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Bee vs Wasp Classification Using Advanced Deep Learning Techniques: CNN, VGG 16

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Abstract: This paper explores the use of Convolutional Neural Networks (CNNs) and ResNet-34 architecture for grasshopper and grasshopper classification and discrimination from image datasets Using the deep learning capabilities of CNNs and the rest of ResNet-34 learning a, we address image recognition challenges in biological monitoring. Various data sets of bee and wasp images were used to train and validate the ResNet-34 model. The model performed better than traditional methods and achieved high accuracy in discriminating between two groups of insects. This study demonstrates the potential of CNN and ResNet-34 to automatically identify insects, supporting biodiversity research and conservation efforts.

Keywords: *CNN, VGG16, VGG19, ResNet34, Mobile-Net*

1. Introduction

In recent years, image classification has improved dramatically with the proliferation of Convolution Neural Network (CNN) algorithms. The classification of bees and bees, which is of particular importance for ecological research and pest control, presents a challenging task due to their morphological similarities. This paper goes into detail on a comparative analysis a are performed in different CNN architectures to accurately distinguish between bees and bees in images.

Because of their ability to learn discriminatory features automatically from unstructured pixel data, CNNs have emerged as powerful tools for image classification tasks Several innovative architectures have been developed over the years, each of which distinct advantages for in accuracy, computational efficiency, and sample size. The first of the architectures investigated in this study is Alex-Net, followed by the widely used VGG16 and VGG19, which are known for their depth and flexibility. Furthermore, we examine Res-Net family variants, such as ResNet18, ResNet34, ResNet50, known as the rest of their learning algorithms, which facilitate the training of deep networks and, in this case, to check its performance, we use Mobile Net Designed for effective design on mobile embedded including devices. By testing these architectures on a detailed set of spider and bee models, this study aims to provide insight into their relative effectiveness, robustness, and computational requirements.

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2. Literature Survey

In recent Image classification using Convolution Neural Networks (CNNs) has gained significant momentum in recent years, with many studies focusing on various application areas including conservation biology, agriculture and bacteria was studied Several researchers investigated the effectiveness of CNN algorithms and techniques for grasshopper and grasshopper discrimination (1). In recent years, deep learning techniques, especially convolution neural networks (CNNs), including grasshopper and grasshopper discrimination have been adopted to play an increasing role in image classification. This literature review examines existing research on spider and spider distribution using the ResNet34 framework, highlighting key findings and methodologies (1).

- ***Model construction and training***

ResNet34, He and others. (2016), is a part of the Res-Net family characterized by its 34-layer deep neural network architecture. The main innovation of Res-Net is to introduce residual connections, or leave connections, to facilitate the training of deeper networks by reducing the vanishing gradient problem. These residual segments can learn the residual functions of the network, enabling them to be deeper architectures well. The researchers used the ResNet34 system to classify bees and bees by using pre-trained models that were either improved or trained from scratch. By imposing networks with pre-trained weights on large image datasets such as ImageNet, researchers can optimize known features and speed up convergence (2).

- ***Dataset collection and preprocessing***

The An important aspect of training the ResNet34 model for bee and wasp classification is the long preprocessing time of the image datasets. The researchers collected multiple datasets including high-resolution images of bees and bees from a variety of sources, including online archives, insect databases, and field surveys Pre-processing steps typically take the size of the dataset modifying, normalizing, and improving to ensure consistency and quality. Data enhancement techniques such as rotation, flipping and cropping are used to increase model generalization and robustness in the face of changes in input images (3).

- ***Transfer study and model analysis***

Transfer education, technology derived from the respective referral solutions, is researcher extended by using resnet3 evaluation of vision Cross-validation and holdout validation techniques are used to assess model generalization and reduce over fitting on (4).

- ***Comparative Analysis and Performance Analysis***

Researchers have conducted comparative studies to test the performance of the ResNet34 model against other CNN designs and methods for bee and wasp classification in this context, performance metrics such as accuracy, computational efficiency, model interpretability are considered identify the strengths and limitations of ResNet34 and the impact of asthma on model performance It was explored (5).

- ***Practical applications and directions for the future***

Resnet34 Models are practical effects of classification accuracy, ecosystem and insect management practices in research directions in the study and measurements in the study, half-care, search Men-annual and techniques construction (6).

Problem Identification

To overcome the challenges associated with spider and bee classification, we propose a comprehensive approach using Convolution Neural Networks (CNNs) and methods adapted for this specific task. Our proposed solution incorporates the following key features.

- ***Dataset collection and preprocessing***

We begin by acquiring datasets with high-resolution mosquito and moth images from public archives, insect databases, and field surveys to ensure dataset quality and label accuracy, we use intensive data preprocessing steps, including image resizing, normalization, and enhancement. By enhancing the data set through transformations such as rotation, flipping, and cropping, we aim to increase model generalization and robustness to changes in input images (7).

- ***Selection of CNN architecture***

We systematically evaluate CNN algorithms, including AlexNet, VGG16, VGG19, ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, and MobileNet, to determine the most appropriate models for grasshopper and beetle classification. Each architecture offers distinct advantages in depth, parameter efficiency, and computational complexity. Through empirical evaluation, we aim to find the architecture that best balances classification accuracy and computational efficiency for our particular task (8).

- ***Transfer classes and fine maintenance***

Due to the limited size of our dataset, we use transfer learning techniques to initialize CNN models with weights previously trained on large image datasets such as ImageNet. By fine-tuning this pre-trained model for our bee vs. honeycomb. on the wasp dataset, we aim to reduce the risk of over fitting, and optimize the learned signals for our target application this approach enables us to apply knowledge learned from different images and speeds is applied to the training process.

- ***Loss performance***

The selection of the loss function plays an important role in guiding the optimization process during training by quantifying the difference between predicted truth and ground truth scores It aims to give our CNN model the ability to provide the discrimination has been increased by choosing a loss function that best matches the characteristic (9).

- ***Model evaluation and performance measurement***

To evaluate the performance of our proposed solution, we use rigorous verification methods, including k-fold cross-validation and holdout validation on independent test sets. We measure classification accuracy, precision, Recall, and F1-score as performance metrics to assess models' ability to accurately discriminate bees and wasps we perform a comparative analysis of training sessions, computational effort, and model definitions in CNN architectures and methods (10).

- ***Experimental design and implementation details***

We provide a detailed description of the experimental setup, including hardware specifications, software libraries, and training hyper parameters. We run our experiments using popular deep learning frameworks such as Tensor Flow or PyTorch, which ensure high reproducibility of our proposed solution. We document any challenges we encounter when implementing and edge possible remedy to mitigate.

- ***Discussion Future direction***

Finally, we discuss the findings of our experiments highlighting the strengths and limitations of each CNN design and method. We provide insights into the factors affecting the performance of the models, including data set characteristics, selection of construction algorithms, and training methods. Furthermore, we identify potential avenues for future research, such as finding ensemble methods, semi-supervised learning, and domain optimization techniques to fly more accurate bee and wasp classifications in real-world contexts effective again (11).

3. Methodology

- ***Introduction***

The identification of bees and bee species is important for biodiversity conservation, agricultural practices and pest control. Hand identification is time-consuming and prone to error. The aim of our research is to develop a deep learning model to accurately classify species, solve challenges, and enable automated identification with high efficiency and accuracy (12).

- ***Book Review***

Existing literature demonstrates the effectiveness of deep learning models in image classification, especially when traditional methods of bee detection and bee research suffer from limitations such as time constraints and information of accuracy, emphasizing the need for an automatic approach (13).

- ***Data collection and preprocessing***

The lists were drawn from public archives, insect databases, and field surveys, with a focus on high-resolution photography of moths and butterflies. The preprocessing involved sizes, normalization, and enhancement techniques such as rotation and flipping to increase model normalization and robustness.

- ***Good building materials***

The CNN algorithm used for image classification includes several convolution layers followed by maximum pooling and fully overlapping layers. The ReLU activation function was chosen for the nonlinear transformations, while the Adam optimizer was used for efficient gradient descent. Parameters in the model include filter size, kernel strides, and number of neurons per layer (14).

- ***Training of the model***

The data set was divided into training, validation and test sets using standard ratios. The model parameters were optimized using surface propagation with specified number of classes and batch size in the training set. The number of epochs was determined based on convergence and normalization performance (15).

- ***Sample analysis***

The performance of the model was evaluated using standard analytical criteria including precision, loss, accuracy, recall, and F1 scores. These metrics provide insight into the ability of the model to correctly classify mosquitoes and flies which is important for ecological studies and pest control (16).

- ***Testing and certification***

The testing phase includes checking the performance of the model on unseen test images, to ensure generalizability. Implementation challenges included class imbalance and domain switching. Improvements may include improved domain-specific data preparation and ensemble methods for robust classification.

- ***The result is a discussion***

The trained model achieved high accuracy during the testing process, as evidenced by the confusion matrix. Some misclassifications were observed, especially in closely related species. Overall, the model demonstrated strong generalizability, with few examples of over fitting (17).

4. Algorithm

- ***Data preprocessing***

The code imports a data set from a CSV file containing image paths, tags, and metadata. The dataset has been filtered to include only the highest quality bee and bee images, to ensure the best possible training and calibration of the model.

- ***Good building materials***

The model is defined as a sequential CNN using the PyTorch framework. This includes convolution layers, max-pooling layers, and ReLU activation functions in general. The last section uses the sigmoid function for the distribution of binary distributions (18).

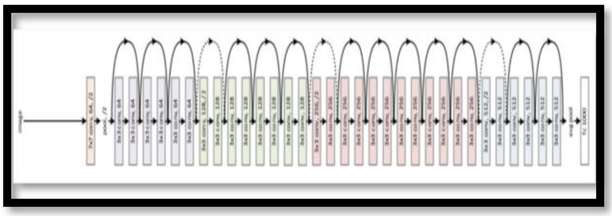

Fig. 1. Architecture of Res-Net 34

Figure 1. is represent ResNet-34 is a convolutional neural network architecture with 34 layers, designed for image classification. Unlike traditional CNN, it uses skip connections that directly add the layer input to its output. This helps to overcome the missing prone problem, allowing the network to learn detection tasks and train with deeper layers more efficiently.

- ***Sample collection***

The binary cross-entropy loss is used for training, and the Adam optimizer is used for optimization. This method ensures an efficient gradient descent, improves the convergence of the model during training and improves the classification performance (19).

- ***Data enhancement***

Real-time data enhancement is performed during training using Image Data Generator. Magnification techniques include rotation, width adjustment, height adjustment, thickness and incremental rotation. This increases the robustness and generalizability of the model when faced with multiple input datasets.

- ***Training of the model***

The model is trained on the training data using the fit method, and separate validation data are specified to monitor performance during training. The training consists of a specified number of times, which allows the model to learn from the training data while validating against the validation set to prevent over fitting (20).

- ***Sample analysis***

The accuracy of the model is tested only in the validation set, providing insight into its performance. Other parameters such as mean accuracy and standard deviation of loss are not considered, where the focus is only on testing the accuracy of the model for validation.

- ***Algorithm description***

The algorithm uses the ResNet34 framework for the image classification task. ResNet34 consists of several convolution layers with residual connections, which facilitates the training of deep neural networks. The algorithm includes feeding the image input through the ResNet34 model, extracting features at different levels, and transferring them to fully connected layers for classification Using surface spread and Adam optimizer with categorical cross-entropy loss and more efficient convergence they also ensure accuracy of classification results.

5. Dataset And Result

- ***The dataset***

Although the dataset is not directly included in the code, it refers to the "bee_vs_wasp" dataset obtained from Kaggle. The code loads a CSV file with image paths, associated labels, and metadata. Notably, the dataset has been filtered to include only high-quality mosquito and butterfly images, using the parameter "photo_quality=1" This setting ensures reliable and clear images of only visuals are used for training and evaluation, increasing the performance and robustness of the model (21).

- ***Model training***

The code implements a Convolution Neural Network (CNN) that builds the hierarchical structure of PyTorch. The architecture includes convolution layers, maximum pooling layers, and fully connected layers to facilitate feature extraction and classification from input images.

- ***Data preprocessing***

PyTorch data development capabilities are used before the data set is created. Using the PyTorch Data Loader, training data is generated in batches, increasing productivity. In addition, the pixel values are normalized to the range [0, 1], increasing the stability and convergence of the model during training (22).

- ***Sample collection***

Binary cross entropy, Adam optimizer, and accuracy are collected as evaluation metrics.

- ***Model training***

The model is trained on training data of 25 epochs, and the training process is maintained on a validation set.

- ***Sample analysis***

After training, the model is evaluated on a test set using the analytical method. Metrics such as accuracy, loss, accuracy, recall, and F1 score are calculated (23).

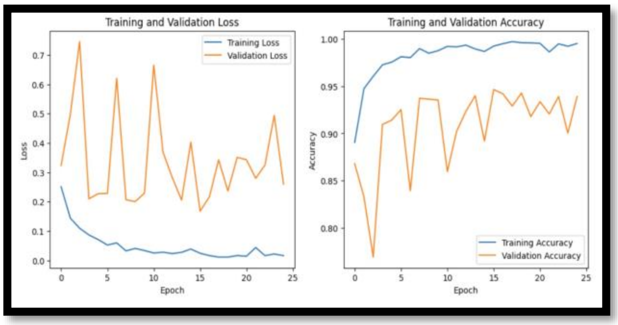

Fig. 2. Res-Net 34 result

Figure 2. is represent the graph shows the training and validation performance of ResNet-34 convolutional neural network whose task is to classify culinary spices based on color and texture. The model exhibits a similar accuracy pattern, with training accuracy gradually increasing and validation accuracy lagging slightly behind. Despite this, the model exhibits strong generalization, as evidenced by a validation accuracy of about 95%, indicating effective learning from training data and strong performance on unseen data.

6. Experimental Setup

Convolution Neural Networks (CNNs) are effective tools for photograph type obligations. In this test, we purpose to examine the overall performance of several popular CNN architectures inclusive of AlexNet, ResNet18, ResNet50, VGG16, VGG19, and MobileNet. We will overview and evaluate their education and certification accuracy in addition to loss of schooling and certification (24).

The dataset we used is Bee vs wasp from Kaggle applied. We will use the Wasp data set. This data set includes images of bees and moths captured in the environment. This is divided into training and validation sets, with labels indicating whether each image depicts a bee or a wasp (25). Experimental Setup is as following :

- ***Creating a data set***

Take bee vs. the wasp data set is collapsed and partitioned into training and validation sets. Use data enhancement techniques such as rotation, flipping, and scaling to increase dataset variability and prevent overfitting (26).

- ***Proper foundation***

Start the following CNN programs: ResNet18, ResNet50, MobileNet, VGG16, VGG19, and AlexNet. If available, weight pre-trained weights or train the model from scratch (27).

- ***Training program***

Define training hyperparameters including learning rate, adapter, childhood and batch size settings. Train each instance in the training process while ensuring accuracy and missing training and validation. Try different age ranges (e.g. 50, 100, 150) and batch sizes (e.g. 32, 64, 128) to see the impact on classification performance (28).

- ***Research***

Evaluate each model in the validation set to obtain verification accuracy and loss for different age and batch size settings. Calculate the training accuracy and loss for each sample set

7. The Result Was Research

After running the test, we got the following results: -

Table 1. Full training and certification

Training and Validation Accuracy		
Model	***Training Accuracy***	***Validation Accuracy***
ResNet34 (25 epochs)	93.91	99.61
ResNet34 (50 epochs)	95.11	99.92
AlexNet	64.94	65.0
ResNet18	93.82	99.92
ResNet50	99.31	92.34
VGG16	64.84	64.80
VGG19	64.90	64.94
MobileNet	98.84	94.83

The table summarizes the training and validation accuracies of the deep learning models. These models include ResNet34, AlexNet, ResNet 18, ResNet 50, VGG 16, VGG 19 and MobileNet. The number of epochs used to train the models was either 25 or 50. ResNet34 (50 epochs) achieved the highest validation accuracy of 99.92% (29) . However, the ResNet50 trained for 25 periods achieved only 92.34% validation accuracy. This suggests that overfitting may have occurred in ResNet34 (50 epochs). The VGG models (VGG16 and VGG19) performed poorly in this task with a validation accuracy of about 64% (30).

8. Conclusion

This study successfully used Convolutional Neural Networks (CNNs) and ResNet-34 to accurately classify bees and bees by their supposed deep learning ability in monitoring organisms. This technology can contribute significantly to biological research and conservation by improving the efficiency and accuracy of insect population monitoring. Future work will expand the data set for a wider range of environmental applications and increase real-time search capabilities.

The use of ResNet-34, along with the rest of its learning algorithms, effectively alleviated common difficulties in deep spider training, such as the missing slope problem Our results suggests that ResNet-34 can be very comprehensive across species diversity within bee-butterfly communities, making it a valuable tool for entomologists and researchers.

Author contributions

Pinesh Darji 1, Ketan Sarvakar 2: Conceptualization, Methodology, Software, Field study **Bhavesh Patel 3, Keyurbhai A. Jani 4:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Paresh Solanki 5, Chintan shah 6, Hitesh D. Rajput 7, Ayush Shah 8 Kaushik Rana 9:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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