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Research Article

Butterfly Species Classification Using CNN and VGG16

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ABSTRACT

Butterflies play a significant part in biodiversity, serving as markers of biological system wellbeing and subjects of environmental and preservation inquire about. With the developing decay of butterfly populaces around the world, robotized methods for precise classification of butterfly species have ended up fundamental for checking and conservation. This consider investigates the utilize of Convolutional Neural Systems (CNNs), with a centre on the VGG16 engineering, for butterfly species classification. Leveraging its profound design and little convolutional channels, VGG16 viably captures complicated designs in butterfly wing pictures, such as colour, surface, and auxiliary subtle elements. The dataset utilized incorporates high-resolution pictures handled through procedures like enlargement and normalization to upgrade show execution. Test comes about illustrate that VGG16 accomplishes tall exactness, outflanking conventional strategies by viably tending to challenges such as intra-class likeness and inter-class inconstancy. This approach contributes essentially to biological observing, helping preservation endeavours and progressing investigate in computer vision- based biodiversity analysis.

Keywords: Butterfly classification, CNN, VGG16

INTRODUCTION

Butterflies, having a place to the arrange Lepidoptera, are not as it were crucial components of environments but moreover serve as basic markers of natural wellbeing and biodiversity. Their dynamic colours, different designs, and environmental importance make them key subjects of preservation and investigate endeavours. Be that as it may, manual recognizable proof of butterfly species is labour-intensive, error-prone, and requires broad ability. The developing dangers to butterfly populaces due to territory annihilation and climate alter have encourage highlighted the require for productive and precise distinguishing proof systems. In later a long time, headways in computer vision and profound learning have changed the field of species distinguishing proof. Among these, Convolutional Neural Systems (CNNs) have developed as a effective instrument for picture classification errands due to their capacity to naturally learn and extricate various levelled highlights from visual information. VGG16, a broadly utilized CNN design, is especially compelling in capturing complicated points of interest of butterfly wings, counting surfaces, colours, and shapes. This capability makes it a perfect choice for handling the challenges postured by tall inter-class likeness and intra-class changeability in butterfly species. This ponders centres on leveraging VGG16 for robotized butterfly picture classification. Utilizing pre-processed datasets improved with enlargement strategies, the demonstrate is prepared to recognize between butterfly species with tall exactness. By tending to impediments of conventional strategies and giving a adaptable arrangement, this approach points to contribute to biodiversity checking and preservation endeavours whereas progressing the application of profound learning in environmental research.

LITERATURE SURVEY

The classification of butterflies has received much attention for the purpose of inventory and monitoring as well as for the improvement of the act of conservation. In respect to the difficulties like species similarity, ecological noise and limited data set, many researchers have attempted to use automated techniques based on deep learning techniques. Almryad and Kutucu suggested the CNNs approach based on dataset containing 17, 769 images of 10 types of butterflies. Their work showed that, these challenges can easily be dealt with by CNN architectures such as the VGG16, VGG19, and ResNet50 as they enjoy high classification accuracy. Likewise, Berger et al. trained ResNet50 and Inception-ResNet-v2 models on the database of 110 butterfly species. Their approach involved augmenting the data and the classes and also weighing the classes and this assure them a of about more than 80% accuracy with Inception-ResNet-v2 outperforming the set standards.

[1]Almryad and Kutucu (2020) developed an approach for the identification of butterfly species through deep learning, to be precise using deep Convolutional Neural Networks. They accumulated a data set of 44 659 butterfly images of 104 species, reduced the samples to 17 769 images of 10 species in order to achieve a better distribution of classes in the given data set. The study used transfer learning to fine-tune pre-existent architectures such as VGG16, VGG19 and ResNet50 for classifying butterfly species proficiently. Background complexity and occlusion were two classic issues that were handled through preprocessing the images and normalizing the size of each image to a standard size of 224 X 224 pixels. In the results, it was possible to show that CNNs can be useful to increase the accuracy of classification as well as providing solutions for noisy and complex ecological backgrounds. [2] Survey of Methods and Difficulties Yasmin et al. (2023) have surveyed general approaches and problem areas of butterfly detection and classification from conventional machine learning to deep learning. They said that unlike previous methods which employed low level features such as the Gray Level Co-occurrence Matrices (GLCMs) as well as Local Binary Patterns (LBP), the coming of the Convolutional Neural Networks (CNNs) changed the butterfly classification. CNNs, because they can construct the hierarchical features without man-made attempts, have shown high effectiveness in detecting the features required for the distinction of the closely related species. The review also depicted a feature of datasets, for instance, low ecological diversity and limited imagery per species, factors that complicate the generation of stable models. We were able to establish that some of the methods that can be used for reducing these problems include transfer learning and data augmentation.[1]

Migration of CNNs to Cloud Platforms: Murthy et al. (2024)

[3] conducted an experiment on the suitability of CNNs for butterfly recognition via Google Colab, a networked environment. The preprocessing undertaken included scaling the pictures to a standardized dimension, standardizing pixel values between 0 and 1, and increasing the size of the training dataset through rotation and flipping. Transfer learning was applied using the VGG16 and ResNet50 models and proved that by pre-training, the training time significantly reduces, and high accuracy is attainable. The study also focused on Google co-lab support for TensorFlow and Py torch for training and evaluation of deep learning models.

Taken together, these works establish that deep learning affords a profound change to butterfly classification challenges. Compared to traditional analytic methods, CNNs for feature learning from images have shown great improvements due to their automatic feature learning. However, the problem of using small datasets has been solved by utilizing transfer learning and data augmentation for classification of other species of butterflies. Google Colab integration as one of the platforms also contributes the usability further, more and more researchers can develop and deploy the models.[2]

METHODOLOGY

A. Introduction: Enhance the results of the butterfly recognition by categorizing them into severally using a machine learning technique. Describe own trained convolutional neural networks for the task, what model was used and the evaluation of applying transfer learning by using VGG16 for feature extraction and exciting classification.

B. Dataset Preparation: The curators also annotated the images with the butterfly species name and metadata are available in Training_set.csv. Data Inspection gives potential imbalances and to better visualize the class distribution. For instance, randomly select a few images and label them, and then see how data consistency is handled.

Fig 1. Random images

C. Preprocessing: Normalize pixel values to [0:1] because it makes the gradients perform better while tuning the network. Resize all images to 224×224 as CNN and VGG16 expect input size as input image. Data is divided into 80% for training and 20% for validation.

D. Data Augmentation: Applications of the ImageDataGenerator include: Rotated, flipped and zoomed images added randomly in order to seem as having large data for details to enhance results rather than over fitting. It is then necessary to rescale the data in order to normalize it.

E. Feature Enhancement and Categorization: In this Feature Extraction we present multiple convolutional layers in order to extract features related to space as well as textures such as edges, patterns, and shapes. Through drawbacks such as MaxPooling2D, layers can focus purely on the important features of its particular feature map with regard to the dimension.

VGG16: Derived from the ImageNet, I, VGG16 offers outstanding and generalised features such as object type outlines. Deleting the last layers of the VGG16 results in feature extraction in which VGG16 weights are frozen and only task-specific classification layers are added. In Classification Method: The last layer use SoftMax activation to give out probabilities of each of the class (butterfly species). The highest probability defines the forecasted species.

F. Model Development, Compilation, Training, and Evaluation: Model Development, Compilation, Training, and Evaluation: The Custom CNN [10] contains convolution layers, 64 to 512, kernel size (3×3), ReLU activation, MaxPooling2D for reducing dimensionality, GlobalAveragePooling2D, and dense layers for the classification and dropout for preventing overfitting.[9] The second model is a VGG16 -based model with only the first set of convolutions being trainable, with GlobalAveragePooling2D layers, dense layers and a SoftMax classifier added in succession with pre-trained VGG16 with fixed weights.

Both models are trained using Adam optimizer, categorical cross entropy as loss function and model accuracy as the evaluation measure. It is trained for 60 epochs using Data Generators and there is Training- Accuracy/Validating-Loss. It consists of plots like accuracy /loss plots and confusion matrices. A comparison shows that the result of using the VGG16 model is the accuracy and its advantage in terms of transfer learning.[8] CNN Data collection and Preparation:

CNN as a way of determining butterfly types from images firstly involves data collection and data preprocessing. A set of images of butterflies is collected, which must be labelled, which means that each image clearly belongs to a particular type of butterfly; they can be found, for example, at Kaggle or any other source, and can be collected independently. Preprocessing of the dataset involves scaling all the images to the same dimensions for instance, use of the 128*128 pixels input dimensions to the CNN. Pixel values are usually normalized, most often brought to the range of 0 to 1, to unify the range throughout the training process. In order to enhance the model's ability to make accurate predictions on new data, additional data is synthesized using rotation, flip, zoom and adjustment of brightness. After data preprocessing, the data set is split in training along with testing data containing 80% of data and 20% data respectively. The training data set helps to model learn about the pattern and features while the testing data set is left for the model to learn its final performance. This in turn guarantees that there is a strong pipeline that helps in the right classification of butterfly species.[15]

CNN Architecture:

The structure and design of a CNN for butterfly image classification entrails of a number of layers that perform specific functionalities to realize the classification of the butterfly images. The input layer accepts the pre- processed images usually consisting of features such as pixel size, colour depths where for RGB images the size input could be 128 x128 x3. The next layers are convolutional layers and here filters – kernels are used to detect edges, textures, patterns and such things by moving over the image and performing element wise multiplication and summation.

These operations produce so called feature maps which correspond to the learned features such as edges or shapes. To complicate the linear relation between the layers, activation function known as Rectified Linear Unit (ReLU)[12] is applied so that any negative value cannot be learnt by the model. Andrew follows this by using Pooling layers like max pooling layers to down sample the feature maps in the cerochanism reducing the spatial dimension of the maps hence lowering the computational effort and bring out main features. For instance, a 128x128 feature map could be thrown down to 64 x64 by applying a 2 x2 pooling window. Following that, fully connected layers (dense layers), take the flattened 1D vector from the feature maps to make predictions, where the final dense neurons would be equal to the number of butterfly species. In the output layer, the raw scores are passed through the SoftMax activation function so as to produce probabilities; with the butterfly species of the class of highest probability being identified.[5]

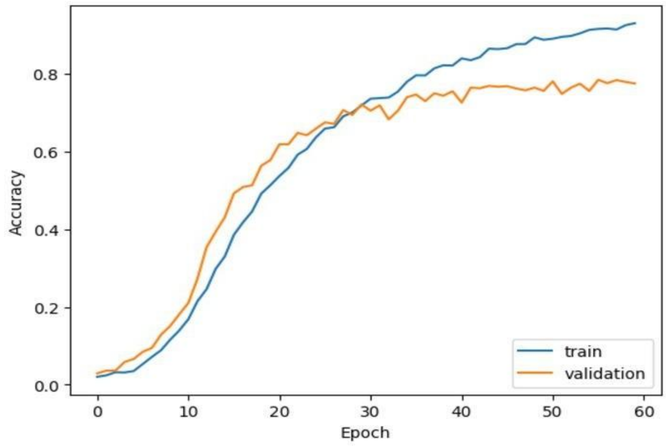
Model evaluation and training:

The structure and design of a CNN for butterfly image classification entrails of a number of layers that perform specific functionalities to realize the classification of the butterfly images. The input layer accepts the pre- processed images usually consisting of features such as pixel size, colour depths where for RGB images the size input could be 128 x128 x3. The next layers are convolutional layers and here filters – kernels are used to detect edges, textures, patterns and such things by moving over the image and performing element wise multiplication and summation. These operations produce so called feature maps which correspond to the learned features such as edges or shapes. To complicate the linear relation between the layers, activation function known as Rectified Linear Unit (ReLU) is applied so that any negative value cannot be learnt by the model. Andrew follows this by using Pooling layers like max pooling layers to down sample the feature maps in the cerochanism reducing the spatial dimension of the maps hence lowering the computational effort and bring out main features. For instance, a 128x128 feature map could be thrown down to 64 x64 by applying a 2 x2 pooling window. Following that, fully connected layers (dense layers), take the flattened 1D vector from the feature maps to make predictions, where the final dense neurons would be equal to the number of butterfly species. In the output layer, the raw scores are passed through the SoftMax activation function so as to produce probabilities; with the butterfly species of the class of highest probability being identified.[6][7]

VGG16: It is a popular deep Convolutional Neural Network that aims at image recognition task. It has fifteen layers with learnable parameters: thirteen convolutional layers and three fully connected layers which make it deep, while, at the same time, not too computationally heavy. It utilizes the small 3x3 convolutional kernels placed via many layers, which provided the network with the necessary foultile and keeps its architecture simple. As non-linearity it uses ReLU[12] activation for non-linearity and has max pooling layers which are useful in spatial down sampling for extracting hierarchical features from the images. As a convolutional neural network VGG16 takes input images of size 224 x 224 x 3 (RGB) and generates class probabilities through a fully connected layer and a SoftMax layer. Again, the architecture is based on the ImageNet dataset, making it particularly suitable for transfer learning where it can be trained for specific tasks such as object recognition and fine tuning for image classification. Due to being modest in their design while providing depth, VGG16 is acknowledged for its high outcomes on the small classifications of images.[14]

RESULT AND DISCUSSION

The butterfly picture classification venture utilizing CNN and VGG16 illustrates profoundly effective comes about, displaying vigorous preparing and approval execution. The to begin with chart highlights a steady increment in precision for both preparing and approval, with approval precision marginally slacking behind preparing after around 30 ages. This demonstrates successful learning but recommends the nearness of minor overfitting as the demonstrate begins to memorize the preparing information more than it generalizes to inconspicuous information. In differentiate, the moment chart shows an outstanding change, with the crevice between preparing and approval precision altogether diminished and both bends focalizing over 80%. This advancement reflects way better generalization, likely accomplished through the application of optimization procedures such as information increase, regularization (e.g., dropout), and fine-tuning of hyperparameters like learning rate and bunch estimate. The utilize of VGG16[14], a pre-trained convolutional neural organize, demonstrated to be a solid choice for this errand. Its profound design empowered the show to extricate complex designs and surfaces special to butterfly species, driving to precise classifications. The steadiness of the learning bends in both charts illustrates the model's viable preparing handle, bolstered by as fitting optimizer and parameter arrangement. This venture effectively addresses a few key challenges in butterfly classification, such as unpretentious inter-class contrasts and potential lesson awkward nature, which are common in biodiversity datasets. By leveraging exchange learning through VGG16 and utilizing astute optimization procedures, the show conveys tall precision and generalization. Moving forward, advance upgrades seem incorporate testing with progressed models like ResNet or Efficient Net, utilizing cross-validation to guarantee vigor, and investigating procedures such as engineered information era to address dataset restrictions. These changes might hoist the model's execution, making it an indeed more effective device for butterfly species recognizable proof.[3]



CONCLUSION

In this work, both a new CNN and a fine-tuned VGG16 network are proposed and tested for butterfly image recognition. The feature extractor CNN was trained from scratch for this specific paper targeting the classification job, whereas the VGG16 incorporated features learned from ImageNet reducing the complexity and providing a solid enhancement base for the classification task. The proposed custom CNN [11] did not learn well probably due to the limited depth and the fact that it was trained from scratch on this complex dataset while the VGG16-based model converged faster with improved accuracy as transfer learning proved efficient. Adding task-specific layers on top of the frozen earlier layers of the VGG16 model proved effective in applying this model to the butterfly dataset while nearly incurring no increase in computational cost. [12]Although it recommended using a pre-trained network for getting the best performance in the real-world image classification problems, the presented work provides a scalable solution for future

applications in other similar domains using transfer learning.

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