SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I5P112

Volume 12 Issue 5, 135-148, May 2025
© 2025 Seventh Sense Research Group®

*Original Article*

# A High-Performance Pest Detection and Classification Model Using Pyramid U-Net Fusion Network (PUFNet) and Partial Reinforcement Optimizer (PaFO) for Precision Farming

R. Prabha[1], K. Selvan[2]

[1,2]*Department of Computer Science, J.J. College of Arts and Science (Autonomous), Pudukkottai, Affiliated to Bharathidasan University, Tiruchirappalli. Tamil Nadu, India.*

[1]*Corresponding Author : prabha.pr@gmail.com*

Received: 08 March 2025 Revised: 11 April 2025 Accepted: 11 May 2025 Published: 27 May 2025

***Abstract*** *- Pest identification and categorization in vegetable crops are essential to support high agricultural yields and food security. Control of pests can be achieved if the pests are identified at an early stage in the crop's development, thus enabling eradication or at least reducing the yield loss and harming some of the yield quality, reducing the use of toxic chemicals and pesticides. Existing pest detection models present several issues, including low accuracy, inability to apply to a wide range of pest kinds, and the need for significant computational resources. These tenders often lead to missed detections and increased numbers of false positives or negatives; pest control is then not effective. To resolve these problems, we introduce the Pyramid U-Net Fusion Network (PUFNet), which is novel and better for pest detection and classification. In the design of PUFNet, the pyramid structure is combined with U-Net so that multi-scale features are utilized to enhance the fusion of related content. Further, we propose the Partial Reinforcement Optimizer (PaFO) for the tuning of parameters, which employs P-R learning to improve the existing model performance. The proposed PUFNet performs better than the existing models of pest detection in all key metrics. It achieves an accuracy of 98.5% and a precision of 98.4%, much better than models like CNN (95%, 84%) and RNN (97%, 96.8%). In addition, PUFNet achieves a recall of 98.45% and an F1-score of 99%, much better than CNN and RNN.*

***Keywords*** *- Classification, Deep learning, Image processing, Optimization, Pest detection in vegetable crops.*

## 1. Introduction

Insect pests pose a major threat to vegetable farming because they affect crops in all developmental stages. These pests are well known to cause havoc to the aerial parts of the plants, more especially the leaves [1]. Each plant cannot be without them (leaves) since they serve more specific functions, including the process of photosynthesis, where they use light to produce energy to support growth. Wherever these important structures are located, they are vulnerable to significant damage by insect pests, which interfere with the plant's processes of generating energy and metabolism [2]. The losses incurred due to insect pests are, in many ways, potential.

Another major problem is that pests, including caterpillars, beetles, and aphids, cut through the shape of an acute triangle, leaving a 'window' around it in the edges of the leaves. Such damage hampers the ability of the leaf to perform photosynthesis and, at the same time, puts the plant in a vulnerable position as it exposes it to other diseases and infections. Moreover, pests also display the trend of being a sucker, where the pests make a hole in the leaves to suck the sap from the plant. Some signs associated with this feeding method include wilting, yellowing and stunted growth. Sap sucking reduces plant vigor, and most of the time, these pests also spread plant virus diseases hence complicating the situation [3]. Defoliation, which is a more severe damage, is when insect pests end up causing the loss of most of the leaves. This poses a lot of problems for the plant and can greatly affect its functions, such as photosynthesis and transpiration, hence resulting in slow growth and low yields. In this respect, it is seen that the combined action of defoliation and other injuries caused by pests also undermines the plant. Their vulnerability increases in terms of their ability to withstand abiotic stress and the attacks of other pests. These pests are apparently very destructive to vegetable crops; hence, early identification and control are

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

essential for the proper health of crops [4]. This is a great concern; if pest control and management measures are not frequently carried out, insect pests pose a serious threat to crops and horticulture, thereby reducing productivity.

Pesticide infestation planning should be minimized at the earliest possible stage of the development of pests in order to reduce soil degradation and the use of high amounts of pesticides so that vegetables can be produced free from pollution. Successful pest prevention strategies not only lead to crop damage reduction but also contribute to sustainable agriculture with the least environmental consequences from chemical interventions [5]. It has been highly ineffective in controlling pests; at the same time, it involves high risks due to the usage of agrochemicals and pesticides. The outcome usually is environmental pollution because of soil and water contamination, with excessive pesticide residues left on vegetables. This not only poses health risks to consumers but also leads to pest resistance, thus lessening the future pest control effect [6]. Also, since the farmer needs to use an increased quantity of pesticides over time in order to achieve the same effective result, the cost of all these chemicals keeps mounting over time. The conventional method further indicates reduced efficiency, increased subjectivity of decisions, and lower precision and punctuality of application [7, 8], which exacerbates the matter even more. Figure 1 shows the general block diagram of the pest detection system.

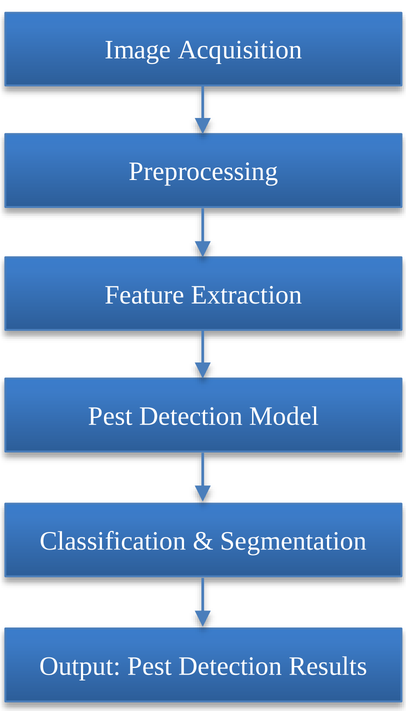


**Fig. 1 Typical pest detection system**

Besides being inefficient, this manual counting process allows very little time for quick response to pest outbreaks, which may result in huge crop losses if the infestation is not addressed in good time [9]. Given these deficiencies, the demand for more reliable and accurate methods to observe and control pest populations in crops is increasing with time. Greater utilization of information technology in pest management is expected to offer a ray of hope for resolving these problems. Advanced technology tools present new paradigms and new dimensions for the detection and control of insect pests. Indeed, farmers can achieve this through automatic and efficient techniques of image recognition to enhance the accuracy of the mode of pest detection and fumigation [10]. These technologies facilitate real-time identification of pests, reducing the frequency of excessive pesticide applications in the entire field by instead necessitating interventions targeted at a smaller scale. This will not only help cut down on expenses by decreasing the volumes of applied chemicals but will further reduce the environmental impact, making it more sustainable. More importantly, mechanization of monitoring and control of pests provides timely and accurate decisions, thus improving general efficiency in combating pests to preserve the health and productivity of an agricultural system.

Most of the improvements in pest detection and classification techniques [11], especially for agricultural applications, have been realized through transfer learning. This becomes a strategy that has been greatly adopted because most of the images are captured in a constrained laboratory setting, whereas very few were captured in real climatic conditions which can be used to build accurate models. Transfer learning capitalizes on pre-trained models created from large and diverse datasets and then fine-tunes them on the actual small dataset relevant to the task. It is especially useful in those cases where it is hard to get enough labeled data, but this approach allows a model to inherit knowledge from a broader domain and have it applied to the tasks at hand: pest detection [12]. The reason is that it is often complex and resource-intensive to access real datasets on diverse climatic conditions and several stages of crop growth. That means a great deal of continuous monitoring and imaging of crops is required under different environments, which is time-consuming, logistically demanding, and may be hard to conduct. Moreover, after the data collection, annotation is required, adding another layer of complexity. Because of this, very few datasets are fully complete for training a machine learning model in relation to pest detection [13]. This scarcity readily makes it difficult to verify and validate the performance of these models since the limited datasets can't represent all conditions encountered in agricultural settings.

ML and DL techniques [14] are increasingly explored for detecting and classifying pests in agricultural environments. These technologies have the potential to automate a great deal and considerably raise the accuracy of pest monitoring, which is traditionally labor-intensive and error-prone. Machine learning algorithms, notably support vector machines and random forests, have already been applied for the classification of pest species using features extracted from images. However, deep learning is really the breakthrough in that domain, mainly due to convolutional neural networks. They can learn hierarchical features from images [15]; hence, they are very effective in object detection and classification tasks, even when the environment is complicated and cluttered, like crop fields.

Deep learning models are trained to identify specific pests from large image datasets, combined with transfer learning; they perform well even when limited data is available. These models analyze images of crops and classify them into different categories with high accuracy after detecting the pests [16]. Deep learning techniques applied in this respect will not only provide speed and precision in the detection of pests but also identify them at an early stage of infestation, most important for the effective management of pests. Moreover, more sophisticated deep learning techniques, such as recurrent neural networks and generative adversarial networks, are being explored in pursuit of improving the robustness and generalization ability of models toward pest detection to work well across very different environmental scenarios and crop types.

The motivation to develop an effective pest detection and classification system for vegetable crops is that there is a critical, overtaking need to enhance agricultural sustainability, crop yield, and food safety. Pests usually attack vegetables, and such attacks can be very dangerous to the growth of such at any stage, leading to massive economic loss to the farmers while reducing the quality of produced vegetables. The traditional methods of pest control dependent on chemical pesticides have become ineffective because, in addition to engendering environmental degradation and accumulation of harmful residues on the vegetables, they engender the development of pest resistance and hence become less effective with time [17, 18].

The traditional manual methods of pest identification are labor-intensive, time-consuming, and greatly prone to human error; hence, they are always delayed and often inaccurate in responding to pest outbreaks. In this case, an innovative solution to overcome these hurdles is much required. This paper presents a system capable of automatically detecting, at the very early stages of their growth, localizing precisely, and classifying efficiently vegetable crop pests by exploiting new evolutions in machine learning and deep learning technologies. It will enable farmers to adopt pertinent, pinpoint, and timely measures to manage the pests, drastically reducing the amount of applied chemical pesticides and lowering production costs so healthier vegetables free of pollution can be provided to consumers. In the setting of sustainable agriculture [19], the proposed work makes much sense: more accurate, faster, and more effective pest detection for environmental and human health protection while ensuring economic viability in vegetable cultivation.

The structure of this paper provides a detailed exploration of the proposed pest detection and classification system in vegetable crops. Literature on existing methodologies used for the detection and classification of these pests, together with their strengths and limitations, has been reviewed, and it is explained how those gaps are proposed to be addressed through this work in Section 2. Section 3 will deal with the proposed methodology in general through an overview of its workflow and the techniques that can be used to ensure high accuracy and efficiency for pest detection. Describes the section of the work that explains novelties brought along, together with methodological details and flow diagrams explaining how the system works from data acquisition to the classification of pests. Section 4 presents the performance results of the model and comparative results for different metrics. In essence, it is an analytical presentation showing how effective the proposed model would be. This adds the full discussion about the used datasets for training and testing to guarantee the results, which verify its application in the real world. Section 5 finally concludes the overall paper with future study.

## 2. Related Works

Ali et al. [20] have proposed a deep-learning-based method called Faster-PestNet to mitigate the massive challenges in physical pest inspection due to the high similarity in the appearance of different types of pests. In this paper, they used a redesigned model of Faster-RCNN with MobileNet as the backbone network, targeting to be targeted in crop pest identification and classification in different categories. Such improved architecture was called Faster-PestNet, considering the MobileNet for extracting sample attributes and the two-step locator of the improved Faster-RCNN model for properly identifying the pests. The authors have conducted extensive experimental analysis on the complex IP102 dataset and achieved an accuracy of 82.43%. Moreover, to test the generalization capability of the model, they also tested the model with a faster-pest-net model on a locally collected crop dataset. They checked its effectiveness and robustness for application. This work has greatly contributed toward promoting automated pest detection methods by providing a practical solution to lift agricultural practice. According to Prasath et al. [21], the process of pest detection, feature extraction, and classification is an infusion of state-of-the-art deep learning and optimization techniques. This starts with the acquisition of input images, and afterwards, the optimized YOLOv3 model takes in these images for pest detection. The new aspect of the approach is the optimization of the YOLOv3 hidden neurons by the Adaptive Energy-based Harris Hawks Optimization algorithm, which makes the detection results very effective and accurate. Deep feature extraction from the identified pests is obtained through a deep feature extraction process using the outputs of two strong models: Residual Network50 and Visual Geometry Group16. These models ensure that features are highly quality and extremely distinctive in character, leading to better classification of pests. A deep neural network model optimized in its weights using weight factors will then perform this final task, in which the weight factors are further optimized by the AE-HHO algorithm. In this dual application of AE-HHO with detection and classification, the model's performance is optimized through which the proposed approach will turn out to be an effective technique in agriculture for the accurate detection and classification of pests. All these state-of-the-art techniques are leveled, thus reflecting the commitment of the authors towards enhancement in state-of-the-art automated pest management systems.

Venkatasaichandrakanthand et al. [9] have explained in detail a clear and systematic approach to dataset preprocessing in predicting image pests, pointing out some advanced techniques to enhance data quality and effectiveness. In the process of preprocessing, moth flame optimization is utilized to refine the dataset's characteristics.

At the same time, the linear projector methodology is applied in image flattening for image quality improvement by addressing the deficiencies in images of pests. The output images are then fed into normalization methods to convert the images into a mathematical format for analysis. Some other methodologies applied to enhance this dataset include the self-attention mechanisms, which contribute to the choice of features influencing the model's accuracy in image predictions involving pests. It is these very features that will be optimized and fed into EViTA. The results obtained from the EViTA model are contrasted with state-of-the-art ones, thus proving that the proposed model, EViTA+PCA+MFO, performs much better in predicting pest images, which gives high accuracy.

All in all, this whole pre-processing and feature selection proves that the authors are committed to developing a very effective model for pest detection. Anwar et al. [22] proposed an ensemble-based robust model using transfer learning for class imbalance problems, resulting in improved prediction accuracy. The final prediction for input samples is returned as an Ensemble Voting Classifier combination. The strategy, at an ensemble level, improves general prediction performance by fusing the dissimilar insight learned from data by individual models, hence avoiding the probable weaknesses in any one of them and improving its robustness. Transfer learning and ensemble methods underpin the approach used by the authors: using already established, well-working models to beat results in their application.

Sanghavi et al. [23] have proposed an optimized deep learning model to improve the accuracy of pest detection: Hunger Games Search-based Deep Convolutional Neural Network. According to the authors, what was novel about this work was that it proposed a new kind of convolutional layer, which reduces the redundancy of the parameters contained therein, hence making the model efficient. There are two major stages involved in this research: pre-processing and augmentation of images, followed by the classification of pests. A new adaptive cascaded filter improves the visual quality of images during the preprocessing stage. This filtering model amalgamates the concepts of decision-based median filtering and guided image filtering, using their merits for improved results in image enhancement. The proposed methodology has been well-articulated, and its authors show a keen interest in enhancing the quality of the preprocessing and classification steps so that the output in pest detection is better. Chodey et al. [24] have integrated an approach toward pest detection through the development of the Self-Improved Tunicate Swarm Optimization Algorithm for recurrent neural network weight optimization. In this paper, the author applies SITSA to optimize the training process to find the most efficient weights that would ensure better network performance. Apart from optimization, it integrates a plethora of techniques through which feature extraction can be driven based on GLCM-based texture features and color, edge, and shape-based features stemming from the segmented images. These are the keys to capturing the minutiae of information about the pests. In the classification phase, this paper has used an LSTM-RNN-based hybrid approach to detect the pesticide effectively. This methodology, therefore, consists of four major phases: I) pre-processing, II) object tracking and segmentation, III) feature extraction, and IV) classification. The multi-phase approach will allow for a thorough and thorough analysis of the accurate detection of pests by integrating the most advanced optimization techniques with robust classification methods.

Mallick et al. [25] propose a new deep learning-based approach, which has been specially designed for the automatic identification of the most common pests and diseases affecting mung beans. It is outlined by a solution in which problems with a lack of images for training the mung bean crop will exist, such as transfer learning employed to address the problem effectively. The method contributes to implementing swift and precise pest and disease detection. For example, the performance of the proposed model in detecting six classes of mung bean diseases was quite successful. In other words, this approach shows the ability of the authors to develop an effective solution for identifying pests and diseases in crops using advanced deep learning methods and transfer learning in cases of scarce training data. Kiobia et al. [26] state that developmental and predacious insects are difficult to detect, and there is a paucity of studies in detecting such hard-to-recognize categories of insects. Thus, developing systems that detect and characterize such elusive insect types raises open problems in the field. The information content of this observation is that further research is needed on the technological features that should enhance the horizon of insect detection for the benefit of enhancing the accuracy and comprehensiveness of the pest management system. Gong et al. [27] proposed a new approach toward insect boundary detection and classification by equipping an FCN with a number of state-of-the-art techniques. In detail, they introduced a new encoder-decoder architecture inside the FCN. A series of sub-networks are combined via jump paths using both long jumps and shortcut connections that may be complex in connectivity to ensure fine-grained and accurate detection of insect boundaries. This is also supplemented with a conditional random field network module to provide refinement on the contours of insects for improved boundary localization. Further, this method is strengthened by a new framework of DenseNet, along with the attention mechanism of Efficient Channel Attention, tailor-made to improve edge feature extraction efficiency in rice pest classification. It is proposed with the integration of several sophisticated techniques to further improve the accuracy and effectiveness of insect detection and classification.

Yang et al. [28] applied the target detection algorithm with a network called Yolov7-tiny, which has many advanced components: deformable convolution, Biformer dynamic attention mechanism, non-maximal suppression algorithm module, and a new implicit decoupling head. These components are all embedded to enhance the model's performance in target detection. Their effectiveness was studied and compared in ablation experiments. Their new model reached an average accuracy of 93.23%. Comparatively, the authors also checked the performance using their model against seven common models for detection to validate its robustness. This showcases a lot of testing in underlining how effective the proposed Yolov7-tiny network is, with advanced features for high accuracy in detection.

Meena et al. [29] pinpoint this as part of deep learning: data augmentation. It increases model performance by substantially increasing the size of the dataset. In this paper, different DCNN models, like DenseNet201, MobileNet, VGG16, and InceptionV3, are designed and evaluated after their hyperparameters and layers have been tuned against agricultural image data. Of these, fine-tuned InceptionV3 turned in very good results, with an accuracy of 87.85%. The result underscores the effectiveness of InceptionV3 in handling agricultural image data when compared with other models tested. Extensive fine-tuning and evaluation of performance show just how systematic the authors were in going about the optimization of deep learning models toward better accuracy in agriculture applications. Tirkey et al. [30] insist on real-time identification and detection of soybean insects by deep learning methods. This paper uses different transfer learning models to evaluate insect detection to ascertain the proposed solution's feasibility and reliability. The results obtained portray high accuracy for the proposed models, where YOLOv5 achieved an accuracy of 98.75%, InceptionV3 achieved an accuracy of 97%, and CNN achieved an accuracy of 97%. Out of these, YOLOv5 was very fast in terms of execution speed and handled 53 frames per second, which makes it quite useful for several real-time applications. The results show the potential of these deep learning models, especially YOLOv5, in both accuracy and speed in the efficient detection of insects in agricultural applications.

This review identifies large gaps in research on insect detection and classification with advanced technologies. For example, despite the large number of models developed so far, most of these models can only cover very few species of insects. Normally, the current models can be applied to a very small subset of pest and beneficial insects, whereas all other species have less coverage, especially the immature and predatory insects. Furthermore, even though techniques such as transfer learning and data augmentation can currently be used to mitigate the issue of scarcity to some extent, more general methods for generating and using larger and more diverse data sets still need to be developed to achieve higher model accuracies and generalization. Another gap would be more fine-grained and efficient algorithms working in real-time with high precision in dynamic agricultural environments. While deep learning models have demonstrated some good results, integrating these models into practical systems handling all complexities of real-world pest detection has not been done, which is itself the greatest challenge. Addressing these gaps could move the field significantly ahead toward more effective and broadly applicable solutions for pest management.

## 3. Materials and Methods

The present section introduces the Pyramid U-Net Fusion Network (PUFNet), a new approach for pest segmentation and classification tasks. PUFNet model exploits the advantages of both the Pyramid Scene Parsing Network (PSPNet) and U-net to perform much better in handling complicated and crowded agricultural images. To overcome the issues of pest size, shape and appearance variation, PUFNet incorporates PSPNet's global context capabilities with the fine-grained segmentation of U-Net. More specifically, the subsequent subsections offer a detailed examination of the PUFNet architecture with reference to the main concepts, main advancements, and optimization strategies implemented, as well as with reference to the improvements upon the PUFNet system designed for increasing the pests' detection and recognition performances. Figure 2 shows the overall flow of the proposed pest detection and classification system.

### *3.1. Pyramid U-Net Fusion Network (PUFNet)*

The Pyramid U-Net Fusion Network is a new algorithm for pest segmentation and classification that incorporates the scene parsing strength of PSPNet with the U-Net architecture. Now, having integrated the multi-scale feature extraction strengths of PSPNet with the fine-grained pixel-level segmentation strength of U-Net, the Pyramid U-Net Fusion method has been the most advanced methodology for pest detection in agricultural imagery. In this paper, PUFNet architecture combines a pyramid Scene Parsing Network with U-Net to solve complex challenges in pest segmentation and classification.

In the network, PSPNet is used for global context capture. Pyramid pooling modules pool at multiple scales, enabling PSPNet to aggregate contextual information from different levels of the image. This forms one major basis for pest recognition in varied and complex scenes. PSPNet pools feature at different scales to get a rich, context-aware representation of the input image. It effectively handles variations in object size and ensures exhaustive feature extraction. On the other hand, it utilizes good performance in pixel-wise segmentation of the U-Net model, which is due to the encoder-decoder structure of the latter.


**Fig. 2 Overall flow of the proposed pest detection system**

Through successive applications of convolutional and pooling layers, the U-Net encoder path hierarchically extracts features from an input image, and the decoder then reconstructs these to obtain a high-resolution segmentation map. Owing to these skip connections in the U-Net, much of the spatial details get passed directly to the decoder from the encoder, thus helping in fine detail and boundary preservation. This will be very useful in accurate pest segmentation, where delineating boundaries around the pests is very important. Due to the fact that the PUFNet framework integrates PSPNet and U-Net, it inherits these advantages. It combines the capability to take advantage of the multi-scale context that PSPNet provides with the detailed segmentation abilities of U-Net. Therefore, accurate segmentation and classification of the pests are realized. This is realized through concatenation, followed by convolutions synthesizing and refining the combined information from both networks. This results in a network that understands the global context's image while precisely delineating pest regions at a pixel level.

The major contributions that PUFNet, the Pyramid U-Net Fusion Network, makes to the field of pest detection and classification in agricultural imagery are profoundly deep and far-reaching. One of the main contributions it makes is its high accuracy performance. With the actual combination of the global contextual capability that the Pyramid Scene Parsing Network has with the detailed pixel-level segmentation power of U-Net, PUFNet detects and classifies pests even in complex and cluttered agricultural images. Its multi-scale pooling modules provide wide context about the scene, which combines with the precise segmentation of U-Net to result in a significant gain of accuracy. Actually, this will be the two-fold strategy to make sure that pests are detected within their local regions and, at the same time, contextualized within the wider scene for more accurate and reliable pest identification.

The other key contribution of PUFNet is improved feature representation. These pyramid pooling layers in PSPNet extract features at varied scales to build a diversity of relevant aspects for the image, which is crucial to understanding complex pest scenarios. This will then combine U-Net's high-resolution segmentation, capturing fine details, to yield highly accurate and maximum-surveyed representations for the pests. This will, hence, enable PUFNet to provide a much richer and more nuanced understanding of the features of pests and deliver superior performance in segmentation and classification tasks.

The robust performance is the major advantage an end-user gets from PUFNet.This is attributed to accommodating variations in the size, shape, and appearance of the pests, which are due to the hybrid architecture of PSPNet and U-Net. This is the type of real-world pest detection scenario robustness, for pests differ in many ways and pose a lot of challenges. Equipped with this adaptability, PUFNet ensures high performance across a wide variety of pests and environmental conditions.

The advantages of PUFNet over traditional pest detection and classification methods are rather obvious. Through the pyramid pooling modules of PSPNet, multi-scale contextual understanding can be captured and integrated. So, PUFNet will understand the complex scene comprehensively with better contextual relationships. The encoder-decoder architecture of U-Net with skip connections ensures high-resolution segmentation to retain fine details and, hence, provide precise boundaries needed for pest identification. A level of detail such as this is important to effect correct differentiation of pests from their background, leading to reliable results. Another main advantage of PUFNet concerns improved generalization. Merging the PSPNet global context with the detailed segmentation of U-Net has added additional power to the model for generalizing across a great variety of pest types and environmental conditions.

As shown in Figure 3, the encoding path based on the U-Net model is computed after getting the input, which integrates both the convolutional and pooling layer operations. It is mathematically represented as shown below.

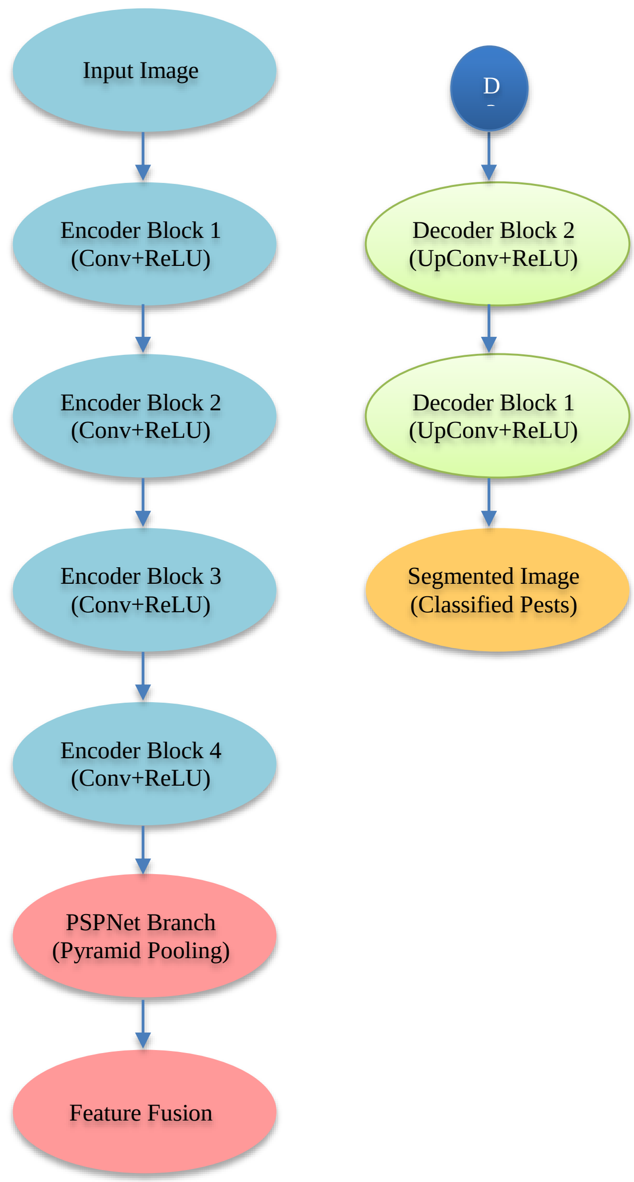


**Fig. 3 Architecture of PUFNet**

$$\mathfrak{F}_{\text{Conv}}(\mathfrak{T}) = \text{ReLU}(\mathfrak{T} \times \kappa + \mathfrak{B}) \quad (1)$$

Where, $\mathfrak{F}_{\text{Conv}}$ is the convolution operation, $\mathfrak{T}$ denotes the input image, κ represents the size of the kernel, and $\mathfrak{B}$ is the bias value.

$$\mathfrak{F}_{\text{Pool}}(\mathfrak{T}) = \text{Max}_{\text{Pool}}(\mathfrak{T}, \wp) \quad (2)$$

Where, $\mathfrak{F}_{\text{Pool}}$ is the pooling operation, and $\wp$ represents the size of the pooling window. As a consequence, the Pyramid Scene Paring (PSP) network function is implemented to improve the feature extraction operation, which integrates the pyramid pooling function at multiple scales. This operation is described as shown in the following equation:

$$\mathfrak{F}_{\text{pp}}(\mathfrak{T}) = [\mathfrak{F}_{\text{Pool}}(\mathfrak{T}, \mathfrak{s}_1), \mathfrak{F}_{\text{Pool}}(\mathfrak{T}, \mathfrak{s}_2), \mathfrak{F}_{\text{Pool}}(\mathfrak{T}, \mathfrak{s}_3), \mathfrak{F}_{\text{Pool}}(\mathfrak{T}, \mathfrak{s}_4)] \quad (3)$$

$$\mathfrak{F}_{\text{Psp}}(\mathfrak{T}) = \text{Conv}_{1\times1}(\mathfrak{F}_{\text{pp}}(\mathfrak{T})) \quad (4)$$

Where, $\mathfrak{s}_1, \mathfrak{s}_2, \mathfrak{s}_3, \mathfrak{s}_4$ are the different pooling sizes. Moreover, the fusion is performed to integrate the PSPNet features with the decoding path of the UNet model using skip connections. This operation is mathematically represented in the following equation:

$$\mathfrak{F}_{\text{Skip}}(\mathfrak{T}) = [\mathfrak{F}_{\text{Enc}}(\mathfrak{T}) \odot \mathfrak{F}_{\text{Psp}}(\mathfrak{T})] \quad (5)$$

After that, the convolution and upsampling operations are parallelly applied on the decoding path according to the following model:

$$\mathfrak{F}_{\text{Up}}(\mathfrak{T}) = \text{Up}_{\text{sample}}(\text{Conv}\left(\mathfrak{F}_{\text{Skip}}(\mathfrak{T})\right)) \quad (6)$$

The final image classification is performed with the final feature map as shown in the following equation:

$$\mathfrak{F}_{\text{C}}(\mathfrak{T}) = \text{Conv}_{1\times1}(\mathfrak{F}_{\text{Up}}(\mathfrak{T})) \quad (7)$$

Where, $\text{Conv}_{1\times1}$ represents the convolution operation that is mainly performed to minimize the number of feature channels that correspond to the number of classes. In order to obtain the final prediction probability, the softmax function is computed as shown in the following equation:

$$\mathbb{P}_{\text{C}}(\mathfrak{T}) = \text{Softmax}(\mathfrak{F}_{\text{C}}(\mathfrak{T})) \quad (8)$$

Consequently, the cross entropy loss function is estimated to properly train the classification model based on the following equation:

$$\mathcal{L}_{\text{CE}}(\mathfrak{T}) = -\sum_{\text{cl}=1}^{\text{C}_{\text{cl}}} \mathbb{p}_{\text{cl}} \log(\mathbb{p}_{\text{cl}}) \quad (9)$$

Where, $\mathbb{p}_{\text{cl}}$ is the predicted probability for the class, and $\mathcal{L}_{\text{CE}}(\mathfrak{T})$ is the loss function. In order to further enhance the generalization capability of the classification model, the data augmentation is performed as represented below:

$$\mathfrak{T}_{\text{a}} = \text{T}_{\text{r}}(\mathfrak{T}) \quad (10)$$

Where, $\text{T}_{\text{r}}$ is the transformation operation and $\mathfrak{T}_{\text{a}}$ is the augmented image.

Algorithm 1 - Pyramid U-Net Fusion Network
Input: Input image $\mathfrak{T}$;
Output: Predicted class probability $\mathbb{P}_{\text{C}}(\mathfrak{T})$;
Step 1: The network parameters are initialized with kernel size, bias value, size of pooling window and No of output classes;
Step 2: Construct encoding operation;
Convolution operation $\mathfrak{F}_{\text{Conv}}(\mathfrak{T})$ is performed based on equ (1);
Pooling operation $\mathfrak{F}_{\text{Pool}}(\mathfrak{T})$ is performed based on equ (2);
Step 3: Perform PSO network operation;
Perform pyramid pooling operation $\mathfrak{F}_{\text{pp}}(\mathfrak{T})$ at multiple scales according to equ (3);
Incorporate pooled features by applying $1 \times 1$ convolution operation $\mathfrak{F}_{\text{Psp}}(\mathfrak{T})$ based on equ (4);
Step 4: Consequently, perform the decoding operation;
Combine the encoded, and PSPNet features for implementing skip connections $\mathfrak{F}_{\text{Skip}}(\mathfrak{T})$ based on equ (5);
Perform convolution and upsampling operations $\mathfrak{F}_{\text{Up}}(\mathfrak{T})$ according equ (6);
Step 5: Perform the final classification $\mathfrak{F}_{\text{C}}(\mathfrak{T})$ using equ (7);
Step 6: Apply the softmax function $\mathbb{P}_{\text{C}}(\mathfrak{T})$ and estimate cross-entropy loss function $\mathcal{L}_{\text{CE}}(\mathfrak{T})$ based on equ (8) and (9);
Step 7: Return the final prediction result;

By doing so, the PUFNet stands for a new benchmark in pest segmentation and classification developed to meet the inherent intricacies of pest detection in agriculture. Thus, along with adopting the global context awareness of PSPNet into the precise localization of U-Net, PUFNet yields better accuracy in pest detection even within a dense and complex environment in the agricultural images. This flexibility of the model, specifically in terms of pest size, shape, and appearance, is perhaps one of the real strengths and ambitions of this work, and it shows the model's applicability to real-world pest problems. Additionally, pyramid pooling modules in the U-Net provide significant multi-scale context understanding in addition to high-resolution segmentation, making a highly effective model for pest type identification and environment generalization. Such attributes, in addition to the actual contribution estimated by the model, which embraced timely and informed pest management decision support, denoted a strong potential of PUFNet on the future of novelties in agriculture disease and pest control, which implies improved crop production. The contribution of PUFNet is in the proposed novel hybrid architecture and in the integration of global and detailed features. Therefore, it constitutes an important contribution to developing agricultural image processing and pest management.

### *3.2. Partial Reinforcement Optimizer (PaFO) for Parameter Tuning*

The Partial Reinforcement Optimizer (PaFO) is a newly developed technique suitable for parameter tuning in difficult neural networks such as the PUFNet, which is used for pest segregation and identification. PaFO brings a new approach, which measures the reinforcement learning aspect where the parameters are not fixed completely to get the best values but are rather partly reinforced to get the best output. This selective reinforcement makes it possible for the optimizer to concentrate only on the parameters that he or she has found to have the greatest impact on the particular process in question, making the tuning method more efficient. Among such features, one can distinguish the capacity of PaFO to regulate the trade-off between exploration and exploitation throughout the optimization. Other types of optimizers like the SGD or Adam have been found to overly exploit or explore the parameters until convergence, taking either a very long time or not [converging optimally. PaFO conversely incorporates a partial reinforcement mechanism regarding the learning rate and update frequency of the parameters within each iteration. This leads to a much better balance whereby the optimizer can go off and search for new regions of parameter space when needed but can also take much better advantage of the knowledge of previous, good settings for the parameters in question. This dynamic adjustment minimizes the risk of over-training and allows the model to reach the best solution much faster.

The value of PaFO is such that it adapts the optimization process to the situation in which a model like PUFNet is developed. In pest segmentation and classification, which requires high accuracy and model robustness, PaFO helps make selective reinforcement that only the key parameters are trained to a very high level while others are updated less frequently. This makes the process of training to be much faster and also makes the model perform better with new data sets. Also, PaFO has a complementary reinforcement mechanism that seems beneficial in the case of PUFNet, as the different layers and modules may be trained using different approaches due to the multi-scale and multimodal nature of the task. With partial updates permitted, PaFO makes it possible to fully entrust the model's perception of the global context and elaborate its segmenting capacities simultaneously.

The advantage of using the PaFO over all other optimization techniques is the ability and flexibility of the PaFO, as well as its ability to cope with various stages of a problem. PaFO decreases the amount of iterations that have to be performed by the algorithm in contrast to traditional full reinforcement methods because the majority of parameters do not have the potential for significant optimization and, therefore, do not need to be considered. This makes the training process efficient, especially when it involves models with high parameter space like PUFNet. Furthermore, PaFO is also flexible to be used and effective in several steps in the training phase – from the exploration phase to the fine-tuning phase, making it a helpful tool for deep learning researchers. Lastly, the stability of PaFO with the aid of the balanced addition of reinforcements, PaFO can handle most situations involving pest detection; this guarantees the attainment of the most accurate results.

## 4. Results and Discussion

In this section, we describe the experimental results of the proposed PUFNet for pest identification and its classification, as well as the performance of the PaFO for optimizing the parameters of pest identification. The PUFNet combines an improved pyramid and U-Net framework and further improves the performance for feature extraction and feature fusion to offer a sound base for pest classification and identification. This is a comparison of the performance of PUFNet with the previous methods of classification using standard measures such as accuracy, precision, recall, and F1-score. Thus, to adjust the hyperparameters of the network, we use the PaFO, based on partial reinforcement learning, allowing for the specified parameters' tuning and an increase in the model's efficiency. The findings indicate that the proposed PUFNet and PaFO have improved detection accuracy and efficiency compared to the existing tools and methods; therefore, they can fight pest classification problems effectively. Figure 4(a) shows the graph of training and validation set accuracy of the Pyramid U-net Fusion Network (PUFNet) for different numbers of epochs. The training accuracy indicates how the model learns the training data, and its corresponding curve depicts the same. The validation accuracy, on the other hand, depicts the ability of the model to generalize the knowledge gained to unseen knowledge. It is seen in the figure that training of PUFNet helps the model in enhancing the accuracy repeatedly, which proves that the model is learning the features of the pest effectively. The validation accuracy, which also increases, affirms it can handle new samples well, which is essential for pest identification in real-world settings. Training accuracy and validation accuracy are close, and the curve does not show a significant sign of overfitting.

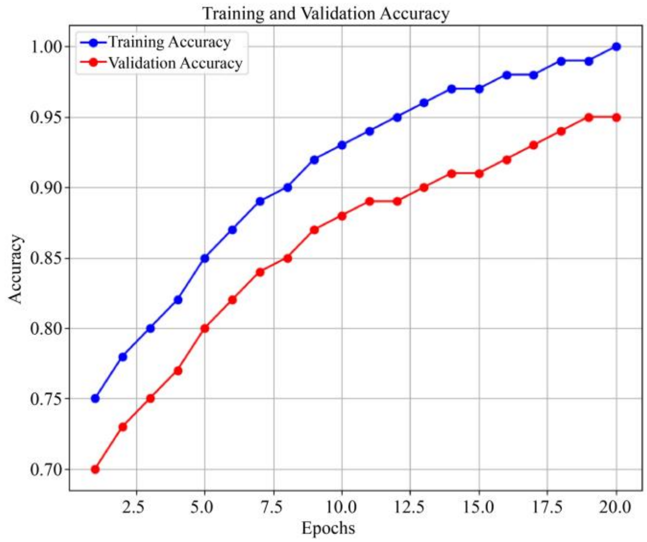


**Fig. 4(a) Training and validation accuracy**

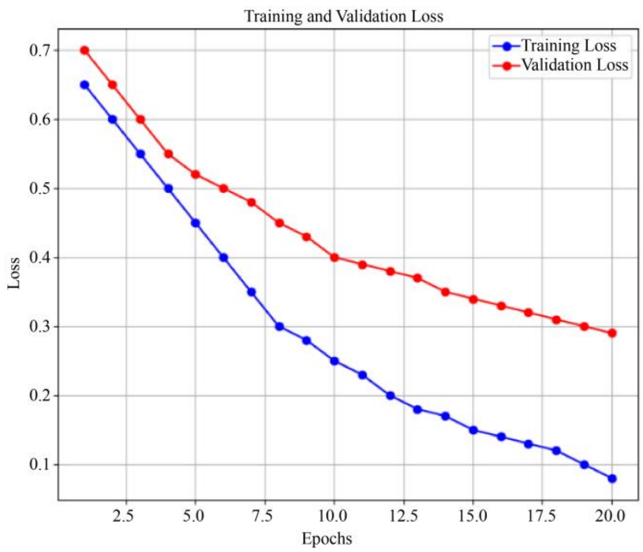


**Fig. 4(b) Training and validation loss**

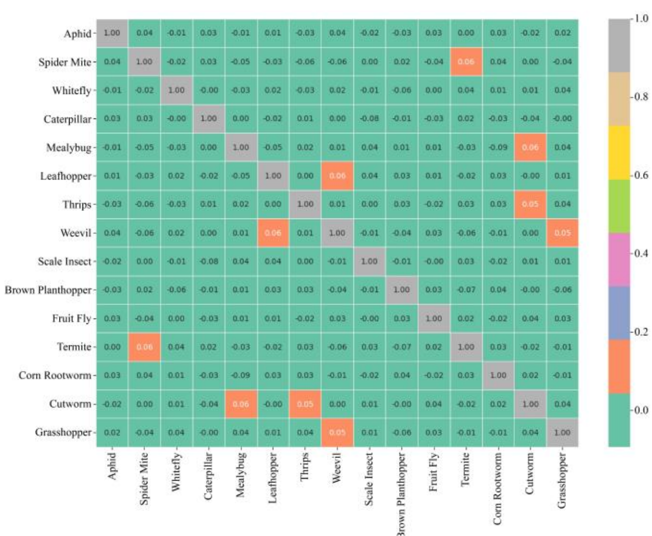


**Fig. 5 Confusion matrix for different pests**

The plots of Training and Validation Loss across the epochs are given in Figure 4(b). So, training loss determines the error rate on the training data, and validation loss gives the error rate on the data that has not been utilized in training the model. The process of learning PUFNet is reflected by the fact that training and validation loss are getting lower. Specifically, validation loss, meaning a general tendency toward a higher visualization of model accuracy in regard to minimizing misclassifications, is significant for accurate pest detection and classification. The overlapping of the loss curves indicates that the proposed model looks quite reasonable and does not overfit, which is crucial for real-life applications of pest detection. The performance of different other recent deep learning models has been compared in Figure 6 for pest detection with PUFNet. It is an essential utilization efficiency indicator that describes the ratio of correct identification of pests among all analyzed samples. The better performance of the PUFNet is evident from the error difference, whereby reduced errors indicate a better capacity of the model in pest instance classification than the other models. This progress is due to the dynamism in feature extraction and feature fusion of PUFNet, which enables it to capture more elaborate patterns of pest images than images of other objects.

Figure 5 shows the performance of a pest detection model classifying plant pest types using image data or other features. Pests depicted are common agricultural threats, including aphid, spider mites, whiteflys, caterpillars, mealybugs, leafhoppers, thrips, weevils, scale insects, brown plant hoppers, fruit flies, termites, corn rootworms, cutworms, grasshoppers. Here, each row of the confusion matrix represents a true class, while each column shows a predicted class. The model, in an ideal way, would have all the values concentrated on the diagonal; hence, it does not find a problem in recognizing each pest correctly. The confusion matrix is the model used to check the strengths and weaknesses of the model in distinguishing types of pests. It comes in handy, as it tells the model which particular pest classes tend to confuse it.

Figure 7(a) further depicts the precision of the pests of distinct deep learning models. Hence, higher precision means fewer pest notifications are detected as non-pest, and the detection system is more reliable. This comparison also illustrates that PUFNet has a higher precision compared to the previous method; this means that PUFNet is better at discerning between actual pest cases and non-pest objects, hence resulting in fewer false alarms to the pest detection systems, especially for pest control, where a small number of false positives is the key to effective pest control resources. As shown in Figure 7(b), recall metrics of various recent deep-learning models used for pest detection have been compared. Sensitivity or Recall is the ratio of the number of actual positive instances, the true pest cases, that the model can flag as positive among all the pest cases in the set. Higher recall means that the model can identify most of the real pest instances and, thus, will not miss many of the instances. The high recall of PUFNet in this comparison indicates that this method is highly effective in finding pest incidences, which is key in pest identification schemes that want to minimize cases of false negatives and, therefore, increase the chances of capturing most of the pest incidences.

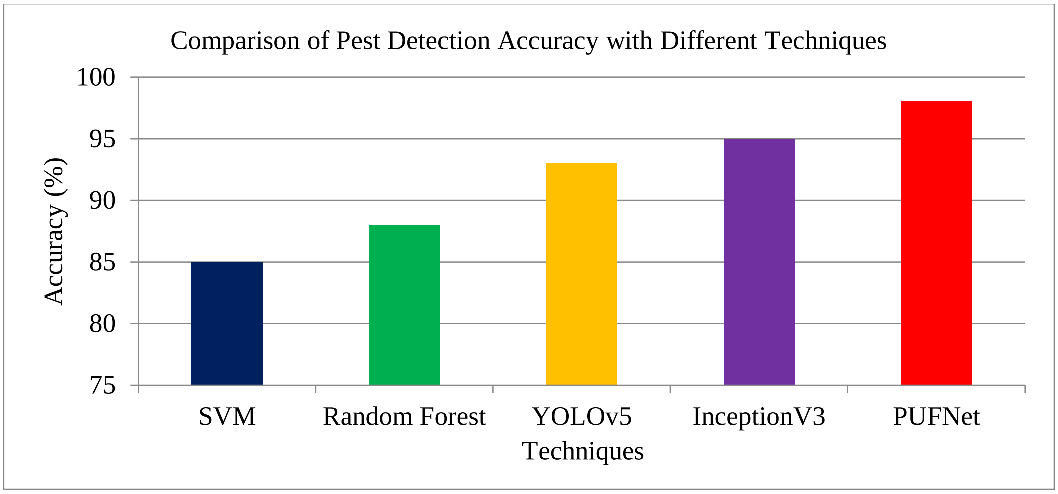


**Fig. 6 Comparison of recent deep learning models based on pest detection accuracy**

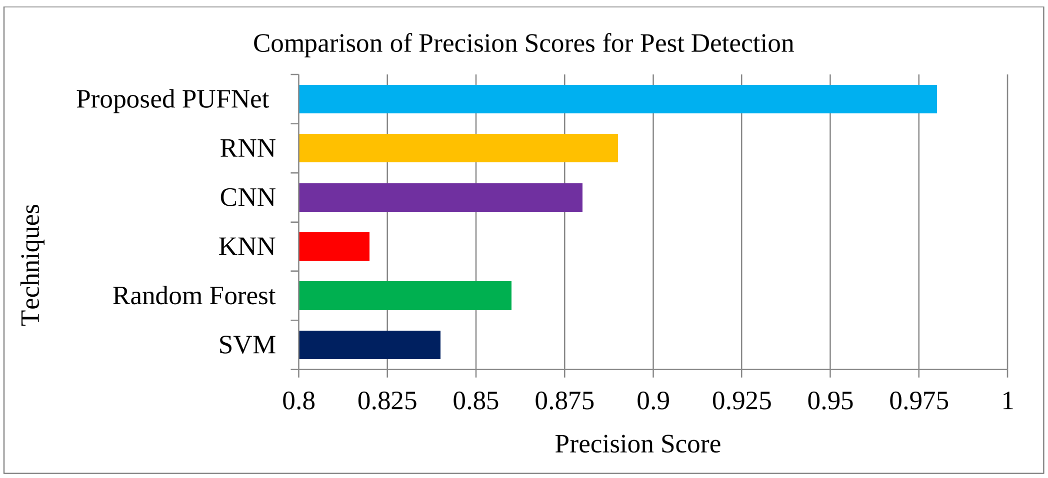


**Fig. 7(a) Comparison of recent deep learning models based on pest detection precision**

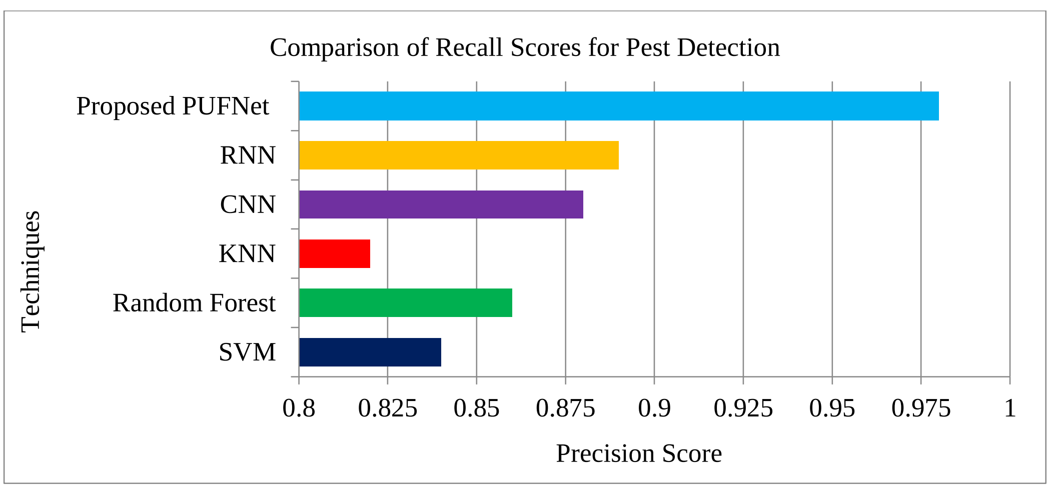


**Fig. 7(b) Comparison of recent deep learning models based on pest detection recall**

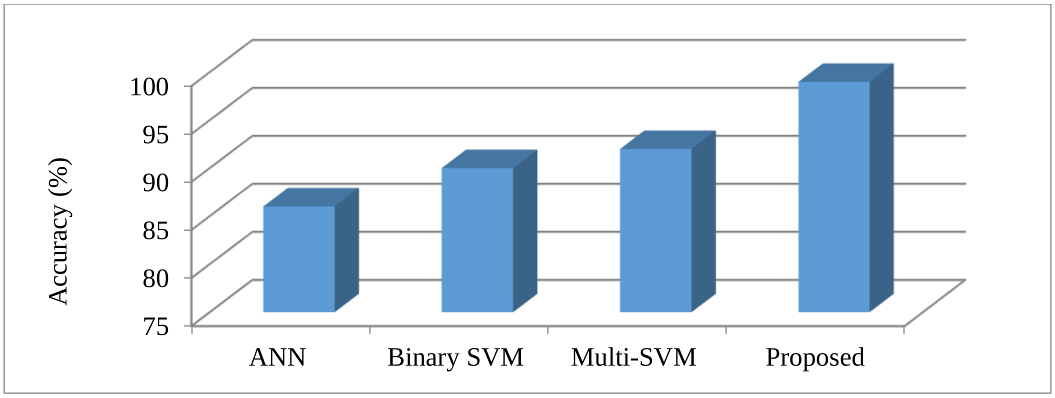


**Fig. 8 Comparison based on detection accuracy with standard machine learning techniques**

The performance of different deep learning models in pest detection has been depicted in Figure 8, along with other standard machine learning algorithms such as SVM, Random Forest and KNN. Purity measures the extent to which an object belongs to a particular class compared to another class. Compared with other traditional machine learning algorithms, PUFNet owns higher recognition accuracy for pests, which affirms that this kind of technique can provide better performance for pest detection jobs. It helps emphasize that PUFNet does indeed do better than more traditional techniques and proves itself viable and useful in practice.

**Table 1. Comparison with other learning models based on accuracy and precision**

| Methods | Accuracy | Precision |
|---|---|---|
| SVM | 85 | 84 |
| RF | 87 | 86 |
| KNN | 82 | 81 |
| CNN | 95 | 84 |
| RNN | 97 | 96.8 |
| Proposed | 98.5 | 98.4 |

Comparing the accuracy and precision of many learning models that are suggested, including the PUFNet model, they are provided in Table 1. Accuracy gives us the number of the right classification done in relation to the total number of instances or cases of the entire dataset, while precision gives the ratio of the actual positives to the total positives. Based on the evaluation of the predicted accuracy and precision, PUFNet reveals the best performance in predicting pest locations.

The high value attained for precision leads to the conclusion that PUFNet not only provides accurate results but is also free from many false positive decisions. This is figured out and presented again in Figure 9 below, where the accuracy and precision of various learning techniques have been compared. It brings out a comparison of the above-mentioned metrics of the proposed PUFNet to the other techniques. For the PUFNet model, the values of these measurements are shown to be higher, proving this model's enhanced ability in pest detection and classification.

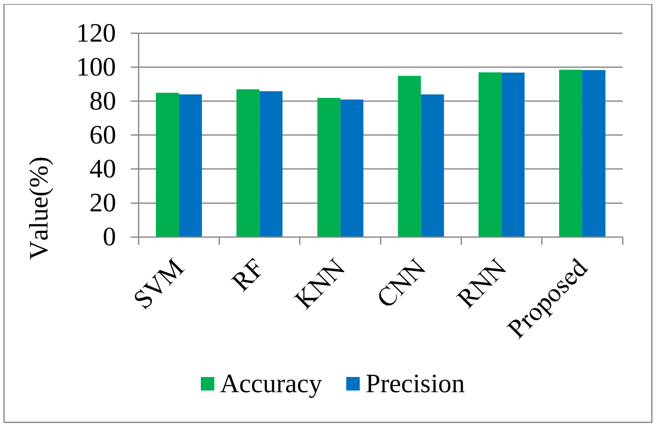


**Fig. 9 Comparison with different learning techniques based on accuracy and precision**

**Table 2. Comparison with other learning models based on recall and f1-score**

| Methods | Recall | F1-score |
|---|---|---|
| SVM | 82 | 83 |
| RF | 85 | 84 |
| KNN | 80 | 81 |
| CNN | 87 | 88 |
| RNN | 96 | 96.5 |
| Proposed | 98.45 | 99 |

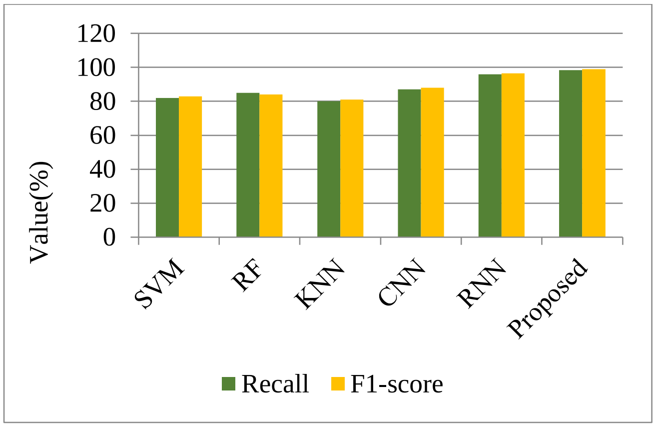


**Fig. 10 Comparison with different learning techniques based on accuracy and precision**

Table 2 focuses on the dependence on recall and F1-score: Accuracy measures the model's effectiveness in predicting all samples and can be seen as a general metric. In contrast, recall computes a measure of concern for all true positives, and the F1 score combines both precision and recall to provide a unique value of concern. The overall results of the proposed PUFNet have far better recall and F1-score, which means that PUFNet outperforms all other models in detecting pests while keeping precision and recall both in reasonable balance. This result reaffirms the ability of PUFNet to perform a stochastic search for a pattern of PU detection and the correct categorisation of the PUs. The comparison of different learning techniques is depicted in Figure 10 on the accuracy and precision parameters. It discusses how various models, such as PUFNet, do concerning these measures. The proposed PUFNet shows excellent results in accuracy and precision compared to other techniques and methods, proving its applicability for practical use and effectiveness in correctly and repeatedly identifying pest instances.

## 5. Conclusion

Integrated pest management for vegetable crops requires precise identification and characterization of pests, hence this study. The task of accurate recognition and monitoring of pests has been a problem from earlier due to various problems that have plagued existing models, such as lack of precision, poor extrapolation ability, and high computational complexity. These challenges make it difficult to contain pests, calling for better techniques to be Procured and implemented. In this paper, we proposed the PUFNet and its associated partial reinforcement optimizer-the PaFO, as a way of overcoming these drawbacks. To improve pest detection accuracy, PUFNet combines a pyramid structure with the U-Net model to better extract multi-scale features. Here, the PaFO Agency has enhanced the hyperparameters by the reinforcement learning method and has a better and more promising model. The experimental results presented in this paper prove that PUFNet, integrated with PaFO, performs clearly better than the current models in terms of accuracy, precision, recall, and F1 score, which are all better in our model compared to the current models. The proposed method not only improves the capability of pest detection but also provides a computationally valuable solution that can be applied in the real-world applications of the agriculture field. This kind of feature extraction is combined with reinforcement-based optimization and represents a new state-of-the-art in pest detection systems. Future work is to improve the model, and more tests will be conducted with more types of pests. Another environment in agriculture will also be tested. The conclusions drawn from our investigation have research implications for the enhancement of pest control technologies and provide a novel avenue in scientific development and practical application in the management of pests in agriculture.

## Acknowledgments

The author, R. Prabha, contributed and put effort on paper to organize the Paper. The author, K. Selvan, made English corrections and grammar checking. Both authors technically contributed to data analysis and were involved in the background study of the paper and also in mathematical derivations.

## References

[1] Qingwen Guo et al., "Automatic Monitoring of Flying Vegetable Insect Pests using an RGB Camera and YOLO-SIP Detector," *Precision Agriculture*, vol. 24, pp. 436-457, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Philipp Batz et al., "From Identification to Forecasting: The Potential of Image Recognition and Artificial Intelligence for Aphid Pest Monitoring," *Frontiers in Plant Science*, vol. 14, pp. 1-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Abderraouf Amrani et al., "Deep Learning-based Detection of Aphid Colonies on Plants from a Reconstructed Brassica Image Dataset," *Computers and Electronics in Agriculture*, vol. 205, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Shansong Wang et al., "ODP-Transformer: Interpretation of Pest Classification Results using Image Caption Generation Techniques," *Computers and Electronics in Agriculture*, vol. 209, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] M. Chithambarathanu, and M.K. Jeyakumar, "Survey on Crop Pest Detection using Deep Learning and Machine Learning Approaches," *Multimedia Tools and Applications*, vol. 82, pp. 42277-42310, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Haram Kim and Dongsoo Kim, "Deep-Learning-Based Strawberry Leaf Pest Classification for Sustainable Smart Farms," *Sustainability*, vol. 15, no. 10, pp. 1-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Hongxing Peng et al., "Crop Pest Image Classification Based on Improved Densely Connected Convolutional Network," *Frontiers in Plant Science*, vol. 14, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] M.Sahaya Sheela et al., "Machine Learning based Lung Disease Prediction Using Convolutional Neural Network Algorithm," *Mesopotamian Journal of Artificial Intelligence in Healthcare*, vol. 2024, pp. 50-58, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] P. Venkatasaichandrakanthand, and M. Iyapparaja, "Pest Detection and Classification in Peanut Crops Using CNN, MFO, and EViTA Algorithms," *IEEE Access*, vol. 11, pp. 54045-54057, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Jamalbek Tussupov et al., "Analysis of Formal Concepts for Verification of Pests and Diseases of Crops Using Machine Learning Methods," *IEEE Access*, vol. 12, pp. 19902-19910, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] R. Rajkumar et al., "DARKNET-53 Convolutional Neural Network-Based Image Processing for Breast Cancer Detection," *Mesopotamian Journal of Artificial Intelligence in Healthcare*, vol. 2024, pp. 59-68, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Abu Hanif, and Harpreet Kaur, "Plant Disease Detection with Finetuned - ResNet18 for Several Plant's Like Tomato, Grape, Orange, Soybean, Squash, Potato, Corn_(maize), Strawberry," *Social Science Journal*, vol. 13, pp. 1703-1715, 2023. [Google Scholar] [Publisher Link]

[13] Evangelos Anastasiou et al., "Precision Farming Technologies for Crop Protection: A Meta-Analysis," *Smart Agricultural Technology*, vol. 5, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Saud Yonbawi et al., "Modified Metaheuristics with Transfer Learning Based Insect Pest Classification for Agricultural Crops," *Computer Systems Science & Engineering*, vol. 46, no. 3, pp. 3847-3864, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] E.D. Kanmani Ruby et al., "Advanced Image Processing Techniques for Automated Detection of Healthy and Infected Leaves in Agricultural Systems," *Mesopotamian Journal of Computer Science*, vol. 2024, pp. 44-52, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Guilhermi Martins Crispi et al., "Using Deep Neural Networks to Evaluate Leafminer Fly Attacks on Tomato Plants," *AgriEngineering*, vol. 15, no. 1, pp. 273-286, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Wenyi Hu et al., "A Study on Tomato Disease and Pest Detection Method," *Applied Sciences*, vol. 13, no. 18, pp. 1-21, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] G. Maheswari, and S. Gopalakrishnan, "A Smart Multimodal Framework based on Squeeze Excitation Capsule Network (SECNet) Model for Disease Diagnosis using Dissimilar Medical Images," *International Journal of Information Technology*, vol. 17, pp. 49-67, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] Min Dai et al., "A New Pest Detection Method Based on Improved YOLOv5m," *Insects*, vol. 14, no. 1, pp. 1-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Farooq Ali, Huma Qayyum, and Muhammad Javed Iqbal "Faster-PestNet: A Lightweight Deep Learning Framework for Crop Pest Detection and Classification," *IEEE Access*, vol. 11, pp. 104016-104027, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] B. Prasath and M. Akila, "IoT-based Pest Detection and Classification using Deep Features with Enhanced Deep Learning Strategies," *Engineering Applications of Artificial Intelligence*, vol. 121, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[22] Zeba Anwar, and Sarfaraz Masood, "Exploring Deep Ensemble Model for Insect and Pest Detection from Images," *Procedia Computer Science*, vol. 218, pp. 2328-2337, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Vishakha B. Sanghavi, Harshad Bhadka, and Vijay Dubey, "Hunger Games Search based Deep Convolutional Neural Network for Crop Pest Identification and Classification with Transfer Learning," *Evolving Systems*, vol. 14, pp. 649-671, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Madhuri Devi Chodey, and C. Noorullah Shariff, "Pest Detection via Hybrid Classification Model with Fuzzy C-means Segmentation and Proposed Texture Feature," *Biomedical Signal Processing and Control*, vol. 84, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[25] MD Tausif Mallick et al., "Deep Learning based Automated Disease Detection and Pest Classification in Indian Mung Bean," *Multimedia Tools and Applications*, vol. 82, pp. 12017-12041, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Denis O. Kiobia et al., "A Review of Successes and Impeding Challenges of IoT-Based Insect Pest Detection Systems for Estimating Agroecosystem Health and Productivity of Cotton," *Sensors*, vol. 23, no. 8, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[27] He Gong et al., "Based on FCN and DenseNet Framework for the Research of Rice Pest Identification Methods," *Agronomy*, vol. 13, no. 2, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[28] Zijia Yang et al., "Tea Tree Pest Detection Algorithm Based on Improved Yolov7-Tiny," *Agriculture*, vol. 13, no. 5, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[29] S Divya Meena et al., "Crop Yield Improvement with Weeds, Pest and Disease Detection," *Procedia Computer Science*, vol. 218, pp. 2369-2382, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[30] Divyanshu Tirkey, Kshitiz Kumar Singh, and Shrivishal Tripathi, "Performance Analysis of AI-based Solutions for Crop Disease Identification, Detection, and Classification," *Smart Agricultural Technology*, vol. 5, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]