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A novel insect and pest identification model based on a weighted multipath convolutional neural network and generative adversarial network

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Keywords

Classification, Generative adversarial networks, Insect identification, Multipath CNN, Pest and Insect Identification

Cover Page Footnote

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RESEARCH PAPER

A Novel Insect and Pest Identification Model Based on a Weighted Multipath Convolutional Neural Network and Generative Adversarial Network

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Abstract

Timely identification of insects and their management play a significant role in sustainable agriculture development. The proposed hybrid model integrates a weighted multipath convolutional neural network and generative adversarial network to identify insects efficiently. To address the shortcomings of single-path networks, this novel model takes input from numerous iterations of the same image to learn more specific features. To avoid redundancy produced due to multipath, weights have been assigned to each path. For Xie2 dataset, the model shows 3.75%, 2.74%, 1.54%, 1.76%, 1.76%, 2.744%, and 2.14% performance improvement from AlexNet, ResNet50, ResNet101, GoogleNet, VGG-16, VGG-19, and simple CNN respectively. To the best of our knowledge, no researchers have used a multipath convolution neural network in insect identification.

Keywords: Classification, Generative adversarial networks, Insect identification, Multipath CNN, Pest and insect identification

1. Introduction

Real-time monitoring and management of pests and insects are essential for the healthy growth of crops. Every year about 37% of rice crop gets damaged due to pests and insects. Farmers could have lost about 70% of their crops without any preventive measures due to pests and insects [1].

Crop loss statistics differ significantly from one country to another and from one crop to another. For perennial crops like stone fruits and apples, up to 5% of production losses are typical in the Netherlands, whereas a coffee crop in Brazil may experience losses of up to 45%. Agricultural research emphasizes models that consider a few parameters, from qualitative crop injuries to quantitative losses, from pre-to post-harvest damage, even though crop loss assessments are notoriously difficult to execute. The current crop losses due to insects to major crops in India [2] are shown in Table 1.

Integrated crop management, which includes pest management, is the only option available for improving crop yield [3] and ensuring food security [4].

In recent years, Artificial Intelligence-based techniques have been prevalent in insect identification. Deep learning models and convolutional neural networks are up-and-coming for identifying and classifying insects. The high accuracy of the model is also one of the reasons for the popularity of Convolutional Neural Networks (CNN) among researchers.

When competing in the ImageNet Large-Scale Visual Recognition Challenges, CNN shows excellent results [5]. The findings, however, are only

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Table 1. Current crop losses due to insects to major crops in India (Source: [2]).

Crop	Actual Production (million tonnes)	The approximate estimated loss in yield		The monetary value of the estimated loss (USD million)
		%	Total (million tonnes)	
Cotton	58.17	30	24.93	15,767.69
Rice	106.65	25	35.55	8467.36
Maize	24.26	18	5.33	1268.41
Rapeseed mustard	7.88	20	1.97	1026.7
Other oilseeds	15.16	12	2.07	1215.55
Groundnut	9.71	15	1.71	1172.13
Pulses	19.78	15	3.49	2285.29
Coarse cereals	19.03	8	1.65	378.2
Sugar Cane	352.14	20	88.04	3160.25
Wheat	93.51	5	4.92	1135.75
Total average		16.8		3877.32

presented as overall performance for all image classes. There is no additional study of why specific images perform worse than others or suggestions for improving them. Single-path CNN is more likely to retrieve the image's high-frequency components. However, after multiple iterations of convolution and pooling, single path CNN allows the simple shape and less-textured objects to eventually vanish in the clustered background. As a result, the final feature vector cannot effectively depict foreground objects and produces poor prediction results. To address the shortcomings of single-path structure networks, in this research, a new multiple pathways convolutional neural network in combination with Generative Adversarial Network (GAN) has been proposed to identify pests and insects. The proposed model takes input from numerous iterations of the same image to learn more specific features. This paradigm more effectively delivers visuals than the traditional single-path model. CNN is a data-hungry model, which requires extensive data set for training. The collected dataset is increased by 30 times using GAN.

The main objective of taking multipath is the ability to identify image information from all planes [6]. To reduce the redundancy produced by multipath, weights have been assigned to each path. The weighted multipath network overcomes the drawback of a single-path network. These paths learn different aspects of images and retain more valid information than a single path. So far, this concept has not been used in insect identification.

The model's performance is compared with AlexNet, ResNet50, ResNet101, GoogleNet, VGG-16, VGG-19, and simple CNN . The proposed model showed the highest accuracy of 98.16% and outperformed the compared models. The model has high practical application value and can be integrated with mobile devices for practical insect control and management tasks.

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, preprocessing techniques, and the proposed weighted multipath CNN methodology. Section 4 presents results and the comparative analysis of work done with other states of the art. Finally, section 5 concluded the work.

2. Related work

Machine learning, in combination with Image processing, is revolutionizing the applications of computers in day-to-day life. It is being used in diverse fields, including for the identification of plants [7], recognition of fruits and vegetables [8], extraction of features for disease detection [9], fraud detection [10], surveillance applications [11], Internet of Things based applications [12], and even in the prediction of stock exchange [13].

2.1. Insect identification using computer-aided techniques

Various image-processing techniques were used for insect identification [14]. Most image processing techniques require preprocessing, like segmentation and feature extraction. The preprocessing techniques, features selected to be extracted, classifier used, and the knowledge of the suitability of the classifier play an important role in modeling an efficient algorithm for the identification of insects. Still, one cannot set a priori among different preprocessing techniques and shallow classifiers.

In the paper [15], the authors have used the SURF algorithm in insect images to extract local features.

To accomplish this, firstly, 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. As a result, the accuracy of the Speeded Up Robust Features (SURF) based recognition algorithm is 89%.

The work described in the paper [16] 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 Support Vector Machine (SVM) structure. For image acquisition, a mobile agricultural robot is used. However, images are taken under natural light. For gamma operators, the grayscale images were not suitable as input. Therefore, gamma operators were utilized with the captured RGB images. Parasites were classified using an SVM classifier. Suitable regions and color indexes were chosen to successfully detect strawberries' targeted thrips and parasites.

For the identification of stonefly larvae, the studies conducted in [17] proposed a computer vision approach. Images of stonefly larvae are captured through a semi-automated mechanical manipulation device. The concatenated feature histogram method is presented in the paper. At first, the region of interest is identified, and the identified areas are represented as scale-invariant feature transform (SIFT) vectors. The SIFT vectors are further classified as learned features for generating a histogram of detected features.

These steps were collectively named as concatenated feature histogram method. The watershed segmentation algorithm and the curvature-based region (PCBR) are used to find the stable regions of high curvature. A separate dictionary is computed and concatenated for each region detector with the histograms before the final classification step. The effectiveness of this work was demonstrated by the fact that this proposed approach can be used to differentiate some stonefly taxa, two of which, Calineuria and Doroneuria, are found to be hard to discriminate even by experts. Three-class accuracy(pooling Calineuria and Doro-neuria) of 95% and a four-class accuracy of 82% were achieved by all three detectors.

In the paper [18], 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. Segmentation, morphological operations, and color property estimation were used to detect the insects, and a feed-forward artificial neural network was employed for classifying insects. The researchers reported a high precision of (0.96), recall of (0.95), and F-measure of (0.95) values for recognition of whitefly. However, a precision of 0.92, recall of 0.96, and F-measure of 0.94 were obtained for the thrips identification.

The studies conducted in [19] have introduced a low-cost and long-term automatic pest identification system. 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. Even for the low-resolution images, the correlations of determination were found to be different for different insects. i.e., for whitefly, thrips, and aphids.

In the paper [20], researchers expanded their previous version of the LOSS algorithm. Researchers found that the efficiency of the LOSS algorithm can be increased, if the scale-invariant feature transform is used to detect and classify a more significant number of pests. Therefore, the modeled LOSS V2 algorithm, which is a machine vision system, uses the LOSS algorithm followed by scale-invariant feature transform. The LOSS V2 algorithm shows greater accuracy, with a determination coefficient $R2 = 0.99$.

All the discussed techniques need a feature extraction step. The image has to be gone through a feature extraction process that requires human supervision. The prime benefit of using CNN for recognition compared to its predecessors is that it detects the essential features without needing human expertise.

2.2. *Insect identification using convolutional neural networks*

Researchers have recently studied deep-learning applications in plant diseases and insect identification [21]. In addition, CNN has shown outstanding performance in classifying plant diseases [22]. In CNN, the convolution layer is a feature extractor. Therefore, it requires no explicit feature extraction step. Instead, the image can be given as input directly.

The dataset of tomato pests and diseases will be compiled in the study [23] under real-world environmental conditions. Furthermore, the feature layer of the Yolo V3 model will be optimized using an image pyramid to achieve multi-scale, which enhances the Yolo V3 model's speed and accuracy of feature recognition and rapidly and precisely

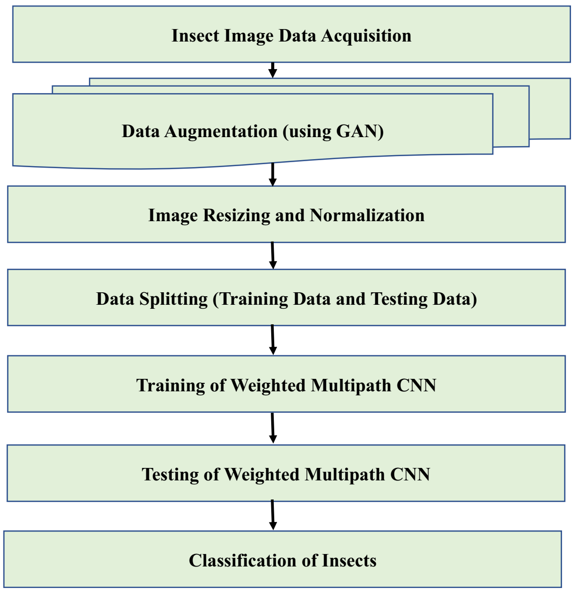

Fig. 1. Workflow for the methodology of the insect identification model.

identify the type and location of tomato diseases and pests. The research, as mentioned earlier, has made significant advancements in the core technology for recognizing tomato pests in natural environments, which serves as a model for intelligent recognition and technical applications of plant diseases and pest detection.

To classify insects at the species level from habitus images, CNN is used in [24]. Researchers have created a database of 361 carabid beetle species to accomplish this task. The CNN successfully classified 51.9% of test data at the species level and 74.9% at the genus level.

In the paper [25], a small CNN model is proposed 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 devised model is compared with NasNet Mobile, MobileNet, and SqueezeNet CNN architecture. The model has achieved an accuracy of 93%. The size of this small CNN is 99% smaller than VGG16.

Authors in the paper [26] used a convolutional neural network on a database of 500 images of rice diseases, which include Rice Bacterial Wilt (RBW), Rice Blast (RB), Rice Bananas 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). The model is very efficient and more accurate than the support vector machine (SVM), standard BP algorithm, and particle swarm optimization (PSO) in identifying the rice diseases of 10 classes.

An improved convolutional neural network is proposed in the paper [27]. In the proposed work, for generating a relatively smaller number of proposal windows, the Region Proposal Network is used, which improves prediction accuracy and accelerates the computations.

To ensure food security, early detection and management of pests are necessary, but it is also essential to keep stored grain safely. In the paper [28], for the recognition and detection of eight common stored grain insects, an R-FCNR-FCN is proposed, which uses the concept of neural network architecture. To precisely locate the insects in stored grain, RPN from the feature map was used. Furthermore, to improve the accuracy and speed of detection of stored grain insects, an improved DenseNet-121 was suggested in the research. As a result, the accuracy of the model is achieved to be 88.06%.

A deep residual learning model is proposed in [29] to identify the pest in images with a complex background. The proposed model was much more accurate than the support vector machine and BP neural network. In the study, the authors have suggested that the efficiency of training the deep convolutional neural network models can be improved if one can use deep residual learning. The model was tested for the ten classes of pests, and this ResNet-101-based model's accuracy was 98.67%.

In the paper [30], the authors have used CNN with an 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, a trained CNN took preprocessed images as input. The precision-recall AUC achieved was 0.934, and the log average miss rate was 0.0916.

In this regard, in a study in [31], a performance comparison of 10 deep learning models using the PlantVillage dataset, namely AlexNet, ResNet-101, GoogleNet, DenseNet201, Vgg16, Inceptionv3, InceptionResNetv2, SqueezeNet, ShuffleNet, and MobileNet has been done by researchers. Each model has specific strengths and weaknesses. In comparison, MobileNet, ShuffleNet, and SqueezeNet, with their small architectures, are suitable for mobile applications and embedded systems with limited computational resources but can achieve high accuracy with short training times and small memory requirements.

Table 2. Different category/class names of insects of dataset IGKV1.

Sr.No.	Category/class name	No of images
1	Green Horned Caterpillar	3135
2	*Acronicta tridens* caterpillar	3270
3	Rice Stink Bug	3000
4	Helicoverpa	3561
5	Thistle Caterpillars	3019
6	Dysdercus Cingulatus	3061

CNN has been found to be very popular in recent years for insect identification. Many researchers have also focused on recognizing different pests, insects, and diseases using different architectures of CNN [22,32,33,34]. The limitation of CNN is that it requires extensive data to train the network. Secondly, it requires going deeper to find good efficiency.

To overcome these drawbacks, a weighted multipath CNN is proposed in the paper. Furthermore, to augment the data to 30-fold, GAN is used.

3. Materials and methods

The workflow of the model is depicted in Fig. 1. Firstly, images of insects of six classes have been collected. Then, the collected data was augmented 30 times using GAN. GAN is popularly used to generate the synthetic dataset. Augmented data is resized and normalized. Then, the dataset is partitioned into testing and training data. 80% of the data is used to train the proposed multipath weighted CNN. Finally, the model is tested on the rest of the 20% data. The detailed description of the model is as follows:

3.1. Insect image acquisition

In the process of insect image acquisition, 3135 images of Green Horned Caterpillar, 3270 images of the *Acronicta tridens* caterpillar, 3000 images of Rice Stink Bug, 3561 images of Helicoverpa, 3019 images of Thistle Caterpillars and 3061 images of Dysdercus Cingulatus have been collected from the fields of Durg and Raipur Districts of Chhattisgarh, India with the help of Indira Gandhi Krishi Vishwa Vidyalaya, Raipur. Images were acquired between July'2021 to Oct'2021 using five types of mobile cameras. The acquired dataset is named as IGKV1. Table 2 shows the different categories of insects. Sample image of each class of insects is shown in Fig. 2.

3.2. Data augmentation

Data augmentation techniques are used to resolve the problem of the unavailability of sufficient datasets for training. The generator adversarial network

Fig. 2. Sample images of each category of insects used in multipath weighted CNN for insect identification.

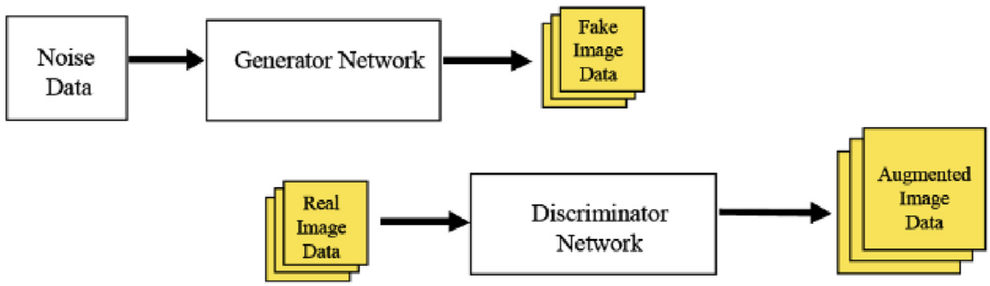

Fig. 3. Generator Adversarial Network for augmenting insect data to many folds.

used for augmenting the insect image data is shown in Fig. 3.

It has two networks, a generator network and a discriminator network [35]. The generator network artificially generates fake data, while the discriminator network tries to discriminate between real and counterfeit data [36]. The generator adversarial network used for augmenting the insect image data is shown in Fig. 3.

In the GAN model, the generator network attempts to fool the discriminator network, and the discriminator network tries to struggle against being fooled [37].

The used generator network has five transposed convolutional layers, four ReLU layers, four batch normalization layers, and a Tanh Layer at the end of the model. The discriminator network has five convolutional layers, four leaky ReLU, and three batch normalization layers [38].A detailed description of GAN is shown in Fig. 4.

The performance of CNN depends on the size of the training data set. Due to the small size of insects and the varying life cycle, acquiring a large dataset is difficult. Hence in the research work, data is augmented 30 times using the GAN model. The generated and actual data are used to train the model and subsequently increase the model's efficiency.

3.3. Resizing and normalization of image data

Augmented data is resized to the same size of 299 × 299. Normalization is applied to all the resized images. For normalization, pixel values are subtracted by the mean of all image pixels and divided by the variance, as given in Eq. (1),

$$y = \frac{x - \overline{x}}{\sigma} \tag{1}$$

where $\overline{x}$ is the mean of all pixels, y is the normalized pixel value, and σ is the variance.

3.4. Data partitioning

After preprocessing, the augmented dataset is partitioned into two sets training set and a testing set. 80% of the dataset is used for training, while 20% is used for testing.

3.5. Crop insect identification model

Traditional image processing methods require complex image preprocessing and human expertise. In recent years, CNN has been quite popular in image analysis and performing well in object recognition. In the present study, a multipath weighted convolutional neural network [39] is proven to be an effective way to improve the performance of CNN models for insect identification. In the proposed model, three pathways are used, out of which the first and second paths are used to better approximate local dependencies. In contrast, the third path is used to approximate global dependencies of the neighboring pixels, followed by a machine learning classifier to categorize the insects. To each path, images with different field sizes are given as input. To find the impact of an average field size of images, a concatenation function Eq. (2), has been used. It concatenates the output of the last convolution layers of each path, followed by a SoftMax function.

$$x_i = concat(conv_1(x_i), conv_2(x_i), conv_3(x_i)) \tag{2}$$

Different paths can be used to design different feature extractors. The multipath architecture of CNN allows several sparse local and global features to merge. When the width of the network increases, several paths can introduce redundancy. This may lead to overfitting. Therefore a weighted multipath CNN [40] was introduced to avoid the redundancy produced by multiple paths. A multipath weighted CNN for insect identification is shown in Fig. 5.

As shown in Fig. 5, each path has been assigned a weight coefficient during the network training.

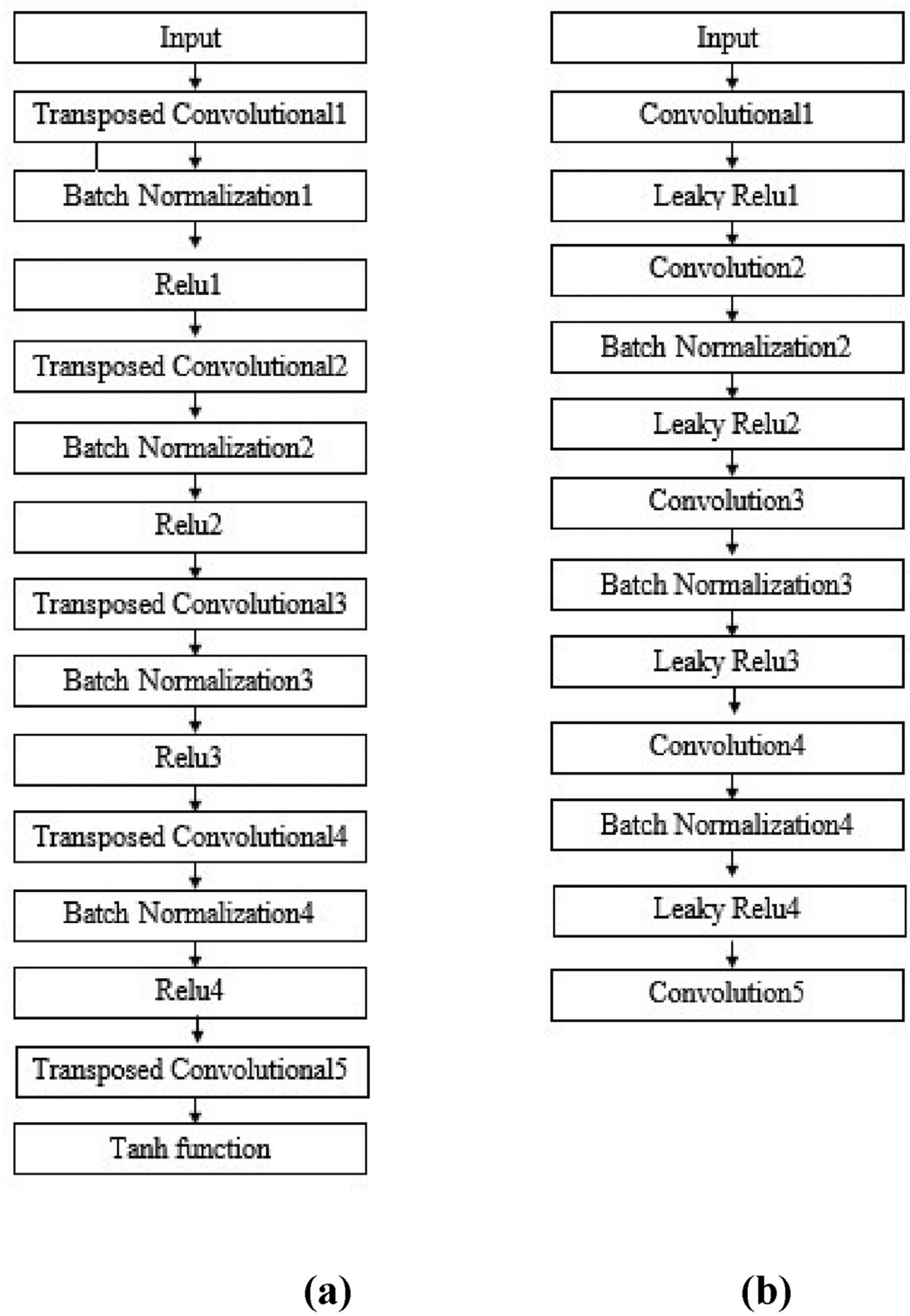

Fig. 4. Detailed description of GAN (a) Generator Network (b) Discriminator Network.

These weights are evaluated randomly at the time of the initialization process and updated at the time of network training. The output of each path is multiplied by the weight of that path to find the average of these weighted outputs, as shown in Eq. (3),

$$x_i = \frac{w1{*}conv_1(x_i) + w_2{*}conv_2(x_i) + w_2{*}conv_2(x_i)}{n} \tag{3}$$

4. Experiment and results

To implement the model, Anaconda, a distribution of Python, has been used for voluminous data processing. 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.

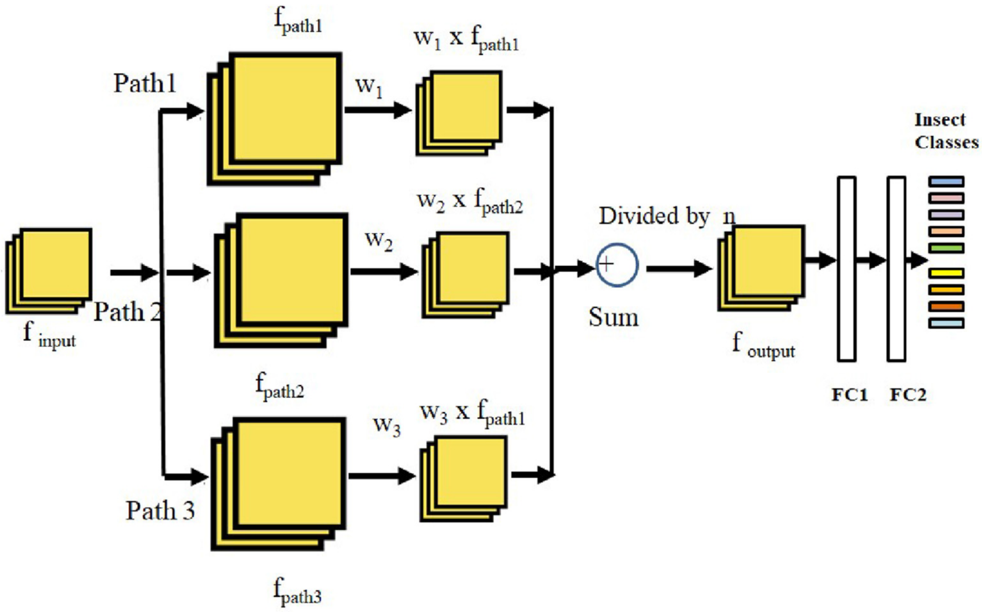

Fig. 5. Weighted multipath CNN for insect identification.

Table 3. Performance of Weighted Multipath CNN on various Insect Datasets.

Data set	Accuracy (in %)
NBAIR	95.12
Xie1	96.12
Xie2	95.45
IGKV1	98.16

In CNN, the convolutional layer is used for feature extraction. To learn more about global and local features, different paths have been used in the proposed model. When we increase the number of layers in multipath CNN, the chance of overfitting increases, and redundancy may also introduce due to multipath. Hence weights have been assigned to each path.

The performance of Weighted Multipath CNN is tested on various Insect Datasets. The performance of the model on four datasets is shown in Table 3.

This weighted multipath CNN gives an accuracy of 95.12% on NBAIR, 96.12% on Xie1, 95.45% on Xie2, and 98.16% on the dataset IGKV1, which

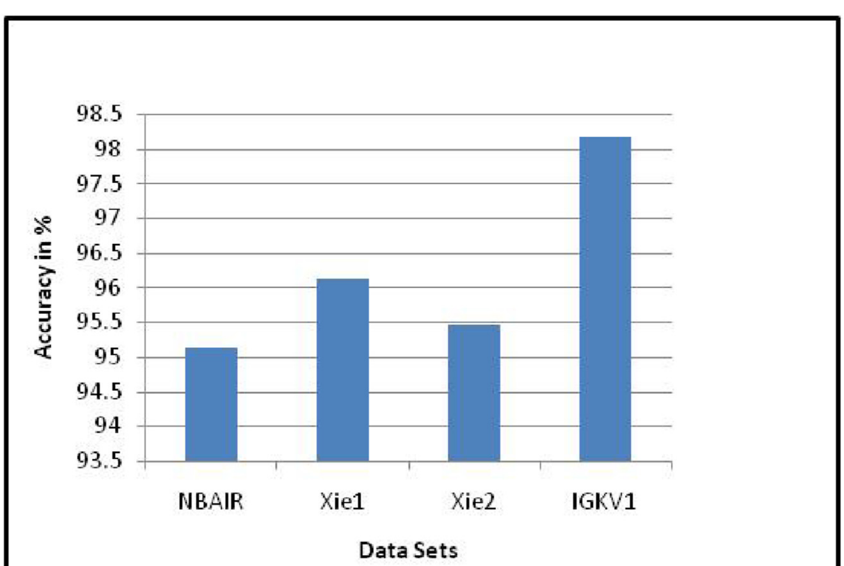

Fig. 6. Accuracy Comparison of model with different datasets.

Table 4. Comparison of Weighted Multipath CNN with other models on various insect datasets.

Model/Dataset	NBAIR	Xie1	Xie2	IGKV1
AlexNet	93.8	94	92	93.4
ResNet50	95.2	95.8	92.9	95.12
ResNet101	95	95	94	94.1
GoogLeNet	93.9	96.2	93.8	94.1
VGG-16	92.9	96.2	93.8	94.1
VGG-19	93.1	94.9	92.9	93.1
Simple CNN	93.12	94.1	93.45	96.12
Proposed Weighted Multipath CNN	95.12	96.12	95.45	98.16

simple CNN respectively, while for Xie1 dataset, the model is showing 2.26%, 0.33%, 1.18%, 1.29% and 2.15% performance improvement from AlexNet, ResNet50, ResNet101, VGG-19, and simple CNN respectively.

On the other hand, for the Xie2 dataset, the model is showing 3.75%, 2.74%, 1.54%, 1.76%, 1.76%, 2.74%, and 2.14% performance improvement from AlexNet, ResNet50, ResNet101, GoogLeNet, VGG-16, VGG-19 and for IGKV1 the model is showing 5.10%, 3.20%, 4.31%, 4.31%,

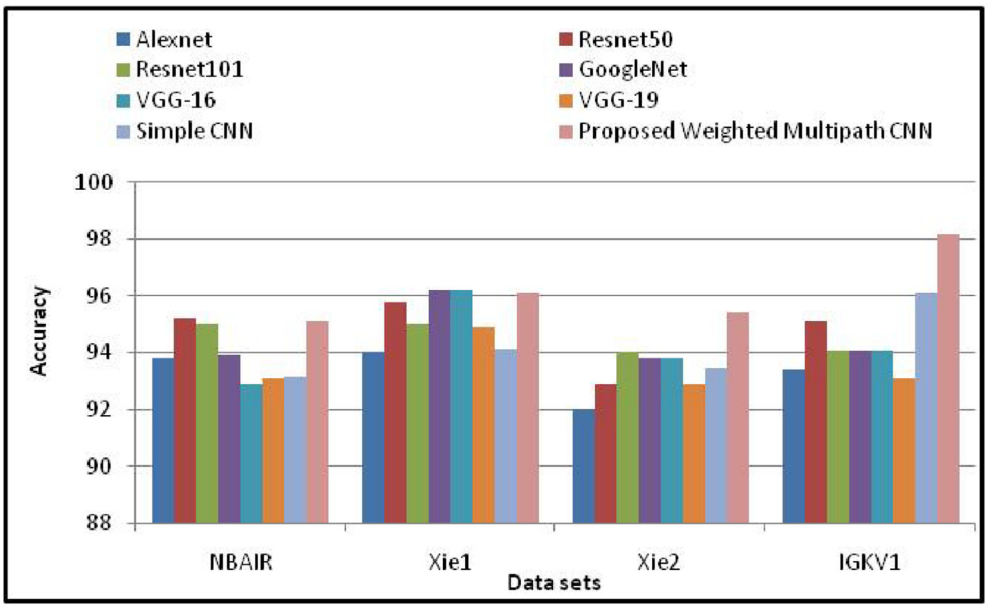

Fig. 7. Accuracy Comparison with different models for different datasets.

outperforms other models. The comparative performance analysis of the model on four different datasets is shown in Fig. 6.

The proposed multipath weighted CNN model's performance is compared with seven different models, namely AlexNet, ResNet50, ResNet101, GoogLeNet, VGG-16, VGG-19, and simple CNN on four datasets for insect identification. Three of these datasets are publicly available insect datasets: NBAIR, Xie1, and Xie2 datasets, and the fourth dataset is acquired and augmented dataset IGKV1. The National Bureau of Agricultural Insect Resources (NBAIR) dataset consists of 40 classes of insect images, while the second and third dataset (Xie1, Xie2) contains 24 and 40 classes of insect images, respectively.

On comparing the performance of the proposed model for the NBAIR dataset, the proposed model is showing 1.41%, 0.13%, 1.30%, 2.39%, 2.17%, and 2.15% performance improvement from AlexNet, ResNet101, GoogLeNet, VGG-16, VGG-19, and 4.31%, 5.44% and 2.12% performance improvement from AlexNet, ResNet50, ResNet101, GoogLeNet, VGG-16, VGG-19, and simple CNN respectively. The comparative analysis of the model with other models is shown in Table 4.

As compared to other methods, the proposed algorithm is found to be more effective for insect identification. The comparative analysis is shown in Fig. 7.

5. Conclusion

This contribution presented an insect identification model that uses a weighted multipath CNN and GAN. The proposed model gives the best classification accuracy results for different categories of insects. The comparison of the result with the traditional insect identification algorithm showed a noteworthy improvement in the accuracy of insect identification. A combination of weighted multipath

CNN and GAN is a positive attempt to tackle insect identification in a simple way. The proposed work is expected to assist researchers and entomologists who are working in the area of insect identification and pest management. All the images were taken on sunny days, so expected to fail abysmally. In the future, the model will be trained to cover images of insects taken in all weather conditions. The proposed model can also be used for the early identification of plant diseases.

Conflict of interest

There is no conflict of interest. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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