

Integration of a Dual Hybrid Deep Convolutional Neural Network Framework for Insect Taxonomic Classification

M. Santhiya ¹, Dr. S. Karpagavalli ²

¹Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore

²Associate Professor and Head, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore

E-mail: santhiyam310phd@gmail.com

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Abstract:

Insects constitute a vital element within numerous ecosystems, exerting significant influence on biodiversity, ecological dynamics, and the well-being of human health as well as natural resources. The taxonomic group "Insecta" stands out as one of the largest and most extensive within the realm of biodiversity taxonomy. Given their importance, sustainable management of insects, ecosystems, and their interrelationships is vital for the survival of all organisms. The novel approach for classifying insect images presented in this research is based on systematic taxonomic ranks at the order, family, and species levels and combining deep convolutional neural network, termed as "Dual Hybrid". Convolutional Neural Network This model utilized a total of 6060 images for classification at the order level, 3740 images for the family level, and 1582 images for the species level. Various fine-tuned pre-trained DCNN models were employed to create the hybrid model. This proposed research work mainly focuses on increasing accuracy and efficiency of taxonomic level insect images classification and identification. Experimental results indicate promising outcomes. The DHDCNet model proposed in this research achieved classification accuracies of 98.97% for order classification, 97.37% for family classification, and 89% for species classification across five distinct insect classes. A detailed evaluation of the model's performance was conducted using metrics such as precision, recall, and F1-score, which provided valuable insights into its effectiveness across various dimensions.

Keywords: Insect classification and identification, Data Augmentation, Pre-Trained Models, Deep Convolutional Neural Networks (DCNN), Deep Learning, Hybrid Method, Dual Hybrid Deep Convolutional Neural Network.

1. Introduction

Establishing precise understanding of the identity, geographic prevalence, and evolutionary pathways of living species is crucial not only for sustainable human development but also for the preservation of biodiversity [1]. Insects constitute over 50% of all documented species within the "Animalia" kingdom and "Arthropoda" phylum, representing a substantial portion of the Earth's overall biodiversity [2]. In the traditional approach, resulting in a labour-intensive process with limited speed, time-consuming and need experts' knowledge. This approach falls short in fulfilling the requirements for effective insect identification and detection [3]. Hence, there is considerable importance in investigating the principles and techniques for computer Vision based automatic insect classification.

In recent times, the computer vision technology has laid the technical foundation for achieving image classification. Machine learning (ML) has demonstrated considerable success results in image

classification tasks. However, it encounters challenges in learning complex patterns present in images of insect species, particularly when these species have morphological similarities. Deep learning (DL) represents advanced approach that leverages neural networks (NN) designed to function in a manner comparable to the functioning of the human brain [4]. Recent advancements in DL include the use of Deep Convolutional Neural Networks (DCNNs) with fine-tuned pre-trained models and the adoption of hybrid approaches to design model architectures. These advancements have jointly enhanced the precision and effectiveness of insect species identification and classification processes [5]. In DCNN, fine-tuning is a widely employed and efficient approach that used a pre-trained NN model, often trained on large datasets like ImageNet [6].

Choosing the most effective classification technique is vital for accurately distinguishing insect species through general image classification. Key considerations include the specific insect groups under study, the experimental setup (e.g., digital or manual, in-field or off-field), and the evaluation of image-based insect detection and classification methods. Assessing these methods requires analysing performance factors such as time complexity, memory usage, precision, and recall, along with the image acquisition techniques employed. This comprehensive evaluation ensures accurate and reliable insect identification. From this perspective, multi-class classification of insects using CNN frameworks like VGG19 [7] has been explored in previous research. The taxonomic classification focused on five insect categories within the class Insecta: butterfly, dragonfly, grasshopper, ladybird, and mosquito. Data for these insects was collected and utilized for training, testing, and validating the CNN model. In addition, various data augmentation techniques were used to ensure a balanced dataset, reducing overfitting in the CNN model.

The primary objective of this research work is to employ hybrid models based on DCNN for classifying insect species within six different insect orders, focusing particularly on the “Andrena” species within the “Andrenidae” family, which is derived from the “Hymenoptera” order in systematic taxonomic hierarchy. The proposed model “DHDCNet Model”, was selected for its superior performance and high accuracy in achieving the expected results across all taxonomic levels. This paper used three distinct datasets—order level, family level, and species level—to classify the images of insects at the taxonomic hierarchy levels. The images were trained utilizing fine-tuned pre-trained DCNN models including Xception, Resnet 152, VGG 19, Inception v3, and Mobile Net V2. The rest of this research work is structured as follows: Section 2 presents a review of relevant researches on taxonomic-level insect image classification. Section 3 describes the materials and methods, including DCNN and pre-trained models, the methodology of the proposed approach, and a brief explanation of data collection and preprocessing techniques such as augmentation. The experimental results are discussed in Section 4, and Section 5 concludes the paper with a review of the study and recommendations for future research directions.

2. Related Works

In recent times, numerous studies have leveraged DL particularly CNN methods for many species image classification and identification like plants, fish species, birds and insects, yielding promising outcomes. The following presents a concise summary of notable accomplishments within this research field. In [8] Ong, Song-Quan, and Suhaila Ab. Hamid proposed a classification task based on the taxonomic ranks of insects, specifically orders, families, and genera. They conducted a comparison of

the generalization capabilities of four advanced DCNN architectures. For the order level, they utilized three specimens, consisting of 7 classes, family level, 5 specimens were employed, representing 25 classes. Additionally, at the genus level, 5 specimens were used, encompassing 25 classes. They used Mobile Net V2, Xception, VGG 19 and Inception V3 architectures for classification task. But low performance in classifying genus level.

In [9], Yang, Fan, and their team developed a Fine-Grained Visual Classification (FGVC) approach using deep learning to investigate insect recognition and classification. They utilized Inception V3, VGG16_bn, and ResNet50 models in their research. Inception V3 achieved an accuracy of 98.69%, while VGG16_bn and ResNet50 achieved accuracies of 97.80% and 97.94%, respectively. To enhance model accuracy further, they implemented label smoothing technology to mitigate errors originating from label inaccuracies. Several CNN architectures, including ResNet101, Wide-ResNet101, InceptionV3, and MnasNet-A1 [10], were tested for identifying bumble bee species from images. However, these models did not achieve high accuracy and recall. Kaiming He [11] proposed Resnet 152 architecture for image recognition task. But the accuracy was not effective. In order to resolve the classification problem for plant species described in [12], Wei Liu et al. utilized the Flavia and HN plant datasets. The Flavia dataset contained 32 plant species, while the HN dataset included 10 plant species. The researchers proposed a deep convolutional neural network architecture called ResNet. However, these models did not achieve high accuracy and recall.

In [13] Cao, Xu, and other collaborators introduce a novel approach in their research, focusing on the recognition of common field insects through TL. Their research involves the collection and classification of 9 distinct insect species, utilizing digital image processing techniques and generative adversarial networks to expand the insect dataset. They establish a model based on TL, harnessing the learned features of VGG16, VGG19, InceptionV3, and InceptionV4 from the ImageNet dataset to classify and recognize insects. In [14], Valan, Miroslav, et al. proposed an innovative approach aimed at developing an efficient method for transferring CNN features. Their study involved the utilization of four distinct datasets. VGG16 achieved more than 90% of accuracy in the classification tasks. In [15] Hansen, Oskar L. P., and their team developed a fine-tuned CNN image classification approach in their research. The CNN demonstrated an accuracy of 51.9% in correctly classifying 19,164 test images at the species level and achieved 74.9% of low level accuracy at the genus level.

In the study by Anwar, Zeba, and Sarfaraz Masood [16], an ensemble-based model leveraging transfer learning (TL) was proposed. The experimental setup incorporated pre-trained models such as VGG16, VGG19, and ResNet50, which were combined using a voting classifier ensemble technique. The model was evaluated on the IP102 dataset, a benchmark dataset comprising over 75,000 samples across 102 classes. The Automated Bee Identification System (DeepABIS) [17], a deep learning-based system built on the MobileNetV2 model, was developed for bee identification. However, its accuracy and precision were found to be unsatisfactory. In [18], the author used data from three fish species captured by the Deep Vision trawl camera system. The proposed CNN model achieved an accuracy of 94%. In [19], the author collected images of 68 Pantanal fish species sourced from Google Images, categorized by taxonomic levels. Several pre-trained models were tested, with Inception V3 ultimately achieving 87.3% accuracy at the species level. However, its accuracy and precision were still deemed unsatisfactory. A new technique [20] was developed for classifying butterfly species using pre-trained

CNN frameworks, including VGG16, VGG19, MobileNet, Xception, ResNet50, and InceptionV3. However, these models exhibited low recall and precision. Based on the insights from the aforementioned literature and related studies, it would be beneficial to explore the development and training of various pre-trained DCNN models to achieve more accurate classification of insect species.

3. Proposed Methodology

In this section, the presented DHDCNet model for classifying and identifying of order, family and species level insect images. Figure 1 illustrates the procedural diagram of the proposed methodology.

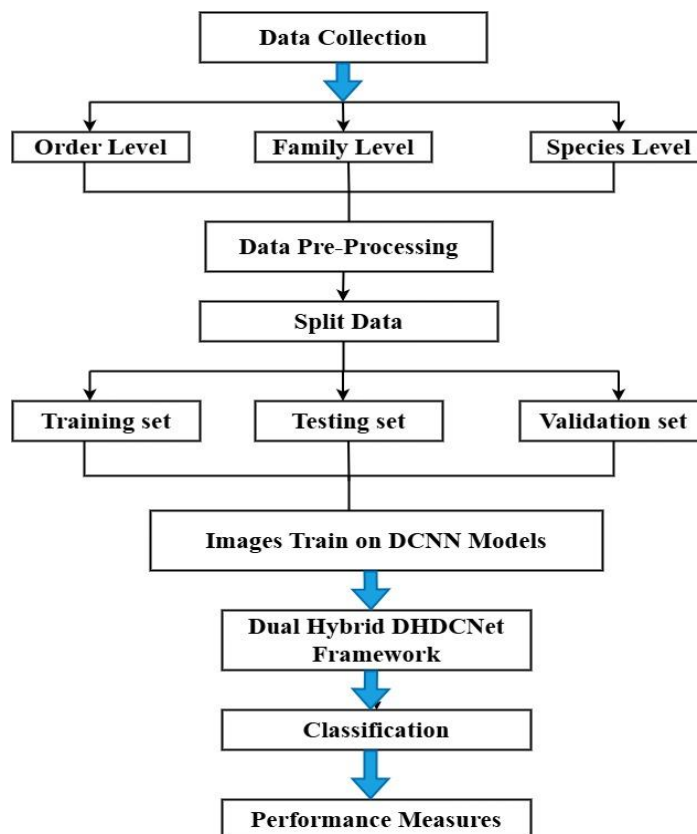


Figure 1: Procedural diagram of the suggested research work

3.1 Data collection

In the context of a data collection focused on insects, Images were collected from various online sources such as Kaggle, GBIF - Insecta (gbif.org) and Bug guide - Class Insecta - Insects - BugGuide.Net. This study involved the use of three levels of datasets. First one is order level and included six different classes: Diptera, Coleoptera, Hemiptera, Hymenoptera, Lepidoptera, and Odonata. In this order level data comprises 100 images per class, totalling 600 images in all. On the other hand, was more specific, concentrating on insect families. It encompassed five different family classes: Andrenidae, Anthophoridae, Apidae, Colletidae, and Dasaypodaidae. In this level each class contains between 68 and 80 images, with a total of 374 across all classes.

Finally, species level data delved even deeper, focusing on insect species. It featured five distinct species classes: *Andrena Scotica*, *Andrena fulva*, *Andrena Haemorrhhoa*, *Andrena cineraria*, and *Andrena vaga*. In this species level dataset, each class contains between 33 and 57 images, totalling

230 images were utilized. Figure 2 depicts the sample images in order, family and species levels. This comprehensive approach was collected and organized insect image data according to various taxonomic levels likely enabled a more detailed and precise analysis of insect diversity and classification. These collected data were utilized to classification and identification tasks. Table 1 illustrates the different classes in taxonomic levels.

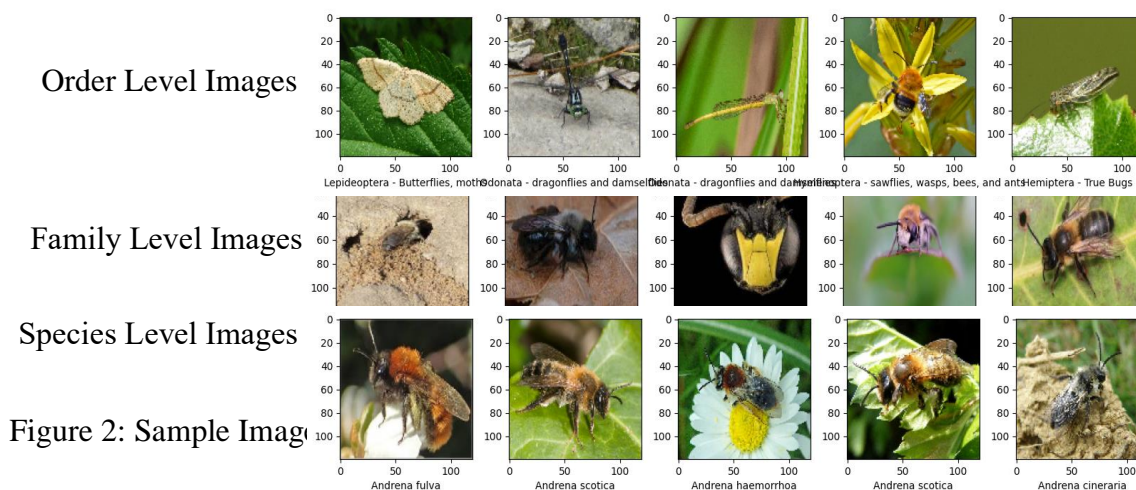


Figure 2: Sample Images

Table 1: Data collection with classes in order, family and species taxonomic levels

| Order Level Classes | Family Level Classes | Species Level Classes |
|---------------------|----------------------|-----------------------|
| Diptera | <u>Andrenidae</u> | Andrena Scotica |
| Coleoptera | Anthophoridae | Andrena fulva |
| Hemiptera | Apidae | Andrena Haemorrhoea |
| <u>Hymenoptera</u> | Colletidae | Andrena cineraria |
| Lepidoptera | Dasypodidae | Andrena vaga |
| Odonata | - | - |

3.2 Data preprocessing

In the preprocessing stage of the image classification pipeline, the input data for DCNN models was prepared. Initially, all images underwent resizing to a resolution of 224x224 pixels. This resizing step ensures consistent and compatibility of the input data with the network architectures being utilized, thereby enhancing the effectiveness of the subsequent feature extraction process. To improve the quality and clarity of the images, employ various image enhancement techniques, such as contrast adjustment, brightness correction, and noise reduction. Additionally, utilize lambda functions to

further process and standardize the data. Lambda functions enable the application of custom transformations to the images, encompassing data augmentation, normalization, and colour channel adjustments.

Several functions were applied in the data augmentation process: the fill mode was configured to nearest; both horizontal and vertical flip functions were activated, with the rotation range of 2 degrees; and the width, height, shear, and zoom ranges were all set to 0.2. These processes led to an expansion in the dataset volume. At the order level, the dataset was expanded through data augmentation, resulting in a total of 6060 images. Of these, 4242 images were allocated for training, 908 for testing, and the remaining images for validation. In the family-level dataset, each class contained 680–800 images, totalling 3740 images. Among these, 2616 images were used for training, 560 for testing, and 564 for validation. The species-level dataset consisted of 1582 images, with 1105 designated for training, 235 for testing, and 242 for validation purposes.

Subsequently, the dataset was partitioned into three sections: 70% used for training, 15% for testing, and 15% for validation. These steps ensure that the images are prepared for efficient training, enabling the DCNN models to effectively learn features from the data and make accurate and reliable predictions for insect image classification.

3.3 Taxonomic Level Insect Image Classification using DCNN

An explanation of the DCNN-based models is given in this section. The aim of present research work is to create an efficient method for classifying and identifying insect images at various taxonomic levels. Following preprocessing, the classification networks include Inception V3[10], VGG19[7], Resnet 152[11], Mobile Net V2[17], and Xception [20] structure-based DCNN classifiers used for classification task in order, family and species levels. Adam optimizer, configured with a learning rate of 0.0001, was employed during the training, which lasted for 50 epochs with a batch size of 32. Categorical cross entropy was employed as the loss function, while SoftMax and ReLU were selected as activation functions in all taxonomic levels including order, family and species levels. Table 2 displays the training hyperparameters for five different DCNN models.

Table 2: Hyperparameters for Deep Convolutional Neural network (DCNN) Models

| Parameters | Range |
|--|---------------------------|
| Models: Inception v3 [10], Resnet 152 [11], VGG 19 [7], Mobile Net V2 [17], Xception [20] | |
| Optimizer | Adam |
| Learning rate | 0.0001 |
| Epochs | 50 |
| Batch size | 32 |
| Loss Function | Categorical Cross Entropy |
| Activation Function | SoftMax, ReLU |

3.3.1 InceptionV3

Inception V3 [10] is a powerful and efficient architecture for image classification tasks, offering a good balance between accuracy of all levels. A combination of parallel convolutional operations, pooling, and concatenation, formulated as:

$$Y = \text{Concat} (C_{1 \times 1}(x), C_{3 \times 3}(x), C_{5 \times 5}(x), \text{Pavg}(x)) \quad (1)$$

Where Y is the output feature representation. $C_{k \times k}$ represents a convolutional operation with a $k \times k$ kernel applied to (x) . $\text{Pavg}(x)$ denotes the Global Average Pooling operation. Additionally, in this architecture have Batch Normalization and SoftMax as activation function to classify the images. Eq. (1) encapsulates the architecture of Inception V3 model. Particularly in this study Inception V3 has an accuracy of 96.15% at the order level, 86.21% at the family level, and 79.24% at the species level.

3.3.2 ResNet-152

ResNet 152 [11] model architecture involves the concept of multiple residual connections. In this study ResNet-152 architecture utilized to classify the insect images. ResNet-152 architecture expressed as Eq. (2).

$$\text{ResNet} - 152(x) = \text{Concat} (C_{1 \times 1}(x), C_{3 \times 3}(x), C_{3 \times 3}(x), \text{Avg}_{\text{pool}(x)} + x) \quad (2)$$

Where X represents the input images, $C_{1 \times 1}(x)$ denotes a convolutional operation with a 1×1 filter size. $C_{3 \times 3}(x)$ represents a convolutional operation with a 3×3 filter size. $\text{Avg}_{\text{pool}(x)}$ is the result of Global Average pooling operation applied to x . The addition operation $+$ indicates the element-wise addition of the input tensor x to the output of pooling operation, known as the residual connection. In this study, ResNet-152 model demonstrates the 40.23% of accuracy in order level data 26.60% of accuracy in family level data and 24.38% of accuracy results in species level data.

3.3.3 VGG 19

VGG 19 [7] features a series of convolutional layers combined with max-pooling layers, succeeded by a fully connected layer to perform classification. It is characterized by deeper layer structure which enables it to learn complex features in insect images. The structure of VGG 19 can be expresses as follows in Eq. (3)

$$\begin{aligned} \text{VGG19}(x) = & \text{Conv2D}(x) \rightarrow \text{MaxPooling2D}(x) \rightarrow \text{conv2D}(x) \rightarrow \text{MaxPooling2D}(x) \rightarrow \\ & \text{Conv3x3}(x) \rightarrow \text{Conv3x3}(x) \rightarrow \text{MaxPooling2D}(x) \rightarrow \text{Conv3x3}(x) \rightarrow \text{Conv3x3}(x) \rightarrow \\ & \text{MaxPooling2D}(x) \rightarrow \text{Conv3x3}(x) \rightarrow \text{Conv3x3}(x) \rightarrow \text{MaxPooling2D}(x) \rightarrow \text{Flatten}(x) \rightarrow \\ & \text{Dense}(x) \rightarrow \text{Dense}(x) \rightarrow \text{Dense}(x) \end{aligned} \quad (3)$$

Where X represents the input images, $\text{Conv2D}(x)$ and $\text{MaxPooling2D}(x)$ denotes 2D convolutional layer and 2D max-pooling layer respectively. $\text{Conv3x3}(x)$ represents a 3×3 convolution function. $\text{Flatten}(x)$ flattens the input images into a 1D vector. And $\text{Dense}(x)$ indicates a fully connected layer. In this study, VGG 19 model has an accuracy of 90% in order level 87.23% of accuracy in family level and 82.64% of accuracy in species level. Figure 3 shown the VGG 19 model architecture.

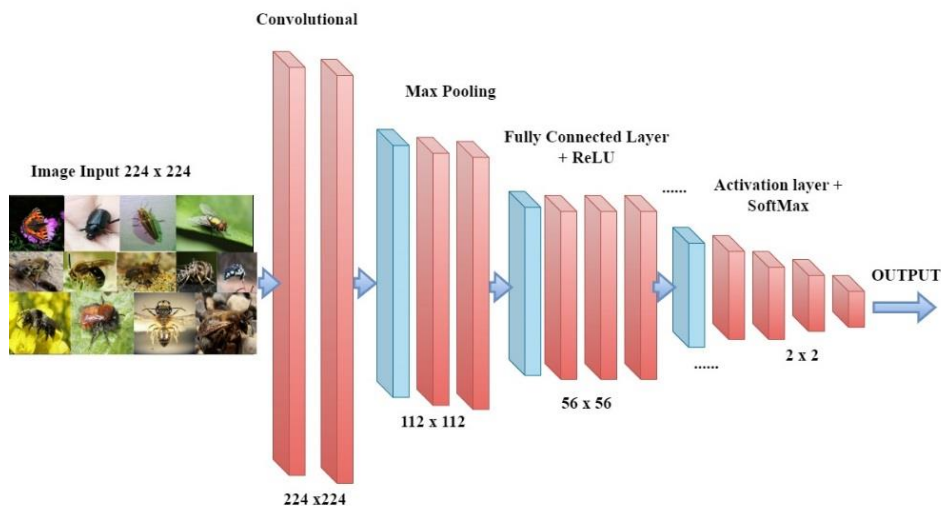


Figure 3: Architecture of VGG 19 Model

3.3.4 Mobile Net V2

The Mobile Net V2 [17] architecture can be summarized as follows in Eq. (4).

$$MobileNet V2(x) = Conv2D(x) \rightarrow BottleneckBlock(x) \rightarrow BottleneckBlock(x) \dots \rightarrow BottleneckBlock(x) \rightarrow GlobalAveragePooling2D(x) \rightarrow Dense(x) \rightarrow Dense(x) \quad (4)$$

Here, x represents the input images. $Conv2D(x)$ denotes the initial convolutional layer with 224×224 pixels. $BottleneckBlock(x)$ represents a series of bottle neck blocks, each including depth wise separable convolution layers, followed by pointwise convolution layers. $GlobalAveragePooling2D(x)$ calculates the mean value for each feature representation over its spatial extent, producing a single feature vector per channel. And $Dense(x)$ denotes fully connected layers for classification. The bottleneck blocks help to capture complex features in the input data, making Mobile Net V2 suitable for taxonomic level classification task. In this study, the Mobile Net V2 model has an accuracy of 98.36% in order level, 93.26% of accuracy in family level and 88.33% of accuracy in species level classification.

3.3.5 Xception

Xception [20] architecture is characterized by its extreme depth and use of depthwise separable convolutions, which allows it to capture complex patterns and achieve best accuracy in species level image classification. The Xception architecture can be represented as follows in Eq. (5).

$$Xception(x) = EntryFlow(x) \rightarrow MiddleFlow(x) \rightarrow MiddleFlow(x) \rightarrow \dots \rightarrow MiddleFlow(x) \rightarrow ExitFlow(x) \rightarrow GlobalAveragePooling2D(x) \rightarrow Dense(x) \rightarrow Dense(x) \quad (5)$$

Here, x represents the input images. $EntryFlow(x)$ denotes the entry flow of the Xception model, which consists of several convolutional and depth wise separable convolutional layers. $MiddleFlow(x)$ represents the middle flow, which repeats a series of depthwise separable convolutional layers multiple times to capture complex features. $ExitFlow(x)$ denotes the exit flow, which further processes the features extracted by the middle flow before global pooling and classification. $GlobalAveragePooling2D(x)$ averages each feature map over its spatial dimensions,

producing a single feature vector for every channel. $Dense(x)$ denotes fully connected layers for classification. In this study, Xception model has demonstrates the accuracy 98.02% in order level, 94.57% in family level and 80.58% in species level insect image classification. Figure 4 shown the Xception model architecture.

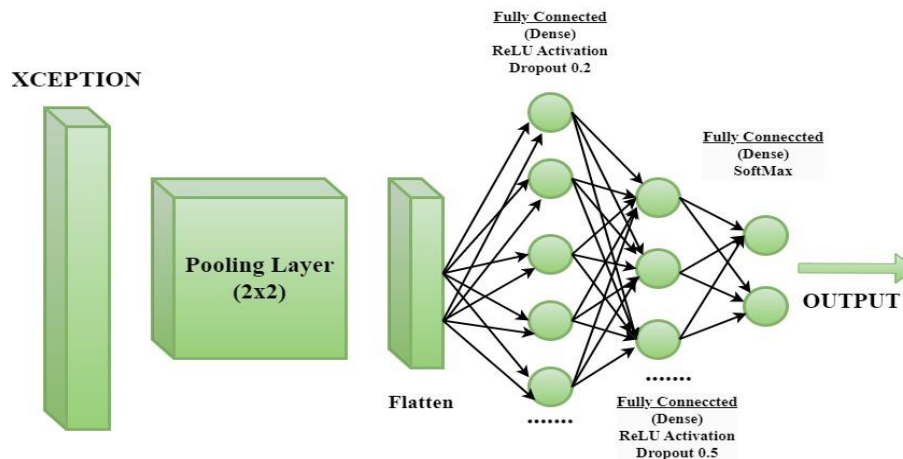


Figure 4: Architecture of Xception Model

3.4 Dual Hybrid Deep Convolutional Neural Network Model

In the realm of insect species classification and identification, DL-based models through ensemble techniques holds significant promise for achieving higher accuracy. This research explores the efficacy of a hybrid approach combining the strengths of VGG19 and Xception models for accurate insect species classification across multiple taxonomic levels. After DCNN based pre-trained models were trained on three distinct taxonomic insect image datasets. The accuracy was evaluated and training images were fed into the DHDCNet based model for efficient classification. Dual Hybrid framework based proposed model termed as “DHDCNet”, combines the predictions of VGG19 and Xception models by averaging their softmax outputs for classification. Mathematically, this can be represented in eq. (6):

$$DHDCNet\ prediction = \frac{1}{2}(Softmax(VGG19) + Softmax(Xception)) \quad (6)$$

Here, $softmax(VGG19)$ represents the softmax output probabilities predicted by the VGG 19 model, and $softmax(Xception)$ represents the softmax output probabilities predicted by the Xception model. The division by 2 used to normalize the prediction. Table 3 shown the layers and parameters and input and output shapes of DHDCNet model. Compared with other DCNN models the proposed DHDCNet model has achieved high accuracy as 98.97% in order level classification, 97.37% of accuracy in family level and 89.79% of accuracy in species level classification. Through rigorous experimentation and evaluation, the effectiveness of this Dual hybrid-based approach in achieved superior classification performance was thoroughly examined, offering valuable insights into the potential of automated insect taxonomy and identification. Figure 5 displays the Dual Hybrid Deep CNN - DHDCNet model architecture.

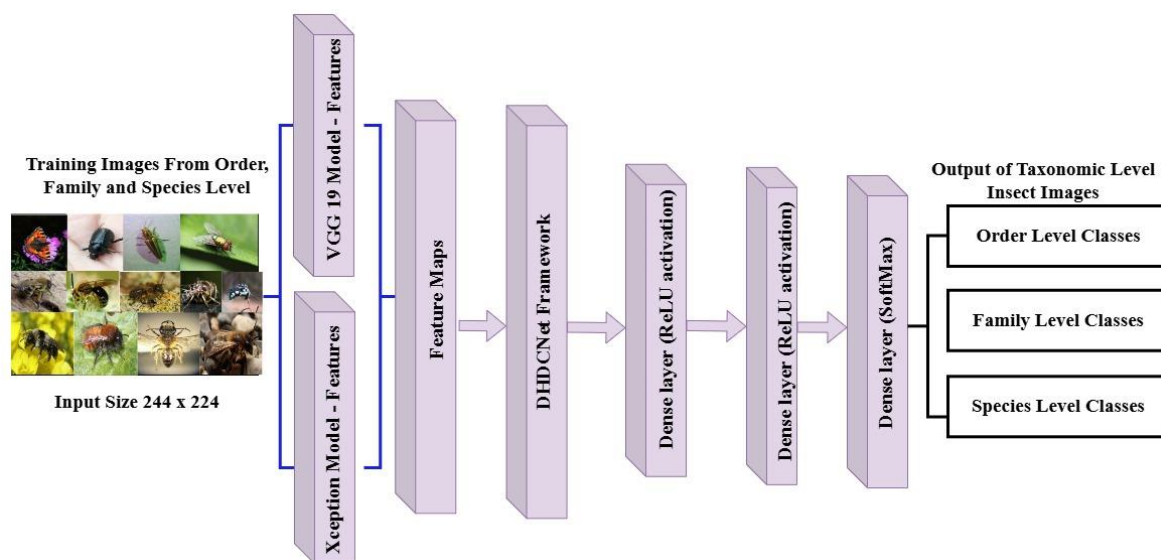


Figure 5: Dual Hybrid Deep Convolutional Neural Network Architecture

Table 3: Layers and parameters of DHDCNet model

| Layer (type) | Output Shape | Parameters | Connected to |
|----------------------|-----------------------|------------|------------------------------------|
| input_5 (InputLayer) | [(None, 224, 224, 3)] | 0 | [] |
| model1 (Functional) | (None, 5) | 22964781 | ['input_5[0][0]'] |
| model2 (Functional) | (None, 5) | 20554821 | ['input_5[0][0]'] |
| average_1 (Average) | (None, 5) | 0 | ['model1[0][0]' 'model2[0][0]'] |

Algorithm for DHDCNet model for taxonomic level insect image classification and identification:

Input: Order level, family level and species level insect images

Output: Classified insect images

Begin

for(every insect image)

 Perform pre-processing;

 Dataset segmented into training, testing and validation;

end for

Training images fed into the DCNN based pre-trained models;

Training images into ensemble model “Dual Hybrid Deep Convolutional Neural Network – DHDCNet Model”;

Validate the classifiers using test dataset to classify the insect images at order, family and species taxonomic levels;

End

4. Experimental Results and Insights

The following section provides experimental results and outcomes of insect image classification utilize hybrid-based approach framework. The comparison of DCNN models and the proposed DHDCNet model across three taxonomic levels - order, family, and species - is presented in Table 4, with evaluation metrics like precision, recall, F1-Score, and accuracy. Figure 6 illustrates the accuracy comparison between all DCNN models and proposed model.

Table 4: Comparison results of DCNN models with proposed DHDCNet model

| Taxonomic Level of Insects | DCNN Models | Precision | Recall | F1-Score | Accuracy |
|-----------------------------------|-------------------------|------------------|---------------|-----------------|-----------------|
| Order Level | Inception V3 | 0.96 | 0.95 | 0.96 | 96.15% |
| | Resnet 152 | 0.39 | 0.40 | 0.39 | 40.23% |
| | VGG 19 | 0.88 | 0.87 | 0.88 | 88.66% |
| | Mobile Net V2 | 0.98 | 0.98 | 0.98 | 98.36% |
| | Xception | 0.98 | 0.98 | 0.98 | 98.02% |
| | Proposed DHDCNet | 0.98 | 0.99 | 0.99 | 98.97% |
| Family Level | Inception V3 | 0.87 | 0.86 | 0.86 | 86.21% |
| | Resnet 152 | 0.09 | 0.24 | 0.12 | 26.60% |
| | VGG 19 | 0.87 | 0.86 | 0.86 | 87.23% |
| | Mobile Net V2 | 0.92 | 0.93 | 0.93 | 93.26% |
| | Xception | 0.94 | 0.91 | 0.91 | 94.57% |
| | Proposed DHDCNet | 0.96 | 0.97 | 0.97 | 97.37% |
| Species level | Inception V3 | 0.80 | 0.79 | 0.79 | 79.24% |
| | Resnet 152 | 0.09 | 0.24 | 0.12 | 24.38% |
| | VGG 19 | 0.83 | 0.83 | 0.83 | 82.64% |
| | Mobile Net V2 | 0.87 | 0.88 | 0.88 | 88.33% |
| | Xception | 0.85 | 0.81 | 0.81 | 80.58% |
| | Proposed DHDCNet | 0.88 | 0.89 | 0.88 | 89.79% |

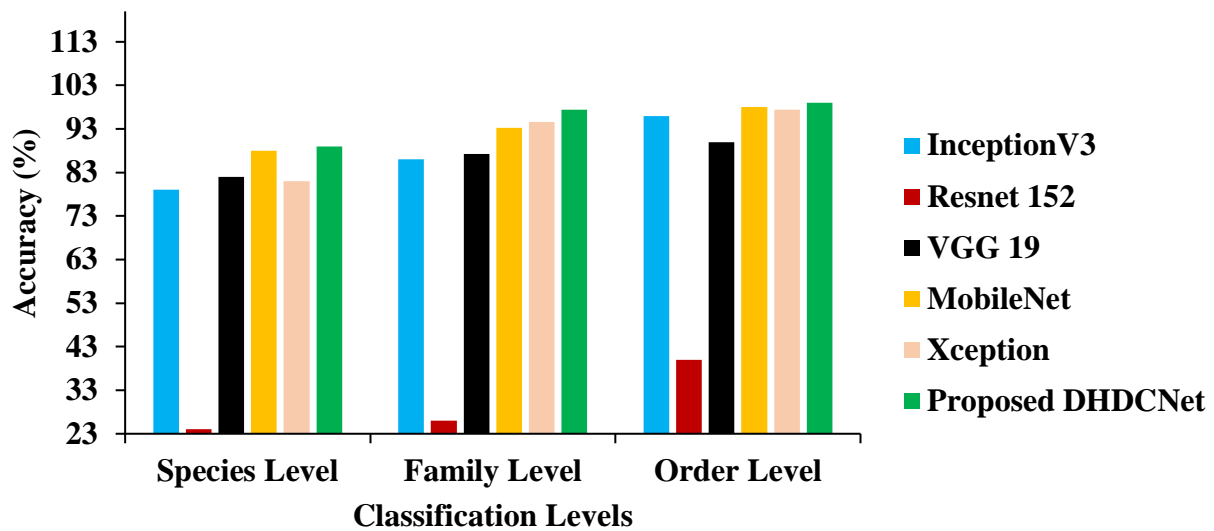


Figure 6: Accuracy Comparison

$$Precision = \frac{True\ Positives\ (insect\ images\ correctly\ identified)}{True\ Positives\ (insect\ images\ correctly\ identified) + False\ Positives\ (non-insect\ images\ incorrectly\ identified\ as\ insects)} \quad (7)$$

$$Recall = \frac{True\ Positives\ (insect\ images\ correctly\ identified)}{False\ Negatives\ (insect\ images\ incorrectly\ classified) + True\ Positives\ (insect\ images\ incorrectly\ identified)} \quad (8)$$

$$F1 - Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (9)$$

$$Accuracy = \frac{TP + True\ Negative\ (TN)}{TP + TN + FP + FN} \quad (10)$$

Eq. (7), (8), (9), and (10) represents the measures and calculation of classification performance metrics including precision, recall, F1-Score and accuracy. This comparative result ensures the proposed integrative hybrid framework model “DHDCNet Model” was classified and achieved high accuracy in various taxonomic level of insect images in efficient manner.

5. Conclusion and Future Challenges

In summary, this work demonstrates the effectiveness of deep learning in insect image classification across different taxonomic levels. Various DCNN models, including Inception v3, Resnet 152, VGG 19, Mobile Net V2, and Xception, and introducing the innovative "Dual Hybrid Deep CNN - DHDCNet" framework, our study achieves outstanding results. Notably, it attains an accuracy of 98.97% at the order level and 97.37% at the family and 89.79% at the species level, all with significantly reduced training durations compared to individual pre-trained models. These remarkable outcomes hold great promise for entomology, ecology, and conservation efforts, paving the way for more efficient and accurate insect classification processes. Beyond its academic significance, this

research offers practical applications in the development of automated systems for rapid and reliable insect identification, benefitting researchers and environmental preservation endeavours. Ultimately, this study significantly enhances our understanding of insect diversity and ecological roles, highlighting the vast capabilities of DL in the field of insect taxonomy and image classification. Future investigations will aim to broaden the research's scope to encompass a wider variety of insect species across various taxonomic levels, further improving the capabilities of the classification system.

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