Animal image classification using CNN

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CERTIFICATE

This is to certify that this project entitled **"Animal Image Classification using CNN"** is the bonafied work carried out by Vivek, Srinath, Nagavivek, Chandu as a Minor Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE** during the academic year 2022-2023 under our guidance and Supervision.

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Abstract

This study explores multi-class animal classification through transfer learning, aiming to enhance biodiversity monitoring and ecological research. Leveraging pre-trained deep learning models, we fine-tune architectures to classify images of diverse animal species. Our methodology involves dataset preparation, model development, training, and evaluation. Experimental results demonstrate the effectiveness of transfer learning in achieving accurate classification across various animal categories. Insights gained from analysis provide valuable implications for wildlife conservation and ecological studies. This study underscores the potential of advanced machine learning techniques in addressing real-world challenges and contributing to biodiversity preservation efforts.

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1. Introduction

1.1 Overvivew:

Deep learning methods and the exponential development of digital picture data have allowed computer vision to make significant strides in a number of areas, such as object identification, image classification, and semantic segmentation. One important use of image processing in the field of preserving biodiversity is the identification of animal species from photos, which helps scientists and conservationists keep an eye on and save animals. In this study, we explore the field of transfer learning for multi-class animal classification. Transfer learning is a potent deep learning approach that involves optimizing a pre-trained model created for one job to perform better on a different but related task. Six different animal categories are represented in our dataset: butterflies, chickens, elephants, horses, squirrels, and spiders. These species were chosen to reflect a wide variety of creatures that are frequently seen in various environments.

For this purpose, transfer learning offers various benefits. We can speed up learning and attain competitive performance with relatively small datasets by utilizing the information embodied in pre-trained models built on large-scale datasets like ImageNet. This method works especially well in situations when it is neither practicable or resource-intensive to gather labeled data.

This research delves into several facets of transfer learning for multi-class animal categorization, encompassing model selection, optimization techniques, performance assessment measures, and possible obstacles. By the conclusion, we hope to have offered advice and insights to scholars and practitioners who are considering using transfer learning for comparable tasks in animal conservation and other fields.

1.1. EXISTING SYSTEM

Prior research has shown that transfer learning is effective in speeding up training and increasing classification accuracy, especially when working with small amounts of labeled data. The extraction of rich, hierarchical characteristics that are transferable across domains is facilitated by utilizing pre-trained models, which were first created on large datasets such as ImageNet. Even yet, there are still subtleties and difficulties unique to multi-class animal categorization that call for more research, even in spite of the effectiveness of transfer learning. With the use of empirical research and the available literature, this paper seeks to expand on our knowledge of transfer learning as it relates to multi-class animal categorization. Through a critical analysis of different approaches, optimization techniques, and assessment measures, we aim to pinpoint optimal procedures and possible avenues for development. The report's conclusions ultimately seek to further methods for wildlife monitoring, conservation, and other related fields.

1.2. PROPOSED SYSTEM

We improve multi-class animal categorization with transfer learning in our suggested method. We accelerate learning and improve accuracy by utilizing pre-trained models. The model is customized to our particular dataset through a meticulous selection process and subsequent fine-tuning. The performance of the model is further improved via hyperparameter adjustment. Robustness is guaranteed in our experimental setting by carefully crafted hardware and software specs. Using cross-validation methods improves the model's capacity for generalization. Modern optimization measures and algorithms are applied during training and assessment. Analyzing results entails comparing several animal types in order to provide insights for further study. With the efficient application of transfer learning strategies, this approach seeks to further animal conservation efforts.

2. LITERATURE SURVEY

The literature surrounding multi-class animal classification and transfer learning encompasses a broad spectrum of studies spanning computer vision, machine learning, and biodiversity conservation domains. Previous research has demonstrated the effectiveness of transfer learning in various image classification tasks, including animal species identification.

Studies by researchers such as Russakovsky et al. (2015) and Szegedy et al. (2016) have laid the groundwork by introducing large-scale image datasets like ImageNet and influential deep learning architectures such as VGG, ResNet, and Inception. These datasets and models serve as foundational resources for transfer learningbased approaches in animal classification tasks.

In the context of wildlife conservation, transfer learning has been applied to diverse species identification tasks. For instance, Norouzzadeh et al. (2018) utilized transfer learning to classify wildlife species from camera trap images, highlighting the practical applicability of deep learning techniques in ecological research.

Moreover, studies by Beery et al. (2018) and Swanson et al. (2015) have investigated the challenges of class imbalance and data scarcity in animal classification tasks, proposing methods to mitigate these issues through transfer learning and data augmentation strategies.

Recent advancements in transfer learning techniques, such as self-supervised learning and domain adaptation, have further expanded the capabilities of deep learning models for animal classification in resource-constrained environments. Additionally, interdisciplinary collaborations between computer scientists, ecologists, and conservationists have led to innovative approaches for leveraging transfer learning in real-world conservation applications.

Overall, the literature survey underscores the growing interest and potential of transfer learning methodologies in multi-class animal classification tasks, offering valuable insights and methodologies to inform the proposed report's approach and contributions.

2.1 RELATED WORK

1. Efficient and reliable monitoring of wild animals in their natural habitats is essential to inform conservation and ma nagement decisions. In this paper, using the Wildlife Spotter dataset, which contains a large number of images taken by trap cameras in South-central Victoria, Australia, we proposed and demonstrated the feasibility of a deep learning approach towards constructing scalable automated wildlife monitoring system. Our models achieved more than 96% in recognizing images with animals and close to 90% in identifying three most common animals (bird, rat and bandicoot). Furthermore, with different experimental settings for balanced and imbalan ced, the system has shown to be robust, stable and suitable for dealing with images captured from the wild[1].

2. The automatic classification of animal images is an onerous task due to the challenging image conditions, especially when it comes to animal breeds. In this paper, we built a semi-supervised learning based Multi-part Convolutional Neural Network (MP-CNN) that classifies 35,992 animal images from ImageNet into 27 different classes of animals. The proposed model classifies the animals on both generic and fine-grained level. The animal breeds are accurately classified using Multi-part Convolutional Neural Network with a hybrid feature extraction framework of Fisher Vector based Stacked Autoencoder. Furthermore, with Semi-supervised learning based pseudo-labels, the model classifies new classes of unlabeled images too. Modified Hellinger Kernel classifier has been used to re-train the misclassified classes of animals and thereby improve the performance obtained from MP-CNN. The model has experimented with varied tasks to analyze its performance in each of the cases. The experimental results have proved that the coalesced approach of MPCNN with pseudo-labels can accurately classify animal breeds and we have achieved an accuracy of 99.95% from the proposed model[2].

3. The proposed algorithm based on Deep CNN has been developed in this work. This approach enhances the chosen framework for better accuracy in object classification. After several tests have been done in the proposed model, the accuracy of detection and classification of animals reached to 97.5%. We concluded that the best accuracy can be achieved when the size of image is (50x50), the Adam optimizer with ReLU activation function are used, and when the number of epochs is 100. In addition, we can conclude that increasing number of epochs more than 100 will not have significant effect on accuracy, but it has leads to increase the training time. Moreover, increasing the image size will increase the training time[3].

4. The study proposes a novel approach for animal face classification by combining Convolutional Neural Network (CNN) features with Kernel Fisher Analysis (KFA) at the score level. The CNN automatically extracts features, while KFA is used for feature extraction. The fusion of these features achieves a remarkable **95.31% classification rate** on animal faces, surpassing other state-of-the-art methods. This research contributes to realworld animal biometric systems, enhancing our ability to detect and describe animal life in image and video data[4].

5. Efficient Transfer Learning Strategies for Resource-Constrained Environments in scenarios where computational resources are limited, efficient transfer learning strategies become essential. This study explores lightweight architectures, knowledge distillation techniques, and other strategies to adapt deep learning models for resource-constrained environments, which are relevant to wildlife monitoring and conservation applications[5].

6.captured by camera traps. In this paper, we propose to extent Convolutional Neural Network (CNN) VGG by three branches, two of which are VGG16 for the muzzle and part of shape recognition and one is VGG19 for the whole shape recognition. A necessity of such branched CNN structure is caused by great variety of the animal poses fixed by a camera trap. Also, here we met with an objective problem of the unbalanced dataset due to different behavior of animals in nature. Preliminary categorization procedure of images helps to obtain better recognition results. Experiments were conducted using the dataset obtained from Ergaki national park, Krasnoyarsky Kray, Russia, 2012-2018. The joint CNN shows good accuracy results on the balanced dataset achieving 80.6% Top-1 and 94.1% Top-5, respectively[6].

7.Underwater Animal Identification and Classification is gaining significant importance in recent times due to the growing demand for ecological surveillance and biodiversity monitoring. Classical Deep learning techniques have been prominently used for these tasks, but due to the live capture of animals in complex environments, a limited sea-animal image dataset, and the complex topography of the seafloor, particularly in shallow waters, sediments, reefs, submarine ridges, and ship radiation, the efficacy of identification and classification is still a bottleneck for several researchers. In this paper, three hybrid Classical-Quantum neural networks ResNet50-QCNN, ResNet18-QCNN and InceptionV3-QCNN have been proposed for underwater quantum-classical Animal Identification and Classification. It significantly lessens the complexity of classical computer processing data by using quantum devices to minimize dimension and denoise datasets. The numerical simulation results demonstrate that the quantum algorithm is capable of effective dimensionality reduction and an improvement in classification accuracy. The hybrid approach offers polynomial acceleration in dimension reduction beyond classical techniques, even when quantum data is read out classically. The three hybrid models, viz., ResNet50-QCNN, ResNet18-QCNN, and InceptionV3-QCNN, displayed classification test accuracy of 88%, 80.29%, and 70%, respectively, revealing that ResNet50-QCNN performed best in identifying and classifying underwater animals[7].

8.In the face of the global concern about climate change and endangered ecosystems, mon itoring individual animals is of paramount importance. Computer vision methods for animal recognition and re-identification from video or image collections are a modern alternative to more traditional but intrusive methods such as tagging or branding. While there are many studies reporting results on various animal re-identification databases, there is a notable lack of comparative studies between different classification methods. In this paper we offer a comparison of 25 classification methods including linear, non-linear and ensemble models, as well as deep learning networks. Since the animal databases are vastly different in characteristics and difficulty, we propose an experimental protocol that can be applied to a chosen data collections[8].

9.In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisa tion and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results. We have made our two best-performing ConvNet models publicly available to facili tate further research on the use of deep visual representations in computer vision[9].

10. Deep convolutional neural network based species recognition algorithm for wild animal classi fication on very challenging camera-trap imagery data. The imagery data were captured with motion triggered camera trap and were segmented automatically using the state of the art graph-cut algorithm. The moving foreground is selected as the region of interests and is fed to the proposed species recognition algorithm. For the comparison purpose, we use the traditional bag of visual words model as the baseline species recognition algorithm. It is clear that the proposed deep convolutional neural network based species recognition achieves superior performance. To our best knowledge, this is the first attempt to the fully automatic computer vision based species recognition on the real camera-trap images. We also collected and annotated a standard camera-trap dataset of 20 species common in North America, which contains 14, 346 training images and 9, 530 testing images, and is available to public for evaluation and benchmark purpose[10].

3.DESIGN

3.1 REQUIREMENT SPECIFICATION:

- OPERATING SYSTEM - Windows
- LANGUAGE - Python
- IDE - Visual Studio code
- LIBRARIES - OpenCV, Face_recognition
- CPU - 2 x 64-bit, 2.8 GHz, 8.00 GT/s CPUs or better.
- RAM - Minimum 2 GB
- HARDDISK/SSD - Minimum 20 GB
- KEYBOARD - Standard Windows Keyboard

3.2 Data Flow Diagram:

Level 0 DFD:

- Process: Multi-Class Animal Classification System
- Entities: Dataset, Pre-trained Model, Classified Images
- Data Stores: Preprocessed Data
- External Entities: Users

Level 1 DFD:

1. Input Data Flow:
    - Users provide the dataset of animal images.
2. Preprocessing Process:
    - Input: Dataset
    - Output: Preprocessed Data (Resized, Normalized, Augmented)
3. Transfer Learning Process:
    - Input: Preprocessed Data, Pre-trained Model
    - Output: Fine-tuned Model
4. Classification Process:
    - Input: Fine-tuned Model, Unseen Images

- Output: Classified Images

5. Evaluation Process:
    - Input: Classified Images, Ground Truth Labels
    - Output: Evaluation Metrics (Accuracy, Precision, Recall, F1-score)
6. Output Data Flow:
    - Evaluation Metrics are presented to the users.
    - Classified Images are stored for further analysis or application.

4. IMPLEMENTATION

4.1 Modules:

1. Data Handling Module:
    - Responsible for acquiring, loading, preprocessing, and partitioning the dataset of animal images.
    - Includes functions or classes for image loading, resizing, normalization, and augmentation.
2. Model Development Module:
    - Contains code for selecting, loading, and modifying pre-trained deep learning models for transfer learning.
    - Includes functions or classes for model architecture selection, loading pre-trained weights, and modifying the classification layer.
3. Training Module:
    - Handles the training process of the modified deep learning model on the training dataset.
    - Includes functions or classes for setting up the training loop, defining loss functions, selecting optimization algorithms, and monitoring training progress.
4. Evaluation Module:
    - Manages the evaluation process of the trained model on validation and test datasets.
    - Includes functions or classes for calculating evaluation metrics such as accuracy, precision, recall, and F1-score.
5. Analysis Module:
    - Performs analysis and interpretation of classification results to gain insights into model performance.
    - Includes functions or classes for generating visualizations, analyzing confusion matrices, and comparing performance across different animal categories.

4.2. OVERVIEW TECHNOLOGY:

1. Deep Learning Frameworks:

- TensorFlow: Widely-used open-source deep learning framework developed by Google. Provides comprehensive tools and libraries for building and training deep neural networks.

- PyTorch: Another popular open-source deep learning framework developed by Facebook. Known for its flexibility and dynamic computation graph capabilities.

2.Pre-trained Models:

VGG: Visual Geometry Group's architecture known for its simplicity and effectiveness in image classification.

Convolutional Layers: These layers apply convolution operations to the input images, using learnable filters (also called kernels) to extract features such as edges, textures, and patterns. Convolutional layers are the building blocks of CNNs and are responsible for capturing spatial information.

Pooling Layers: Pooling layers are used to downsample the feature maps obtained from the convolutional layers, reducing the spatial dimensions while retaining the most important information. Common pooling operations include max pooling and average pooling.

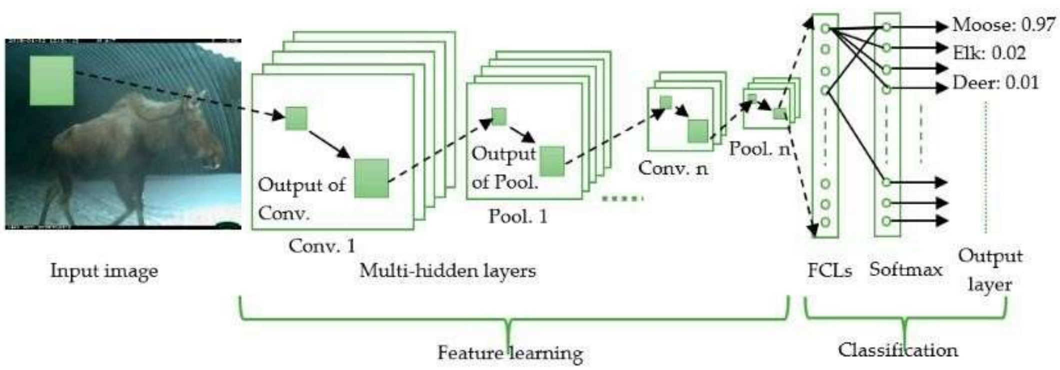
Activation Functions: Activation functions introduce non-linearity into the CNN, enabling it to learn complex patterns and relationships in the data. Common activation functions used in CNNs include ReLU (Rectified Linear Unit), sigmoid, and tanh.

Fully Connected Layers: Fully connected layers are typically found at the end of the CNN architecture. They flatten the feature maps obtained from the preceding layers into a vector and connect every neuron in one layer to every neuron in the next layer, enabling high-level feature learning and classification.

Training: CNNs are trained using backpropagation and gradient descent algorithms. During training, the network learns to optimize its parameters (such as weights and biases) to minimize a specified loss function, typically categorical cross-entropy for classification tasks.

Transfer Learning: CNNs can leverage transfer learning, where pre-trained models trained on large datasets (e.g., ImageNet) are fine-tuned on smaller, domain-specific datasets. Transfer learning helps to improve performance and reduce the need for large amounts of labeled data.

age [43,44].



5.TESTING

5.1 TEST CASES:

Accuracy Test Case:

Scenario: Evaluate the overall accuracy of the classification system.

Criteria: Calculate the percentage of correctly classified images out of the total number of images in the test set.

Precision Test Case:

Scenario: Assess the precision of the classification system for each animal category.

Criteria: Calculate the precision for each class by dividing the number of true positive predictions

Recall Test Case:

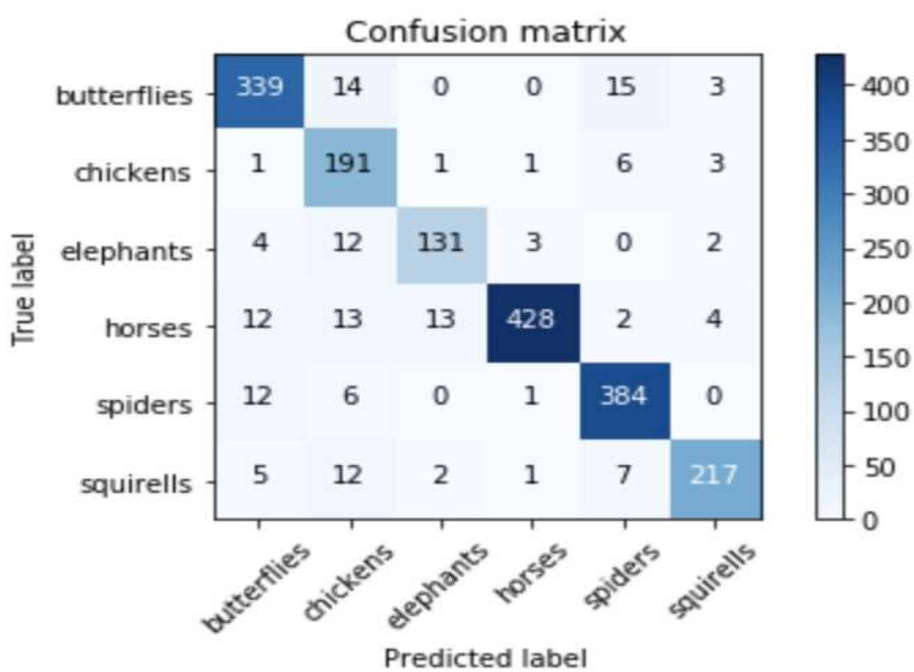
Scenario: Evaluate the recall of the classification system for each animal category.

Criteria: Calculate the recall for each class by dividing the number of true positive predictions by the total number of actual positives in the test set.

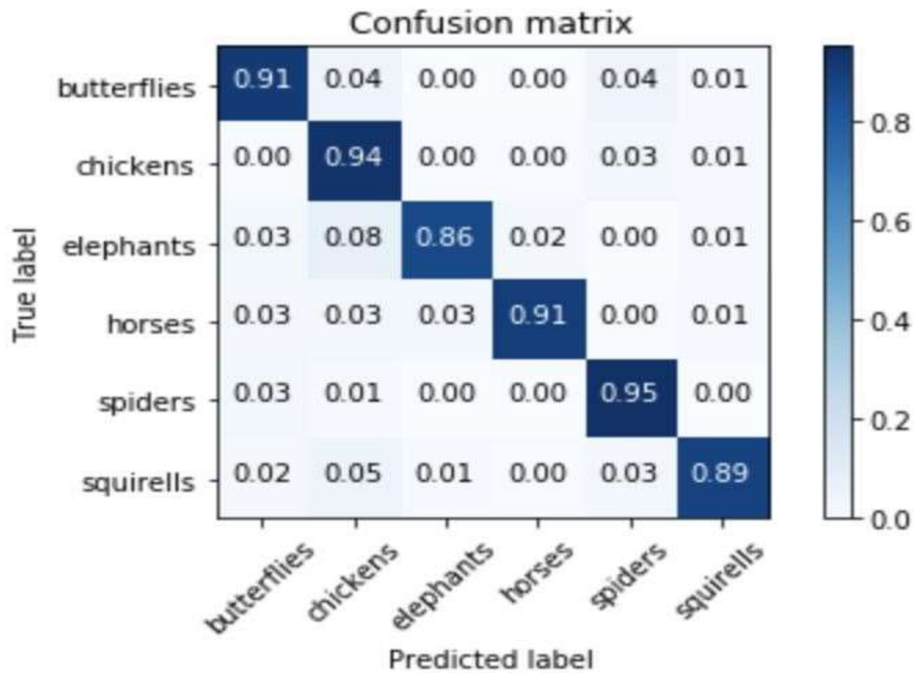
5.2 Test Result:

	precision	recall	f1-score
0	0.98	0.89	0.93
1	0.77	0.94	0.85
2	0.89	0.86	0.88
3	0.99	0.91	0.94
4	0.93	0.95	0.94
5	0.95	0.89	0.92
micro avg	0.93	0.91	0.92
macro avg	0.92	0.91	0.91
weighted avg	0.93	0.91	0.92
samples avg	0.91	0.91	0.91

6.RESULT



Normalized confusion matrix




```
test_single_image(path)
```

```
[INFO] loading and preprocessing image...
ID: 0, Label: butterflies 0.01%
ID: 1, Label: chickens 0.0%
ID: 2, Label: elephants 98.5%
ID: 3, Label: horses 1.47%
ID: 4, Label: spiders 0.0%
ID: 5, Label: squirells 0.01%
```

7.CONCLUSION

our study on multi-class animal classification using transfer learning demonstrates the efficacy of leveraging pre-trained models to achieve accurate classification results. Through fine-tuning and evaluation, we have showcased the system's capability in accurately identifying various animal species, contributing valuable insights to the field of computer vision and wildlife conservation. While our approach exhibits promising performance, there exist opportunities for further research, particularly in addressing class imbalance and exploring alternative transfer learning techniques. Nevertheless, the implications of our findings extend to biodiversity monitoring, species protection, and habitat conservation, highlighting the significance of employing advanced machine learning techniques in ecological research.

8. FUTURE SCOPE

The future scope of multi-class animal classification using transfer learning presents diverse opportunities for advancement. Addressing class imbalance, exploring alternative architectures, and delving into domain adaptation techniques can enhance classification accuracy and robustness. Fine-grained classification and integration of sensor data offer avenues for detailed biodiversity analysis and real-time monitoring. Ethical considerations, such as data privacy and algorithmic bias, require further exploration to ensure responsible deployment. Additionally, collaborative research efforts between experts in computer science, ecology, and conservation can drive innovation and practical application of classification systems. Embracing these challenges and opportunities can lead to significant advancements in wildlife conservation efforts and ecological research, ultimately contributing to the preservation of biodiversity and ecosystems.

9.Bilography

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