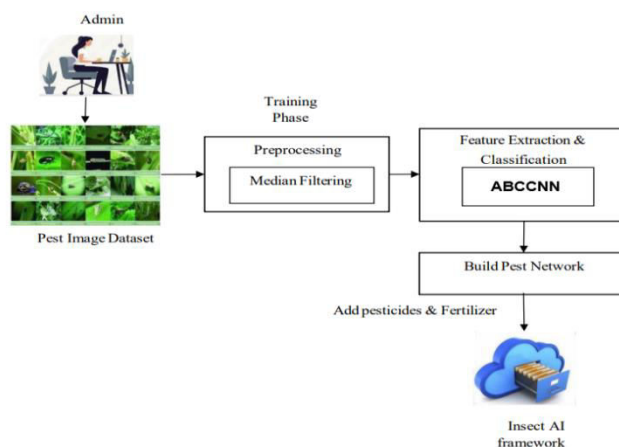
**Research gaps identified**

- IoT and AI can be effectively combined to form the foundation of a pest detection system. However, heterogeneous data sources across large-scale agricultural systems-including sound, visual, and environmental data-becomes an integration challenge. Therefore, much research is still needed to provide scalable solutions to efficiently process and analyze these various streams of data in real time.
- Although significant advances have been made in deep learning models for pest classification, most of the existing systems fail to deliver real-time performance, especially in resource-constrained environments. Optimizing AI models for faster inference with high accuracy remains a critical gap for large-scale deployment in agriculture.
- Most AI-based pest detection systems find it challenging to adapt to dynamic and demanding agricultural environments- varying lighting conditions, occlusions, as well as complex backgrounds. The later research is thus needed to improve the robustness and environmental adaptability of these models in such a way that the pest will be reliably detected across diverse field conditions.

**III. PROPOSED SYSTEM**

Using the compound coefficient, Attention based CNN is a special scaling technique that scales all depth, width, and resolution dimensions consistently. The Effective Nets family of models, which reduce parameter size and FLOPS while outperforming previous convolutional networks in terms of accuracy and efficiency, are created by using neural architecture search to establish an entirely novel baseline network and scaling it up. The technique of altering an input image's width is known as width scaling. More feature maps as well as channels may be created with larger images, which means there is more data to process. The technique of altering an image's resolution is known as resolution scaling. An image's resolution increases with the number of dots per inch. Simply increasing an image's pixel count results in higher resolution. A starting point model known as Attention based CNNwork B0 was established in order to scale all three dimensions. B0 is the initial model, and there exist seven Optimal Net models, numbered B0-B7. Each model has a different entering image size.

The size of the input picture grows as the representation level does. Convoluted neural networks may be efficiently scaled using this adaptable scaling technique, which also improves accuracy with a range of frameworks. As seen in Figure 1, the input picture is dealt with with MBConv obstructions, which use immediate links because they have a lot less channels then growth layers in inverted residual blocks. A layer that expands and then compresses the channels makes up MB Conv's focus blocks, which enable it to maximize channel features with the most knowledge while limiting less important channel features. As the networks depth increases, the MBConv slope does not rapidly disappear, enhancing the efficiency of the model. A swirl variable with no maximum that prevents gradient saturating can be used to enhance the regularization effect [10]. An Ethernet drop join is used to avoid over-fitting and enhance productivity. In relation to blocks, the Economical Net B4 and Economical Net B7 models have nine stages. As seen in Figure 2, blocks offer useful layers, and their distinctive map is linked to the Sector of Interests pooling and the Regional Request system.



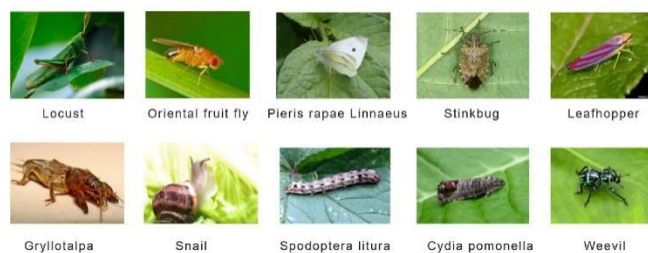
**Figure 1. Overall Architecture of the pest classification module**

### A. Dataset

Despite the fact that all insect pests, depending on the kind and grouping, go through numerous stages throughout their lives, taking pictures of them is a challenging process. The intellectual property102 collection is frequently used to evaluate deep learning-based insect pest categorization and detection. Consequently, we made use of pest photos from the open-source IP102 dataset. About 75,000 photos representing 102 insect problem species are included in the dataset. We have selected five, ten, and fifteen insect pest categories for observation and categorisation. Five pest classes were trained using an array of 14490 pest photos, ten pest classes used 29210 photos, and fifteen pest subclasses used 43210 photos. Eighty percent of the pest photos were used for training, ten percent for verification, and ten percent for tests. Figure 2 shows sample photos of infestations of insects.

### B. Proposed Framework for Detection and Classification

The intellectual property102 dataset's bug photos are fed into the Effective network, where they undergo pre-training on Image Net to produce a feature map. The Swish functionality and networks drop attach are used in Attention based CNN to enhance performance. The recommendation prediction networks receives the list of features and uses it to produce the proposal value and boundaries for the pest photos. ROI pooling is used to identify and group pest photos using the RPN network results and feature map produced by the Attention based CNN method. The subsequent Sections 3C and 3D provide a detailed explanation of the flow of the proposed quicker C-CNN scheme for pest identification and identification.



**Figure 2.** Samples of Pests Images from the IP102 Dataset

### C. Image Pre-processing and Augmentation

During the preparatory phase, pictures become normalized to preserve the standard information pattern and converted to (600,600) in order to preserve the same proportion of pixels. Due to a lack of datasets, the significance of data enrichment for image analysis using classification has already been established. Each insect pest's category in the IP102 dataset is wildly out of balance. Several data augmentation methods, including adjusting, scrolling, including horizontal turning have been employed to expand the data while eliminating the issue of over-fitting. The graphic is first smoothed using a Gaussian filter. After rescaling the photos and making a mask for each one, each sample underwent segmentation. A function applies the procedure of pipelining to every image in the data collection.

### D. Insect Pest Detection & Classification

As illustrated in Figure 3, the aforementioned learning structure is utilized for image processing as well as for the detection and classification of pests using the Efficiency Network and quicker ABCCNN technique. Since both their processing rate and added benefit of being lighter are crucial for our final usage, the convolutional neural system layers Economical Net B4 and Attention based CNN B7 have been chosen as feature extraction methods in this study and for the quicker C-CNN. This Image Net collection was used to train the previously developed weights of Attention based CNN. For this process, the input image's size is set at 224 x 224. Therefore, we create mappings of features for a source image utilizing the Attention based CNN model and send them to the RPN.

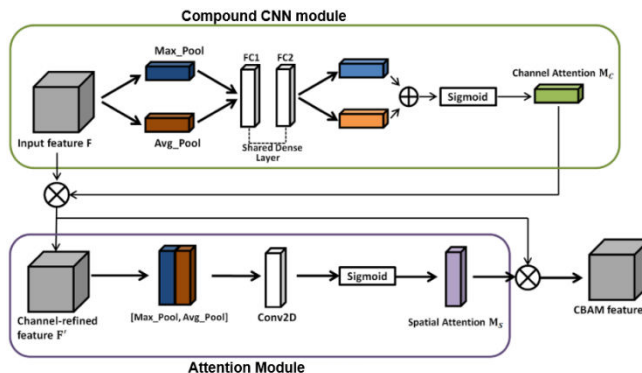


Figure 3. Attention module integration

These feature maps are fed into the RPN, which outputs the objectness score and a collection of rectangle propositions (the boundaries of the boxes) that identify the object, such as a pest, in a convolutional neural network feature list. At this point in time, a grid-anchor with a ratio of [0.25, 0.5, 1.0, 2.0] begins using a 16x16 image size. These anchors indicate accessible items at the appropriate location that vary in size and proportion. The degree to which the bounding box resembles the ground reality of the pest insects image is determined by intersection above union, where both boxes X and Y are two parts of region suggestions as specified in (1). Non maximum suppressed is used to find the bounding boxes that most confidence, ignoring the slight overlaps, in order to enhance the accuracy of the model and lower noise. The cutoff points remained at 0.7. The quicker C-CNN framework is used to generate object-level recommendations. It has a distinct and specific architecture with a regressor and classifiers. One of the key characteristics of the quicker ABCNN is that it's longitudinal unchanging, meaning it is resilient to translations.

Faster -CNN produces a "Pyramid for Anchor" instead of a "Pyramid of Filters" when multiple scales anchors exist, which saves time and money if compared to other architectures. Sending the proposals to the Area of Attention pooling layers is the next stage. Zone of Interest pooling is used to produce one feature map for every proposal that RPN submits in a single run. It is used to solve the problem of identifying items issues caused by limited image size. By using maximum pooling across every input, ROI pooling is used to generate fixed-size map features versus non-uniform data. Two inputs are required by this layer: (i) A feature map obtained from a backbone of Efficient Net B4 or Efficient Net B7 used in our research methodology after multiple convolutions and pooling layers. (ii) 'N' proposals or Region of Interests from region proposal network (RPN).

Group that Concern pool has the advantage of allowing us to use the matching feature map for all proposals. Enabling us to send the entire picture to the convolutional neural networks for processing instead of sending each suggestion separately. The Regions of Interests pooling layer applied the maximum pooling over the subsequent stage to generate the sub-windows, which have an average size that is (N, 7, 7, 512), where N is the total number of sector suggestions the RPN network received. The features pass through two fully connected channels before entering the classification and inference portions. layers. The categorization division assesses the likelihood that the suggested area will contain a harmful insect using the softmax algorithm. Furthermore, the precision of the boundary line created around the insect pest is assessed using intersecting over union results. The boundary of the analysis provides the anchor box dimensions.

### E. Mathematical Model for Compound CNN Feature Extraction in Pest Classification

The extracted characteristics are mapped to grouping results using a fully linked level. The Effective Nets family of models, which reduce parameter size and FLOPS while outperforming previous convolutional networks in terms of accuracy and efficiency, are created by using neural architecture search to establish an entirely novel baseline network and scaling it up. The technique of altering an input image's width is known as width scaling. More feature maps as well as channels may be created with larger images, which means there is more data to process. The technique of altering an image's resolution is known as resolution scaling. An image's resolution increases with the number of dots per inch.

$$IoU = \frac{X \cap Y}{X \cup Y} \quad (1)$$

A Several convolutional layers, pools of layers, and fully interconnected layers are used in a sequencing CNN system to extract hierarchy characteristics from pest photos. Below is the mathematical formulation of the model:

### Input Image Representation

Let the input pest image be represented as:

$$I \in \mathbb{R}^{H \times W \times C} \quad (2)$$

wherein:

- H = Picture of height
- W = Picture of width
- C = No. of channel with color (e.g., 3 for RGB)

### Convolutional Layer Operation

Each convolutional layer applies a set of learnable filters  $W_k$  to extract spatial features. The convolution operation is defined as:

$$F_{i,j}^{(l)} = \sum_{m=1}^M \sum_{n=1}^N \sum_{c=1}^C I_{i+m,j+n,c} W_{m,n,c}^{(l)} + b^{(l)} \quad (3)$$

Where in:

- $W_{m,n,c}^{(l)}$  is the convolution kernel of size  $M \times N$ ,
- $b^{(l)}$  is the bias term,
- $F_{i,j}^{(l)}$  is the feature map at layer l.

The activation function (ReLU) is applied as:

$$A_{i,j}^{(l)} = \max(0, F_{i,j}^{(l)}) \quad (4)$$

### Pooling Layer (Downsampling)

To decrease the number of dimensions while keeping the most important properties, max-pooling is utilised:

$$P_{i,j}^{(l)} = \max_{(m,n) \in R} A_{i+m,j+n}^{(l)} \quad (5)$$

where R is the pooling window size.

### Flattening and Fully Connected Layers

A vector is created by flattening the characteristics mappings after many convolutional and pooled levels:

$$X = \text{Flatten}(P^{(L)}) \quad (6)$$

The extracted characteristics are mapped to classifier results using a fully linked layer:

$$Y = \sigma(W_f X + b_f) \quad (7)$$

Where in:

- $W_f$  matrix of weight,
- $b_f$  term of biases,
- $\sigma$  activated softmax:

$$\sigma(Y_i) = \frac{e^{Y_i}}{\sum_{j=1}^K e^{Y_j}} \quad (8)$$

where K No. of classes in Pest.



**Loss Function (Categorical Cross-Entropy)**

Loss of function with a classifier is:

$$\mathcal{L} = - \sum_{i=1}^K y_i \log(\hat{y}_i) \quad (9)$$

where:

- $y_i$  encoded labeling,
- $\hat{y}_i$  forecasting

**Optimization (Backpropagation)**

Gradient descent updates weights using:

$$W^{(t+1)} = W^{(t)} - \eta \frac{\partial \mathcal{L}}{\partial W} \quad (10)$$

$\eta$  is rate of learning.

The model will process input images of pests through convolutional layers with learnable filters to extract spatial features. ReLU activation is then used for non-linearity. Pooling layers are used for downsampling, where the key features are retained but the dimensionality is reduced. After multiple operations of convolution and pooling, features are flattened into a vector. A fully connected layer maps the features to the output classes with softmax activation. The categorical cross-entropy loss function measures the prediction error, and backpropagation with gradient descent optimizes the weights by updating them based on the gradient of the loss function with respect to the weights.

**IV. PERFORMANCE ANALYSIS**

Rotating estimate is used to validate the pests that are insects of tested photos with the faster CNN technique's projected classifications results, hence measuring the insect identification performance. The metric of False Positive (FP), False Negative (FN), Genuine Positive (TP), and true negative (TN) are used to assess the confusion metrics. The correctly identified current anticipated pesticide class category is shown by the TP. Other groups that are not included in the current pest insect classification group are covered by the TN. The FP relates to another insect-borne disease class category that was mistakenly identified as the present class type. A previous insect pest class group that was misclassified and did not belong to the present class is the subject of the FN. The accuracy of the metric shows the proportion of anticipated beneficial points that are genuinely positive. The recall statistic shows the proportion of truly beneficial elements among all beneficial points. Below are the groups of metrics.

$$\text{accuracy} = \frac{tp + tn}{tp + fp + tn + fn} \quad (11)$$

$$\text{precision} = \frac{tp}{tp + fp} \quad (12)$$

$$\text{recall} = \frac{tp}{tp + fn} \quad (13)$$

$$f1\text{score} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (14)$$

TABLE I. PERFORMANCE METRIC COMPARISON

| Model                        | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|------------------------------|--------------|---------------|------------|--------------|
| Support Vector Machine (SVM) | 64%          | 62%           | 60%        | 61%          |
| Logistic Regression          | 67%          | 65%           | 63%        | 64%          |
| K-Nearest Neighbors (KNN)    | 78%          | 75%           | 76%        | 75.5%        |



|                       |       |     |     |       |
|-----------------------|-------|-----|-----|-------|
| Proposed ABCCNN Model | 96.4% | 96% | 97% | 96.5% |
|-----------------------|-------|-----|-----|-------|

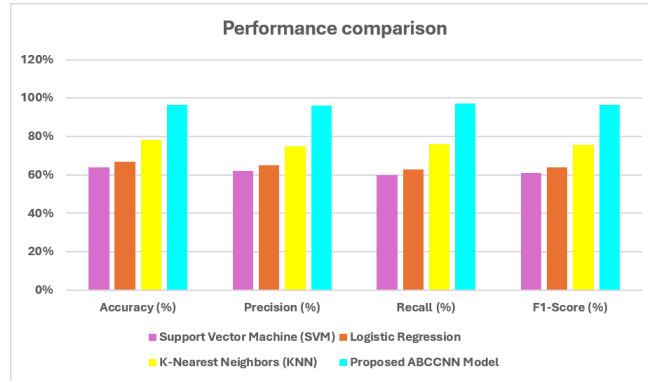


Figure 4. Overall comparison

The comparison table 1 and figure 4 assesses the performance of several machine learning models in crop pest classification based on accuracy, precision, recall, and F1-score. The SVM model, with an RBF kernel and C=1, had the lowest accuracy, 64%, and was poor at distinguishing the pest. Logistic Regression performed marginally better, 67%, but was not effective in managing the complex pest variations. KNN with three neighbors and Minkowski distance metric, gave a non-parametric model a boost in terms of accuracy at 78%. However, ABCCNN presented the model, which far surpassed all at an accuracy of 96.4% while it also surpassed other models with high precision, recall, and F1-score. The robust feature extraction with Parallel Attention Mechanism (PAM) and Residual Blocks (RBs) made it environmental variation-robust. These results demonstrate the capability of ABCCNN for real-time, large-scale agricultural pest detection and management.

The same data set was classified using different models, and their results were compared. The Support Vector Machine (SVM) classifier with Radial Basis Function (RBF) kernel with a regularization parameter (C) of 1 performed poorly at 64%. The Logistic Regression classifier using the "Mgs" solver scored a test accuracy of 67%, which wasn't great either. On the contrary, the KNN classifier with 3 neighbors and the distance metric Minkowski performed well and surpassed the SVM and the Logistic Regression with the highest test accuracy. Still, the model ABCCNN proposed outperformed all classifiers with the highest test accuracy. The curves for these classification models are plotted in Figure 5 as ROC curves, from which it can be seen that the ABCCNN model outperforms others considerably.

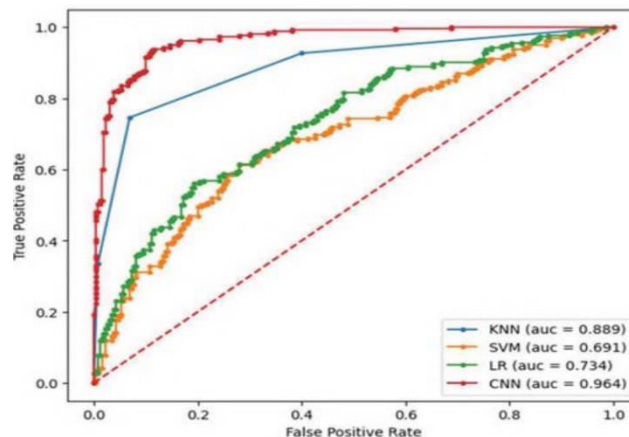
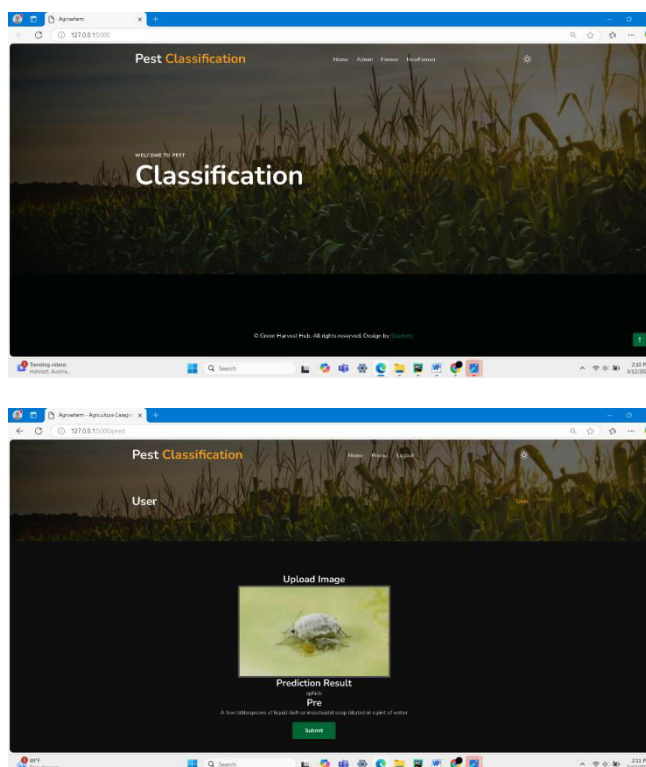


Figure 5. ROC curve

## V. RESULT & CONCLUSION

The implementation of pest classification involves developing a machine learning or deep learning model that can accurately identify and classify different types of pests based on input images. The process begins with gathering a large, labeled dataset of pest images, which includes various pest species commonly found in agricultural settings. These images are preprocessed using techniques such as resizing, grayscale conversion, noise removal and augmentation to enhance the dataset's diversity and improve the model's robustness. A convolutional neural network (CNN) is typically employed for image classification tasks, given its ability to automatically extract features from images. The model is trained using the preprocessed pest images, with layers of the network learning different features such as shapes, textures, and patterns that distinguish one pest from another.



In the future, the pest recognition system using CNN can be further enhanced by incorporating more advanced techniques and expanding the dataset. Expanding the dataset to include more species, variations in environmental conditions, and different pest life stages will also ensure robustness and generalizability. Lastly, integrating this system with decision-making tools, such as predictive models for pest outbreaks or recommendations for pest control measures, could further enhance its practical application in precision agriculture, contributing to more sustainable pest management practices.

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