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A study on image processing techniques and deep learning techniques for insect identification

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Keywords

Convolutional Neural Networks; Deep Learning; Image Processing Techniques; Pest and Insect Identification

Cover Page Footnote

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REVIEW ARTICLE

A Study on Image Processing Techniques and Deep Learning Techniques for Insect Identification

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Abstract

Automatic identification of insects and diseases has attracted researchers for the last few years. Researchers have suggested several algorithms to get around the problems of manually identifying insects and pests. Image processing techniques and deep convolution neural networks can overcome the challenges of manual insect identification and classification. This work focused on optimizing and assessing deep convolutional neural networks for insect identification. AlexNet, MobileNetv2, ResNet-50, ResNet-101, GoogleNet, InceptionV3, SqueezeNet, ShuffleNet, DenseNet201, VGG-16 and VGG-19 are the architectures evaluated on three different datasets. In our experiments, DenseNet 201 performed well with the highest test accuracy. Regarding training time, AlexNet performed well, but ShuffleNet, SqueezeNet, and MobileNet are better alternatives for small architecture.

Keywords: Convolutional neural networks, Deep learning, Image processing techniques, Pest and insect identification

1. Introduction

A lot of research is being done on the agro system to increase productivity and reduce agricultural expenditure. However, pests and insects are one of the major causes of damage to important crops. Moreover, all crops are also affected by the attack of insects and pests. Therefore, a system is needed to manage insects for sustainable agricultural development and to control pests by biological means instead of pesticides, in which early identification of pests and insects can play an important role.

In combination with deep learning, image processing is revolutionizing applications of computers in day-to-day life. It is applied in a variety of disciplines, including fraud detection [1], surveillance applications [2], Internet of Things applications [3], and even stock exchange prediction [4].

Deep learning is widely used in the agricultural domain for various applications like plant identification [5], fruit, leaf, and vegetable recognition [6] [7], automatic fruit counting [8], detection of dropped fruits [9], and insect detection and identification [10] [11]. Deep learning is a modern technological advancement that helps farmers reduce farming losses by offering detailed advice and insights about the crops.

Only 10% more agricultural land was added between 1960 and 2000, while agricultural output increased by 30%. The use of pesticides and fertilizers, the mechanization of farming equipment, and the development of high-yielding crops and livestock kinds were the causes [12]. Over 70% of Indian workers depend directly or indirectly on agriculture.

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However, one of the biggest obstacles to guaranteeing food security is the regular outbreaks of pests and insects. In the past two decades, estimated losses from insects have ranged from 2% in Europe to 31.5% in Asia. Each year, insects and pests cause harm to 37% of the rice crop. Without precautions, we might have lost 70% of crops due to pests and insects.

Deep learning models are up-and-coming for identifying and classifying insects. Researchers prefer Convolutional neural networks (CNN) because there is no need for feature extraction manually. Instead, lower features are extracted in lower layers, while specific features are identified at higher layers. The high accuracy of the model is also one of the reasons for the popularity of Convolutional neural networks among researchers.

Recently, various changes to the CNN Architecture have been suggested by gradually adding more layers. AlexNet, MobileNetv2, ResNet-50, ResNet-101, GoogLeNet, InceptionV3, SqueezeNet, ShuffleNet, DenseNet201, VGG-16 and VGG-19are a few of the architectures. However, there may be issues and problems with these deep networks, including vanishing gradients and degradation throughout the training of the model. Additionally, the degradation problem causes accuracy loss in most deeper networks.

Real-time monitoring and managing pests and insects are essential for global food security. This paper empirically analyses the most advanced deep-learning models for identifying and classifying pests and insects based on test accuracy, training duration, and space requirements.

The workflow of the research proposal is as follows: Section 2 is about related work toward different models proposed in insect identification. Section 3 focuses on the dataset and methodology to compare different deep learning models. Section 4 presents experiments, results, and the comparative analysis of work with other states of the art. Finally, section 5 concluded the work.

2. Related work

Deep convolutional neural networks and image processing have several applications in smart agriculture. Insect and plant disease identification are one of them. The agricultural sector has incorporated many traditional machine learning techniques for the same.

Insect identification publication analysis from 1986 to 2020 is shown in Fig. 1. The period from 2016 to 2021 can be interpreted as a boom in the pest and insect identification field. Consequently, 2021 stands out as the year with the most publications.

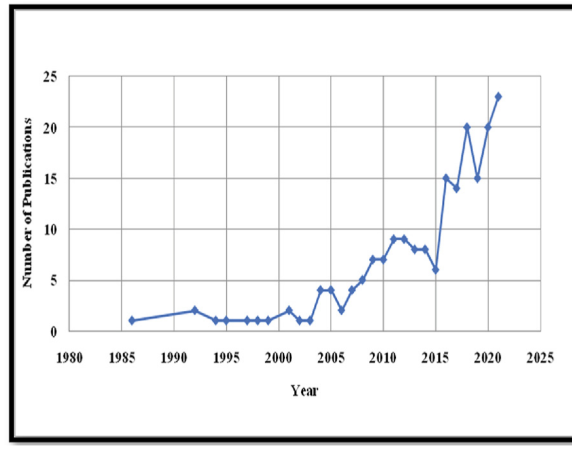

Fig. 1. Yearly publication counts for insect and pest identification (Source: Scopus D.B. accessed on July 11, 2022).

Fig. 2 shows the top journals publishing articles on pest and insect identification. Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering stands first for publishing articles in this area.

2.1. Insect and pest identification using image processing techniques

Various image-processing approaches are used in the agricultural sector to recognize pests and crop diseases. Table 1 depicts the comparative analysis of different image processing approaches for pest and insect identification.

The paper [13] used the SURF algorithm in insect images to extract local features. For this, at first, local features of insects were extracted, and a database of local features of insects was prepared. Then, the extracted local features are given as input to the multi-scale histogram algorithm. The described experiment included 144 images for training the recognition system, and 72 images were used for testing. As a result, the accuracy of the SURF-based recognition algorithm is found to be 89%.

The work described in the paper [14] introduced a naive image processing technique for thrips and parasites of strawberries detection, where researchers used the Support Vector Machine classification method with a different kernel function. Color indexes such as Intensity, Saturation, and Hue were used for designing this new SVM structure. For image acquisition, a mobile agricultural robot is used. However, images are taken under natural light. For gamma operators, the grayscale images

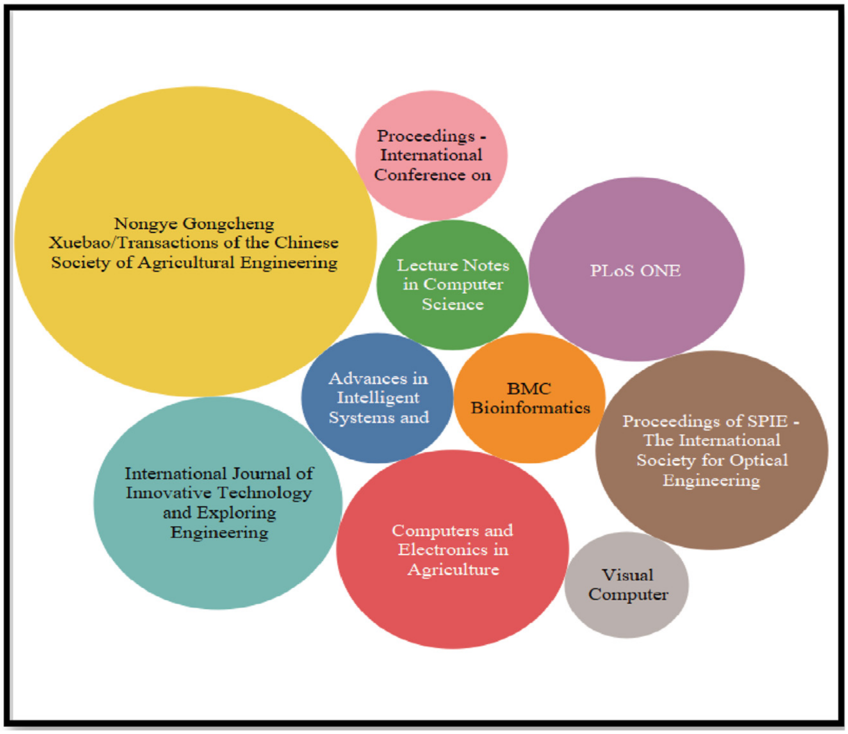

Fig. 2. Top 10 Journals for publishing articles on insect and pest identification for the period of 2004–2021 (Source: Scopus D.B. accessed on July 11, 2022).

were not suitable as input. Therefore, gamma operators were utilized with the captured RGB image.

After this, contrast stretching and Histogram equalization was applied to separate insects from any remaining background. Next, parasites were classified using an SVM classifier. Finally, suitable regions and color indexes were chosen to detect strawberries' targeted thrips and parasites successfully.

The studies in Ref. [15] proposed a computer vision approach to identify stonefly larvae. For conducting the study, four stonefly taxa, namely *Calineuria*, *Doroneuria*, *Hesperoperla,* and *Yoraperla,* were considered, and about 1400 images were taken into consideration. Images of stonefly larvae are captured through a semi-automated mechanical manipulation device. The concatenated feature histogram (CFH) method is proposed in the paper. At first, the region of interest is identified. The identified regions are represented as SIFT vectors to create a histogram of observed features, which are then categorized as learned features. The concatenated feature histogram (CFH) approach was the name given to these actions. Before the final classification phase, a different dictionary is produced for each region detector, and the histograms are combined. The ability of this work to distinguish some stonefly taxa that are known to be tough to discern, even by specialists, is a testament to its efficiency. When Calineuria and Doro-neuria are combined, all three detectors yield a three-class accuracy of 95% and a four-class accuracy of 82%.

In the paper [16], two types of pests, namely (Bemisia tabaci) popularly known as whitefly, and (Frankliniella occidentalis) popularly known as thrip, which affect tomato crops, were classified using a hybrid technique that combines digital image processing techniques and neural networks. For the study, data were collected from the greenhouses of the University of Almería, Spain, research field. Segmentation, morphological operations, and color property estimation, which are several image processing methods, were employed to find the objects. For classifying insects, a feed-forward artificial neural network was also used. For the identification of whiteflies, the researchers achieved good precision (0.96), recall (0.95), and F-measure (0.95) values. But a 0.92 precision for thrip recognition, recall of 0.96, and F-measure of 0.94 were attained.

The studies in Ref. [17] proposed a low-cost and long-term automatic pest identification system. First, the images of pests were captured from the mobile and embedded systems. Initially, the images of whiteflies, aphids, and thrips were segmented

Table 1. Comparative analysis of various image processing techniques for insect identification.

Article	Insect	Data set	Preprocessing Techniques	Features Used	Classifier used	Performance/ Recognition Rate
[13]	Not specified	Not specified	Not specified	Local Features	SURF-based multi-scale Histogram	89%
[14]	Thrips and parasites of Strawberry	100 images	Histogram equalization and contrast stretching	Color	SVM	97%
[4]	Rice Insects	Images of 11 categories of insects, each of size 20*20	Median filter, Morphological operation, Dilation operation.	Not mentioned	Kohonen Self Organizing Maps neural network	For six insects categories, accuracy is 100%, while for other categories, it is between 60 and 88%
[5]	Stonefly larvae	1240 images	Watershed segmentation	Edges, Curvilinear structures	SIFT vectors, histograms of local appearance features	For four-class, accuracy is 82%, while for 3 class, accuracy is 95%
[6]	Thrip (Frankliniell a occidentalis) and whitefly (Bemisia tabaci)	3185 images	segmentation, and morphological and color property estimation	Not mentioned	ANN	For whitefly, high precision of (0.96), recall of (0.95), and F-measure of (0.95) value. For the thrips, the precision of (0.92), recall of (0.96), and F-measure of(0.94) values.
[7]	Whitefly, aphids, thrips		Watershed segmentation	Color	Mahalanobis distance	The 4-class accuracy is 82%, and the 3-class accuracy is 95%.
[8]	Diabroti, Lacewin, Aphids, Glassy, Thrips, Whitefly	Not specified	Segmentation procedure using a Sobel mask	Weight, perimeter, compactness, and center of gravity	LOSS algorithm followed by scale-invariant feature transform (SIFT).	determination coefficient, R2 = 0.99.
[9]	White-backed plant hoppers of paddy fields	4283 WBPH images, 9000 non-planthopper entity images	Not specified	Gabor and LBP Features and HOG features	AdaBoost classifier, a support vector machine, and a histogram of oriented gradient (HOG)features	A false identification rate of 23. and an identification rate of 73.1% and 3%.
[10]	Not Specified	Not Specified	Segmentation	Seven Hu moment invariants, elongation, sphericity, roundness, compactness eccentricity, lobation, and rectangularity	Random trees classifier	97.14%

using the watershed algorithm to separate them from the sticky trap(background). Then, the Mahalanobis distance was calculated to extract the color features of the insects. When the proposed work was compared with the manual identification method, the correlations of determination were found to be very high. Furthermore, even for the low-resolution images, the resolution correlations differed for different insects. i.e., for whitefly, thrips, and aphids.

In the paper [18], researchers expanded their previous version of the LOSS algorithm in the paper. The proposed work was used to detect pest species Diabrotic, Lacewins, Aphids, Glassy, Thrips, and Whiteflies. Researchers found that the efficiency of the LOSS algorithm can be increased. A more significant number of pests are detected and classified using the scale-invariant feature transform (SIFT). Therefore, the modeled LOSS V2 machine vision system uses the LOSS algorithm, followed by

SIFT (scale-invariant feature transform). Two traps (HORIVER Monitoring and HORIVER Capture trap) were used to collect the insects and pests. As a result, the LOSS V2 algorithm shows greater accuracy, with a determination coefficient $R2 = 0.99$.

The paper [19] demonstrated a new three-layer detection method for identifying white-backed planthoppers. In the study, the images of planthoppers, and non-plant hopper images, have been collected. For the study, images of insects were taken by a Smartphone with a digital camera and a stretchable pole to reach close to the insects. A new detection method, which contains three layers, was devised to recognize different stages of white-backed planthoppers of paddy crops. The images were collected as a representative dataset, which covers images of all development stages of the plant hopper. The first and second layers of the proposed model detect the insects in the image using the AdaBoost classifier and SVM classifier to train HOG features and local binary pattern (LBP) features and the Gabor, respectively.

In contrast, the third layer employed an SVM classifier trained on HOG characteristics to recognize white-backed planthoppers. As a result, the illustrated identification and detection method, which includes three-layer, is very effective and efficient compared to other methods. For example, as an illustration, it only required 8 s to find and identify a rice insect in an image, with a 73.1% recognition rate and a 23.3% false recognition rate.

A computer vision-based insect recognition system is suggested in the paper [20]. Instead of using the already used segmentation method, authors have developed their segmentation method. In the proposed segmentation method, images were converted into grayscale, edges were found using the Canny operator, and contours were found using the contour finding algorithm. In this way, the most significant counter found will be the contour of the insect. In addition, 14 contour features, including sphericity, seven Hu moment invariants, rectangularity, elongation, lobation, compactness, roundness, and eccentricity, were calculated from the images of insects. For classification, a random tree classifier is used, classifying insects into one of the seven species of insects.

The average recognition rate is found to be 97.14%. A comparative analysis of various IMP techniques for insect identification is shown in Table 1. Different factors affect the efficiency of insect identification techniques. The preprocessing techniques, features selected to be extracted, classifier used, and the knowledge of which classifier gives the best results with which preprocessing technique play an important role in modeling an efficient algorithm for the identification of insects. Still, we cannot extract some features of insects using handcrafted methods and mathematical tools and set a priori [21] among different preprocessing techniques and different shallow classifiers.

2.2. *Insect and pest identification using convolutional neural network*

In recent years, CNN has been very promising in identifying insects and has shown outstanding performance in classifying and identifying insects. As a result, the agricultural industry has widely embraced conventional machine-learning techniques.

An innovative DeepPestNet architecture for classifying and recognizing pests is presented in the paper [22]. The suggested model comprises eleven learnable layers, three fully connected (FC) layers, and eight convolutional layers. Researchers applied image rotation techniques to boost the dataset size and demonstrate the generalizability of the suggested DeepPestNet strategy. To evaluate the suggested DeepPestNet framework, researchers employed the well-known Deng's crops data set. The insect pests were identified and categorized into ten classes using the proposed model. The suggested approach attained a perfect accuracy of 100%. Researchers have evaluated the suggested DeepPestNet method with conventional deep learning (DL) models that have already been trained. Researchers evaluated the suggested model on the popular Kaggle dataset “Pest Dataset” to identify nine different types of pests, including aphids, armyworms, beetles, bollworms, grasshoppers, mites, mosquitoes, sawflies, and stem borers. We achieved an accuracy of 98.92%. The proposed model may help professionals and farmers identify pests quickly and effectively, thus lowering financial and crop yield losses.

The paper [23] proposes a small CNN model for detecting diseases and pests from rice plant images. The data is collected in a real-life scenario and contains 1426 images of eight rice disease and pest classes. The pest detection model will be more beneficial for the early detection and management of pests. Moreover, it can be used with mobile phones. As large architectures are not recommendable for mobile devices, the authors have suggested a small CNN architecture with only two stages. The devised model is compared with NasNet Mobile, MobileNet, and SqueezeNet CNN architecture.

An accuracy of 93% is achieved by the model. The size of this small CNN is 99% smaller than VGG16.

Authors in the paper [24] used 500 images of rice diseases, which include rice bacterial wilt (RBW), rice blast (R.B.), rice bakanae disease (RBD), rice seeding blight (RSEB), rice brown spot (RBS), rice false smut (RFS), rice sheath blight (RSHB), rice bacterial sheath rot (RBSR), rice bacterial leaf blight (RBLB) and rice sheath rot (RSR). These images were preprocessed, and then preprocessed images were used for training the model. As a result, the model is very efficient and more accurate than the standard B.P. algorithm, support vector machine (SVM), and particle swarm optimization (PSO) in identifying the rice diseases of 10 classes.

In the paper [25], for the detection of moths, the authors have used CNN with an already existing sliding window detection pipeline to classify the images of moths. First, the images of moths were preprocessed, and then to find which image patch contained pest, preprocessed images were given as input to trained CNN. The precision-recall AUC achieved was 0.934, and the log average miss rate was 0.0916.

In the study [26], a unique method for classifying and identifying plant leaves that combines the use of texture and shape features is proposed. The shape of the leaf is captured using a set of curvelet transform coefficients along with invariant moments. In contrast, the texture of the leaf is modeled using the Gabor filter and grey-level co-occurrence matrix (GLCM). Before feature extraction, a preprocessing stage is used to correct for different translation, rotation, and scaling factors because these features are typically sensitive to the orientation and scaling of the leaf image. The effectiveness of the suggested techniques is investigated by discriminating between 31 classes of leaves using two neural classifiers: a neuro-fuzzy controller (NFC) and a feed-forward back-propagation multilayered perceptron (MLP).

Entomology has been used extensively in various biological fields (i.e., insect counting as a biodiversity index). Automated entomology has been used for many years to satisfy increasing biological demand and compensate for shrinking labor. Both computer scientists and actual biologists have taken on this challenge. The study in Ref. [27] looks into forty-four research on the subject and aims to provide a comprehensive overview of the scientific deadlocks and how the issue was handled. Views are adopted regarding the datasets studied, feature extraction, classification algorithms, and image capturing. Finally, a broad discussion is provided on potential unanswered questions, including the description of the issue, whether computer scientists should be involved, and the image-capturing requirements necessary for effective recognition performance.

A deep residual learning model is proposed in Ref. [28] to identify the pest in images with a complex background. The proposed model was much more accurate than the support vector machine and the B.P. neural network. In the study, the authors have suggested that the efficiency of training deep convolutional neural network models can be improved using deep residual learning. The model was tested for the ten classes of pests, and the accuracy of this ResNet-101-based model was achieved to be 98.67%.

In the paper [29], a modern machine-learning technique was modeled to classify and detect the insect of field crops. After extracting the foreground and recognizing the contour in the IP102, Wang, Xie, and Deng datasets, 9-fold cross-validation was used. The Xie dataset contains 24 insect classes, but the Wang dataset only comprises nine insect classifications. For 9 and 24 classes of insects, classification accuracy was 91.5% and 90%, respectively. The suggested CNN model for identifying insect images consists of five convolutional layers, three maxpooling layers, a flattening layer, a fully connected layer, and a SoftMax output layer.

To ensure food security, early detection and management of pests are necessary, but it is also essential to keep stored grain safely. In the experiment [30], a more effective R−FCN neural network model is proposed to identify and detect the stored-grain pest. Eight categories of stored grain insects were studied in the paper. The accuracy of the model is achieved to be 88.06%.

One of the most significant elements that substantially endanger agricultural production is the presence of agricultural diseases and insect pests. Therefore, effectively reducing the economic losses brought on by pests requires early detection and identification of pests. The paper uses a convolution neural network [31] to detect crop diseases automatically. The data set includes 27 images of diseases affecting ten different crops and is taken from the open data set of the AI Challenger Competition in 2018. The Inception-ResNet-v2 model is trained in this study. The residual network unit to the model has a multi-layer convolution and a cross-layer

Table 2. Comparative Analysis of various Deep Learning(CNN) Models for Insect Identification.

Article	Insect/Diseases	Data set	CNN Model	Performance/Recognition Rate
[12]	24-classes pests	25,378 images	AF-RCNN	56.4% mAP and 85.1% mRecall
[13]	Rice diseases and pests of 8 classes	1426 images	two-stage CNN	Accuracy of 93.3%
[15]	1st dataset from NBAIR, 2nd dataset contains 24 insect classes of Xie1 and 3rd dataset contains 40 insect classes of Xie2	Not specified	Deep CNN	Accuracy of 96.75, 97.47, and 95.97% is achieved for three datasets.
[16]	Moth dataset	177 images	CNN	Precision–recall AUC achieved was 0.934, and the log average miss rate was 0.0916
[17]	tomato whitefly and its predatory bugs	597 images	Faster R–CNN	Accuracy of 87.4%
[18]	Not specified	1600 images	CNN	93.46% validation accuracy
[19]	A data set of pest images of 10 classes.	550 images	Deep residual learning	For ten classes, an accuracy of 98.67%
[20]	Wang, Xie, Deng, and IP102 datasets	2706 images	CNN	91.5% and 90% accuracy for 9 and 24 types of insects, respectively
[21]	Dataset 1 of eight kinds of stored grain insects	2500 images	Improved DenseNet –121	Accuracy of 88.06%

direct edge. The connection to the ReLu function activates it when the combined convolution procedure is finished. According to the testing findings, this model's total identification accuracy is 86.1%.

Table 2 displays a comparison of various CNN models for identifying insects.

3. Materials and methods

Deep learning research in computer vision and image categorization has exploded recently. A typical Deep CNN consists of an input layer, multiple hidden layers, an output layer, and a classification layer or an output layer.

Fig. 3 depicts a typical CNN architecture used by several CNN architectures [32]. Many different architectures have since been developed. This study uses three publicly available datasets to evaluate the performance of AlexNet, MobileNetv2, ResNet-50, ResNet-101, GoogLeNet, InceptionV3, SqueezeNet, ShuffleNet, DenseNet201, VGG-16, and VGG-19 for insect identification.

3.1. Dataset

This work evaluates the advanced convolutional neural networks for classifying and identifying insects using three publicly available insect datasets: Xie1, Xie2, and d NBAIR. The details of the dataset are shown in Table 3. The National Bureau of Agricultural Insect Resources (NBAIR) dataset has forty classes of insect images, whereas the second and third datasets (Xie1, Xie2) include 24 and 40 classes, respectively.

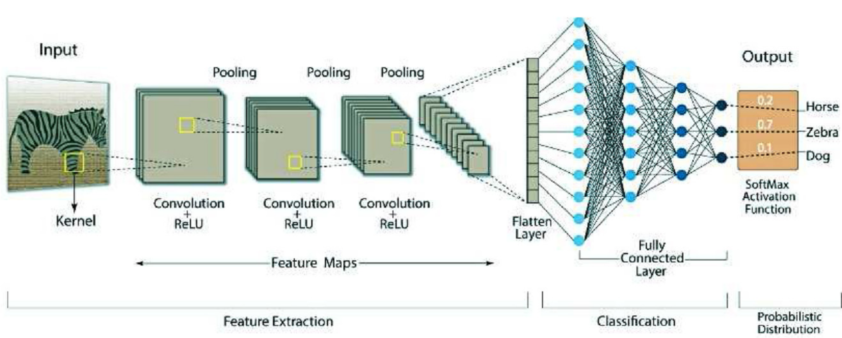

Fig. 3. A typical Deep Learning Model for object identification Source: Medium.com.

Table 3. Details of the dataset used.

Data set	Details of the data set	Resolution of images	Is free available or not?
NBAIR	Image data of 40 classes of insect	227 × 227 x 3	Yes
Xie1	Image data of 24 classes of insect	227 × 227 x 3	Yes
Xie2	Image data of 40 classes of insect	227 × 227 x 3	Yes

The performance of architectures ResNet-101, ResNet-50, AlexNet, GoogLeNet, VGG-19, VGG-16, InceptionV3, SqueezeNet, ShuffleNet, MobileNetv2, and DenseNet201were evaluated using these three datasets. Quick and accurate models for insect identification are necessary to take preventative measures for pest and insect management.

The complete dataset is divided into training and testing datasets to train and assess the accuracy of CNN architectures. In contrast to training by 80%, only 20% of the dataset is used for testing.

3.2. Deep learning image classifiers

There was a breakthrough in image classification by Deep Convolution Neural Network (CNN). The CNN design has recently been subject to several revisions that gradually add more layers. Following are a few of the architectures that were studied.

3.2.1. AlexNet

When it comes to models in the field of computer vision, AlexNet stands out as a top architecture. The 2012 ImageNet large-scale visual recognition competition was won by AlexNet. The approach was put forth by Alex Krizhevsky and his colleagues in their 2012 research publication [33]. Compared to Lenet-5, this model enhanced the network's depth.

3.2.2. ResNet

To reduce the error rate from the first CNN-based design (AlexNet), which won the 2012 ImageNet competition, each successive winning architecture adds a few extra layers to a deep neural network. This model is effective for smaller numbers of layers. Still, when we add more layers, a typical deep learning issue known as the Vanishing gradient arises, which results in the gradient becoming zero or overly large. Therefore, as the number of layers increases, the error rate during training and testing rises.

Residual Network architecture introduced the idea of Residual Blocks to address the vanishing/exploding gradient issue. A method known as skip connections is applied in this network. The skip connection bypasses some levels in between to link layer activations to subsequent layers, which creates a leftover block.

ResNets are built by stacking these extra building blocks. Instead of having layers learn the underlying mapping, this network allows the network to fit the residual mapping.

The paper [33] discusses similarities between ResNet and Inception. Microsoft ResNet models are examined and tested, including ResNet18, ResNet50, ResNet101, and ResNet152.ResNet is widely used for different applications, such as fault diagnosis [34], Facial expression recognition [35], and Face Recognition [36].

3.2.3. GoogLeNet

With the support of numerous institutions, Google researchers debuted Google Net (also known as Inception V1) in 2014. When it came to the 2014 ILSVRC image classification competition, this architecture was the winner. It has produced a considerable error reduction compared to ILSVRC 2012 Winner AlexNet, ILSVRC 2013 Winner ZF-Net, and a considerably lower error rate than V.G.G. (2014 runner-up). Techniques like global average pooling are used in the center of the architecture, and 1-1 convolutions are used. GoogleNet is popularly used in diverse applications. In Ref. [37], GoogleNet is used for scene recognition in Ref. [38] for Circular Fruit and Vegetable Classification, while comparisons of ResNet and GoogleNet models for the detection of malware are done in Ref. [39].

3.2.4. VGG-16 and VGG-19

VGG (Visual Geometry Group) is a deep CNN architecture with several layers. Depending upon the number of layers, the name is given to two versions of this architecture as VGG-16 or VGG-19, respectively, have 16 or 19 convolutional layers. Using this architecture, creative item identification models are created.

Many researchers use VGG networks for various applications like diagnosing papillary thyroid carcinomas [40], chest X-ray image classification [41], and Fundus Image Classification [42]. In addition, many indoor gadgets need information about the user's position and orientation. Therefore, the gadgets can provide users with more relevant and user-oriented information.

The paper [43] introduces a novel building information modeling (BIM) and convolutional neural network-based indoor localization technique (CNNs). To estimate an image's indoor position and orientation, this method creates a dataset from generated BIM images and searches it for images that best resemble indoor images. Then, image feature extraction is done using a pretrained CNN (the VGG network) (BIM rendered and real images) to compare two different types of images. To test the method, experiments were carried out in actual buildings. For a total of 143 tests, the matching accuracy was 91.61%.

Machine learning algorithms and data mining techniques are typically designed to handle problems separately. These approaches in Ref. [44] are used to train the model separately using the same distribution and particular feature space. A model is trained using a machine learning algorithm for a specific task depending on the business case. The idea that test data and training data must have the same feature spaces and the underlying distribution is common in the machine learning community. Instead, if features and distribution change, models may need to be completely recreated in the real world because this assumption may not hold.

Still, there are some limitations of VGG-16.

1) Training is highly laborious (For two to three weeks, the initial VGG model was trained on the Nvidia Titan GPU).
2) The VGG-16 trained ImageNet weights to have a 528 MB file size. Therefore, it is inefficient because it uses much storage bandwidth and space.
3) 138 million parameters cause the problem of exploding gradients.

3.2.5. InceptionV3

Inception Net achieved a landmark in CNN classifiers when earlier models merely moved further to increase performance and accuracy while compromising the computational cost. The Inception network, on the other hand, has advanced engineering.

It employs numerous techniques to boost performance in terms of speed and precision. Since it significantly outperformed ZFNet (the winner in 2013) and AlexNet (the winner in 2012) and has a comparatively lower mistake rate than the VGGNet. The 2014 ImageNet Large Scale Visual Recognition Competition was won by it(1st runner-up in 2014).

It is used in various domains, such as for the diagnosis of prostate cancer [45], Traffic Sign Recognition [46], and image classification [47].

3.2.6. SqueezeNet

SqueezeNet is a convolutional neural network with 18 layers. The ImageNet database contains a pretrained version of the network that was trained on more than a million images. A keyboard, mouse, pencil, and a few different animals are among the 1000 things the pretrained network can classify from images. SqueezeNet achieves AlexNet-level accuracy on ImageNet with 50 times fewer parameters. Additionally, the authors used model compression approaches to reduce SqueezeNet to less than 0.5 MB (510% less than AlexNet).SqueezeNet is used in diverse applications, from Real-Time Vehicle Make and Model Recognition [48], Indoor Obstacle Classification [49] to Fault Diagnosis of High-Speed Train Bogie [50].

3.2.7. ShuffleNet

ShuffleNet is an incredibly computation-efficient CNN architecture [51–53] explicitly created for mobile devices with minimal processing capacity. This new architecture significantly lowers computation costs while retaining accuracy using more recent operations, pointwise group convolution, and channel shuffle.

3.2.8. MobileNetv2

A novel type of convolutional layer, known as Depth wise Separable convolution, is used in the considerably quicker and smaller CNN architecture known as MobileNet. These models are thought to be highly useful for implementation on mobile and embedded devices due to the small size of the model. A practical model for mobile and embedded vision applications is provided by MobileNet, a simplified architecture that builds lightweight deep convolutional neural networks using depth-wise separable convolutions. Because of its small size, it is widely used in various mobile-based applications like the identification of protected birds [54], pattern recognition in the ubiquitous power internet of things [55], and early detection of plant diseases [56].

3.2.9. DenseNet

The DenseNet (Dense Convolutional Network) design attempts to improve the depth of deep learning networks while simultaneously enhancing training effectiveness by utilizing shorter connections between the layers. A convolutional neural network called a DenseNet [51,57] employs dense connections between layers by employing Dense Blocks to connect all layers (with matching feature-map sizes) directly with one another.

3.2.10. Fine-tuning the models

The concept of fine-tuning is referred to as transfer learning. Transfer learning is a machine learning method that uses knowledge learned through training on one kind of problem to train on another related task or domain. The early layers of deep learning are trained to recognize properties unique to a given task. During transfer learning, the final few layers of the learned network can be removed, and it can then be retrained with new layers for the desired task. Adapted learning experiments are still considerably quicker than beginning from zero, though. Compared to models trained from scratch, they are also more accurate.

The models already pre-trained on the Insect dataset were retrained using a 100% fine-tuning technique. Because none of the layers in the pre-trained networks were frozen, the back-propagation algorithm could change all of the network's weights and biases. Using the hyperparameters listed in Table 4, all models were trained using identical hyperparameters for 25 epochs.

The architectures AlexNet, ResNet-50, ResNet-101, GoogLeNet, VGG-16, VGG-19, InceptionV3, SqueezeNet, ShuffleNet, MobileNetv2, and DenseNet201 were improved on the NBAIR, Xie1 and Xie2 datasets.

4. Experiment and results

Anaconda, a Python distribution, has been used for voluminous data processing to assess a model's performance. In addition, Keras, a deep learning Application Programming Interface, is used for implementing the neural network. It is written in Python and is a programmer-friendly API.

The comparative analysis of the performance of different models on three publicly available datasets is shown in Table 5. Our primary focus was on the performance evaluation of AlexNet, ResNet-50, ResNet-101, GoogLeNet, VGG-16, VGG-19, InceptionV3, SqueezeNet, ShuffleNet, MobileNetv2, and DenseNet201.On every dataset, DenseNet201 outperformed all other architectures. ResNet-101 performance was comparable to VGG-16, VGG-19 and Inceptionv3.

Table 4. Training hyperparameters.

Minibatch size	20
Initial learning rate	0.0005
Learning rate decay	10% every five epochs

Table 5. Comparison of performances of different models in terms of test accuracy.

CNN Architecture	Test accuracy	Training duration (in hrs)	Storage requirements (MB)	Parameter (In Millions)
AlexNet	98.95	1.745	229	60
ResNet-50	99.1	21.42	150	44.5
ResNet-101	99.49	24.52	168	45.5
GoogLeNet	98.97	4.72	28	8
VGG16	99.49	129.27	519	135
VGG19	99.54	131.1	554	138
Inceptionv3	99.46	23.11	90	23
SqueezeNet	98.25	2.21	4.7	1.25
ShuffleNet	99.27	7.12	7.1	1.4
MobileNetv2	99.03	8.6	12.59	3.4
DenseNet201	99.71	83.19	79	19

Experimental results are shown in Fig. 4 through 6. As shown in Table 5, the deeper models performed better on the test. SqueezeNet performed poorly with the least accuracy, while DenseNets 201 performed well with the best accuracy. Regarding training time, AlexNet performed well, but ShuffleNet, SqueezeNet, and MobileNets are better alternatives for small architecture.

Deeper models, such as DenseNet201, VGG16, and ResNet-101, outperformed shallower networks, such AlexNet and SqueezeNet, in terms of accuracy. Additionally, deeper networks typically converged in fewer epochs than their shallower equivalent.

DenseNet's benefits include the ability to reuse feature maps through dense connections, reduce interdependence between layers by using feature maps from various layers, provide compact and different input features through shortcut connections of different lengths, and effectively combat gradient disappearance.

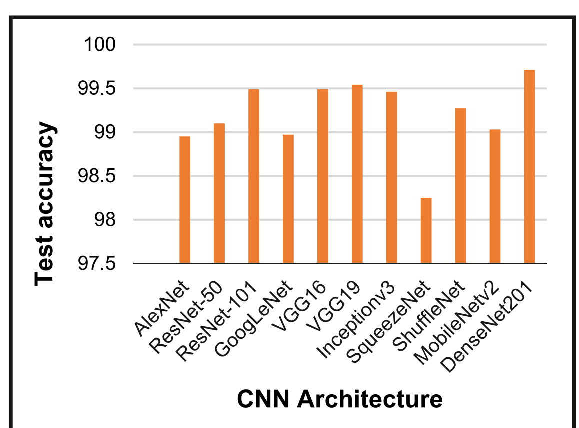

Fig. 4. Comparison of performances of different models in terms of test accuracy.

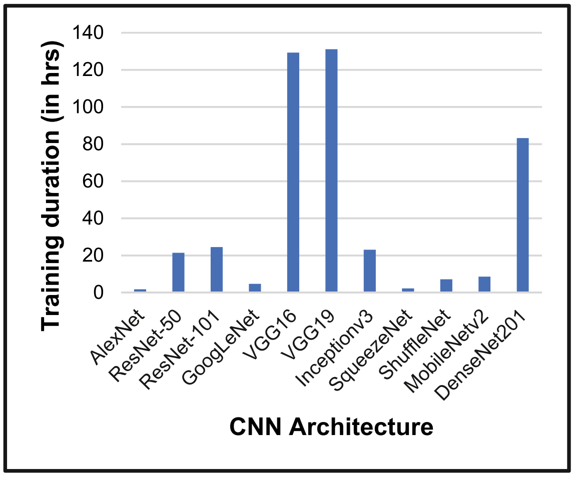

Fig. 5. Comparison of performances of different models in terms of training duration.

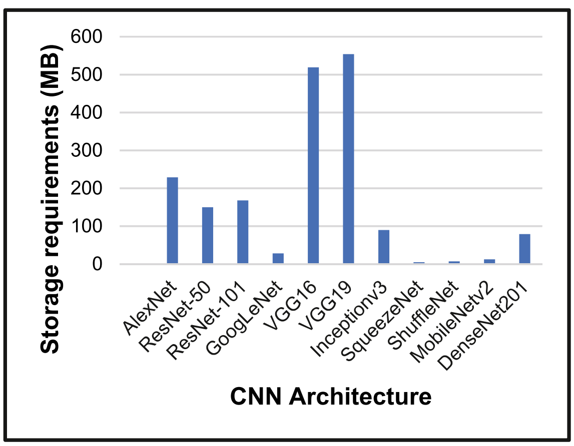

Fig. 6. Comparison of the model's performance in terms of space requirement.

Each architecture has its benefits and drawbacks, and utmost care should be taken when deciding between these networks.

Small CNN architectures are preferred in mobile and embedded applications with limited computer resources. Due to their minimal storage needs and quick training times while achieving high accuracy, ShuffleNet, SqueezeNet, and MobileNets could be considered for deployment in these applications. In particular, ShuffleNet performed better than SqueezeNet and Mobile-Nets while requiring only 7.1 MB of storage.

Unsolved questions and gaps in existing research work for the identification and classification of insects:

Researchers across the globe are working in this area. Still, many goals are yet to be achieved. Following are some gaps that need to be addressed for the timely identification and management of pests.

i. Construction of a Large Dataset

Machine learning models give good accuracy if they are trained on large datasets. However, the construction of a large dataset of insects and pests is itself a challenging task. It requires a lot of human efforts and continuous monitoring of insects in a real field.

ii. Segmentation of insects from the background

Segmentation or separation of insects from the background is one of the challenges researchers face while identifying insects, especially when the background is complex.

iii. Data Augmentation

For small datasets, models do not show good accuracy. In such cases, data augmentation is needed. Data augmentation is found to improve the accuracy of the model significantly.

iv. Differences in Insects in Different States

The complete metamorphosis of insects consists of four stages:

The egg is the primary stage; the larva and pupa are the intermediate stages, while the adult is the final stage of the metamorphosis of insects. Larva, pupas, and adults are quite different from one another. This difference is one of the most promising challenges researchers must address while identifying insects.

5. Conclusion

This paper presents a comparative analysis of work done by researchers in identifying pests and insects using a convolutional neural network and image processing techniques. Various factors affect the efficiency of identification algorithms. Numerous factors, such as the size of the dataset used, the stages of insects, and the weather in which images were taken, have an impact on the accuracy rate of identification. The deep learning-based models are more capable than shallow classifiers based on image processing techniques. DenseNet 201 performed well, with the highest test accuracy. The CNN architectures like Alex-Net, ResNet, GoogLeNet, Inceptionv3, and VGG are prevalent architectures for image identification and classification. However, they all need a large dataset to train the model. These popular models are computationally cumbersome and don't give better accuracy for small datasets.

Moreover, these heavy models are not suitable for mobile and robotics-related applications. For such real-time applications, compact and small CNN models like ShuffleNet, SqueezeNet, and Mobile-Nets are desirable. Each architecture has benefits and drawbacks, and great thought should be used when deciding between these networks.

Conflict of interest

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