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An Enhanced Animal Species Classification and Prediction Engine using CNN

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Abstract— **Animal species classification is a fundamental task in wildlife conservation, animal behavior studies, and biodiversity research. Convolutional Neural Networks (CNNs) have become a potent technique for automatic classification tasks in recent times. This abstract presents an overview of the use of CNNs for animal species classification. The proposed approach involves pre-processing of the input images, followed by feature extraction and classification using CNN architecture. The pre-processing step involves image resizing, normalization, and augmentation to enhance the resilience of the model. The feature extraction is performed by convolutional layers, followed by max-pooling layers, and fully connected layers for classification. Transfer learning is also utilized to leverage the pre-trained CNN models and fine-tune them for specific animal species classification tasks. The proposed approach achieves high accuracy of 98% and can be extended to various animal species classification tasks. Overall, CNNs provide an effective means for automated animal species classification, enabling more efficient and accurate animal behavior studies, and wildlife conservation efforts.**

Keywords— Animal species, Classification, Convolutional Neural Network, Prediction engine, Accuracy.

I. INTRODUCTION

Although image classification has been used for a long time, it continues to be essential in many applications today, especially with the advancements of neural networks. However, image classification is a complex task due to various challenges like pose variations, occlusion, and illumination, among others. Deep learning, a type of machine learning, has enabled the creation of models that can perform image classification directly from various sources through the use of Deep Neural Networks (DNNs). Although creating a DNN from the beginning may result in superior performance, it can be time-consuming and complicated. Thus, transfer learning has been adopted to develop highly efficient neural networks for image classification. Despite the widespread use of image classification, it has not been fully exploited in certain areas like animal species classification.

Because of the particular difficulties provided by animal imagery, the classification of animal species continues an unresolved issue. However, deep learning algorithms can simplify and automate the process of animal species classification, providing valuable insights for researchers and aiding in conservation efforts. Accurately identifying animal species in these images is crucial for taking appropriate measures to protect endangered species. Moreover, a trustworthy tool for academic scholars and animal lovers is provided by the use of contemporary devices. Traditional research methods for animal identification have been challenged by background and noise interference, resulting in accuracy performance degradation. Recent research based on Deep Convolutional Neural Networks (DCNNs) has demonstrated promising results for animal recognition in natural scenes.

II. LITERATURE REVIEW

The objective of the research is to specialize in detecting animals and classifying species in images captured by camera traps amidst dense natural surroundings. To achieve this, we have developed a deep neural network (DNN) model that can effectively differentiate between animal and background images. The DNN model analyses the input images and generates a comprehensive multi-level visual representation of them. With the use of graph cuts and k-mean clustering within the DNN feature domain, they can discover animal interest areas using this representation. After locating these locations, scientists classified them into the appropriate species using DCNN model [1], [2], [4].

The classification of all living beings on Earth as represented by the kingdom Animalia into various categories. Various techniques are available for classifying animals acoustically and visually. Bioacoustics monitoring has emerged as a significant area of research, and classification systems play a vital role in this field. While the visual classification of animals is typically achieved through satellite or established camera images, there may be instances where image processing techniques cannot be used. In such cases, acoustical classification techniques can be utilized to overcome these issues. However, remote observation is still necessary for acoustical methods due to certain limitations. The AdaDelta, Gradient Descent, and RMSProp optimizers provided the best results, each achieving an accuracy rate of 91.3%. In future, a larger dataset will be used to improve accuracy [3], [5], [7]

Despite the many interesting developments in object detection, recognition, and classification using computer vision (CV) systems, detecting and recognizing animals in uncontrolled environments remains a significant challenge. Visual monitoring of animals in various scenes is currently an active research area in CV, and although there have been many studies, real-time methods for dynamic object detection and recognition are still lacking. To address this issue, this paper suggests the use of a DCNN to detect and classify vertebrate classes of animals in digital images. The dataset used for training and evaluation consists of 12,000 images, with 9,600 images for the training stage and 2,400 for the evaluation stage. The proposed system achieved a total performance of 97% for the algorithm being 50x50 and the optimal number of epochs being 100 [6].

III. PROPOSED SYSTEM

A. *Need of proposed system and its workflow*

The methodology described in the work involves using DCNN architecture to classify different animal species from input images. The proposed approach includes the pre-processing step, and the input images undergo resizing, normalization, and augmentation. Feature extraction is performed using convolutional layers, max-pooling layers, and fully connected layers for classification. To enhance the robustness and accuracy of CNN models used in animal species classification, the pre-processing step is a vital component, which includes resizing, normalization, and augmentation techniques. Resizing is necessary to adjust the image size to a uniform size suitable for the CNN model, ensuring that all images have the same dimensions. Normalization transforms the pixel values of input images to have zero mean and unit variance, reducing the effect of illumination and color on the model's performance. Additionally, normalization helps prevent overfitting to training data, which can lead to poor performance on new images. Augmentation generates additional training data by applying various transformations to the original images, such as rotation, flipping, and scaling. This technique helps increase the training dataset size, improving the CNN model's robustness and generalization. Augmentation also decreases the likelihood of overfitting by exposing the model to various input data variations. Overall, these techniques improve the model's accuracy, robustness, and generalization, making it more effective on new and unseen data.

In animal species classification, feature extraction and classification are critical steps in the Convolutional Neural Network (CNN) model. Feature extraction involves identifying unique features of the input images that are important for classification. CNN algorithms are used to extract these features by analyzing the patterns and structures within the images. This process involves passing the images through multiple convolutional layers that identify different features and patterns, followed by pooling layers that reduce the dimensionality of the feature maps. This produces a more condensed representation of the features that are relevant for classification. Once the features have been extracted, the classification step involves using deep learning techniques to identify the animal species. In this step, the feature maps are fed into fully connected layers that learn the relationship between the features and the output labels. The fully connected layers use a ReLU activation function to generate probabilities for each animal species, which are used to predict the most likely species. The combination of feature extraction and classification allows the CNN model to learn the unique features that distinguish one animal species from another. This approach is highly effective in animal species classification tasks, achieving high levels of accuracy and outperforming traditional algorithms. By automating the classification process, CNN models can help to reduce the workload of researchers and conservationists and provide valuable insights into the distribution and behavior of different animal species. To predict animal species, we developed and applied a new prediction engine. It is required to finish the following tasks and activities to fulfill the aforementioned task as represented in below Fig. 1.

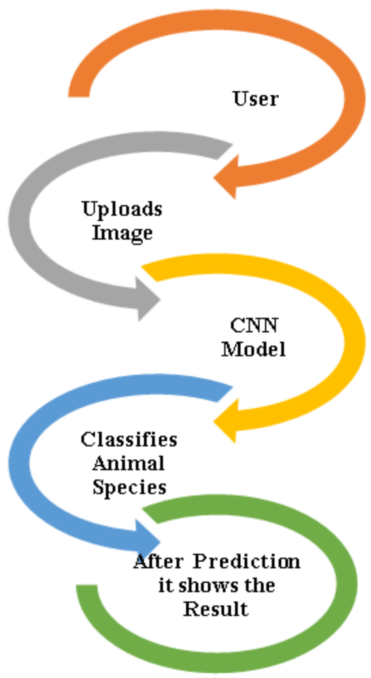


Fig. 1. Workflow

B. *The architecture of the recommendation engine*

To start building a neural network for animal species classification, the first step is to obtain a suitable dataset. This dataset is then divided into a training set and a test set. Next, layers are added to the neural network, and the training images are added to the model and fit. Once the model is trained, a test is run to evaluate its performance, and the model and its dependencies should be saved for future use. Convolutional Neural Networks (CNNs) are then used to extract image features through analysis.

CNNs are part of the deep learning family of techniques, which can handle vast datasets with millions of features by converting them into two-dimensional images and linking the resulting representations to the corresponding outputs. These multilayer networks are supervised and can learn new features dynamically from the datasets. Using the same architecture, CNNs can systematically classify features into multiple categories, as shown in Fig. 2.

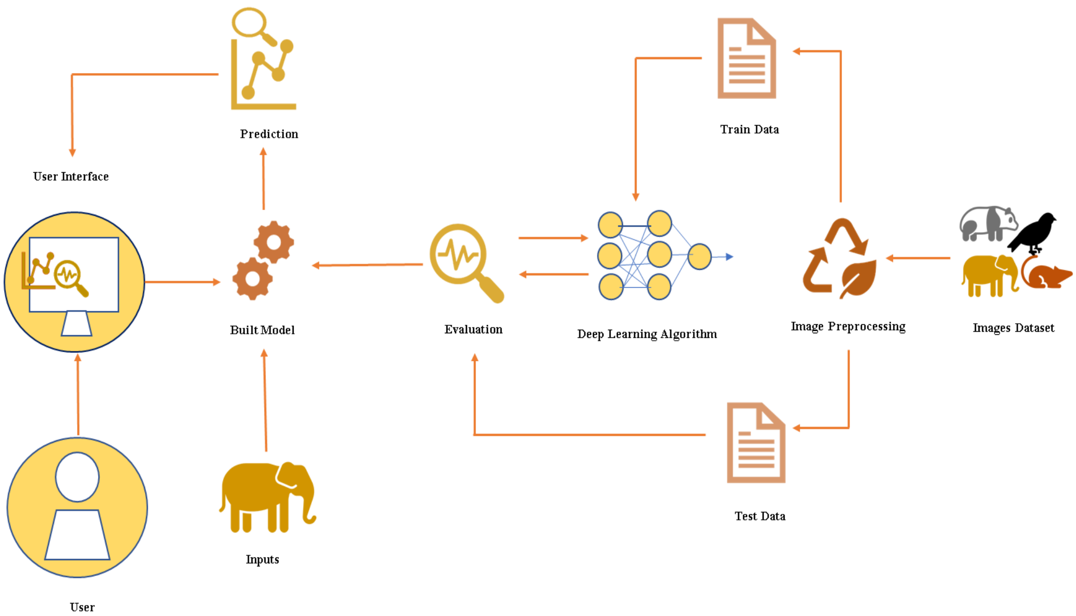


Fig. 2. Animal species of the recommendation engine

C. *Description of dataset*

To develop a deep convolutional neural network capable of identifying diseases in animal species, a dataset consisting of 1238 images belonging to four classes such as elephant, bear, crows, and rats is used for testing. The training data containing 326 images belonging to 4 classes are collected. The images are described in detail in Fig. 3., and example images from the dataset belonging to the four classes are shown in Fig. 4.

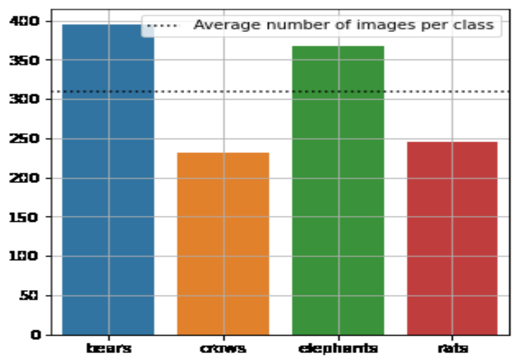


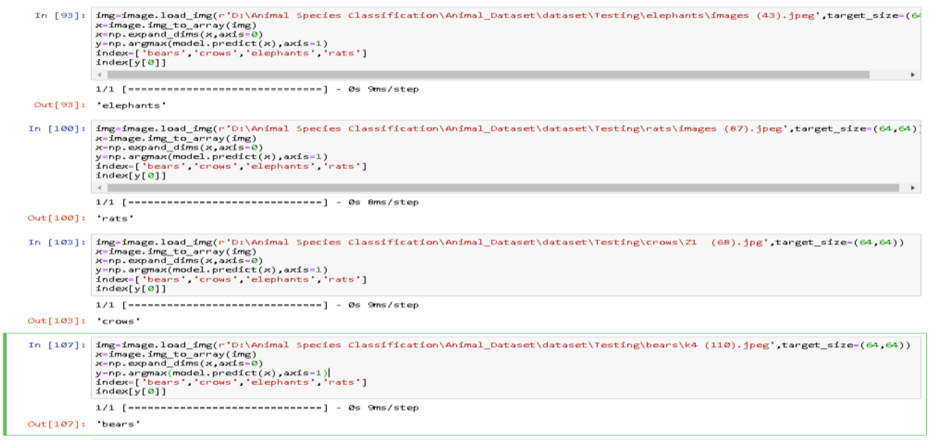
Fig. 3. Description of Dataset

Fig. 4. Sample images of the dataset

IV. METHODOLOGY

A. The training model and its implementation

To begin with, the data samples are gathered and then subjected to pre-processing. Following this, the image augmentation technique is employed, which creates several distinct copies of the same image. This technique enhances the proposed model's resilience. The dataset is then trained and tested, taking into account various factors such as batch size, dense convolution, max pooling, and flattening. The convolution layer incorporates dense, shape, matrix, and ReLU activation functions. Additional dense layers can be included in the hidden layer, and the ReLU activation function is applied at each stage. The resultant model is assessed using test data, as illustrated in Fig. 5., and subsequently saved. Finally, the saved model can be utilized to make predictions through a web application using a flask file.



```
In [93]: img=image.load_img(r'D:\Animal Species Classification\Animal_Dataset\dataset\Testing\elephants\images (43).jpeg',target_size=(64
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['bears','crows','elephants','rats']
index[y[0]]
1/1 [==============================] - 0s 9ms/step
Out[93]: 'elephants'

In [100]: img=image.load_img(r'D:\Animal Species Classification\Animal_Dataset\dataset\Testing\rats\images (87).jpeg',target_size=(64,64)
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['bears','crows','elephants','rats']
index[y[0]]
1/1 [==============================] - 0s 8ms/step
Out[100]: 'rats'

In [103]: img=image.load_img(r'D:\Animal Species Classification\Animal_Dataset\dataset\Testing\crows\Z1  (68).jpg',target_size=(64,64))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['bears','crows','elephants','rats']
index[y[0]]
1/1 [==============================] - 0s 9ms/step
Out[103]: 'crows'

In [107]: img=image.load_img(r'D:\Animal Species Classification\Animal_Dataset\dataset\Testing\bears\k4 (110).jpeg',target_size=(64,64))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
index=['bears','crows','elephants','rats']
index[y[0]]
1/1 [==============================] - 0s 9ms/step
Out[107]: 'bears'
```

Fig. 5. Implementing the model against test data

The user interface that enables the user to upload an image for analysis. The uploaded image is processed by a saved model, and the results are displayed on the user interface. The purpose of this application is to determine animal species. The Adam optimizer is used to calculate the respective loss, resulting in optimized accuracy. The model is based on deep learning algorithms and is integrated with a Flask-based web application that offers an intuitive user interface. One significant advantage of the model is that it can identify animal faces from a single image, although only a limited number of animal species are currently supported. Future work aims to expand coverage to the majority of animal species The output predictions for the predicted animal are depicted in Fig. 6. respectively.

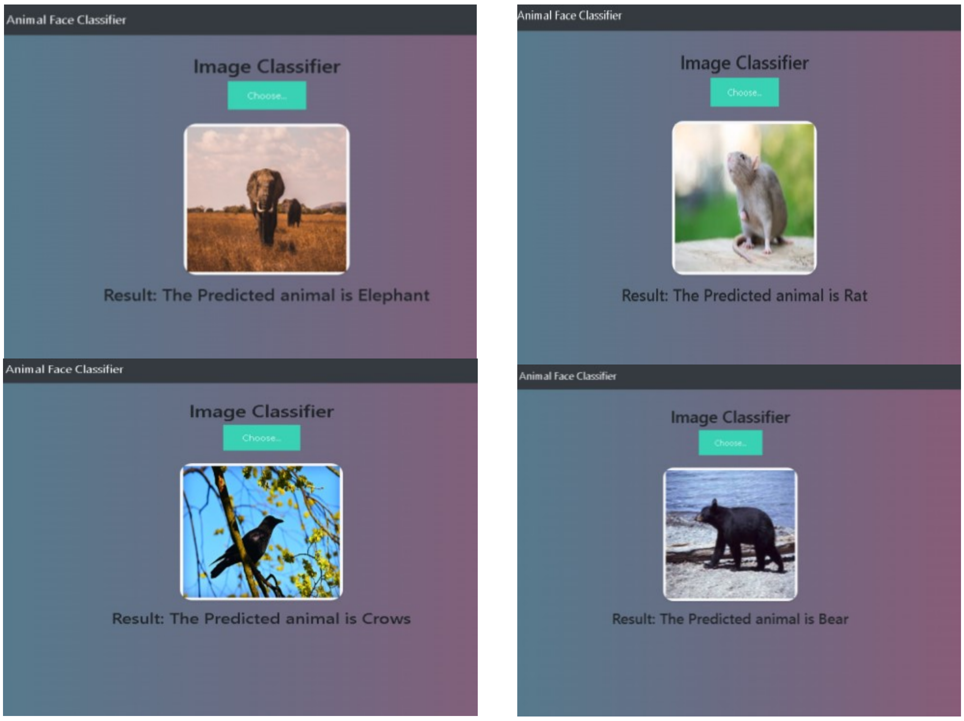


Fig. 6. Prediction and animal species classification engine

B. Accuracy

To develop a more complex convolutional neural network capable of identifying diseases, a dataset of 1,238 samples containing four classes is utilized. The model was assessed based on the number of epochs, loss, and performance accuracy of the test results. Fig. 7. demonstrated the prediction performance accuracy, achieving 98% accuracy on both training and validation sets.

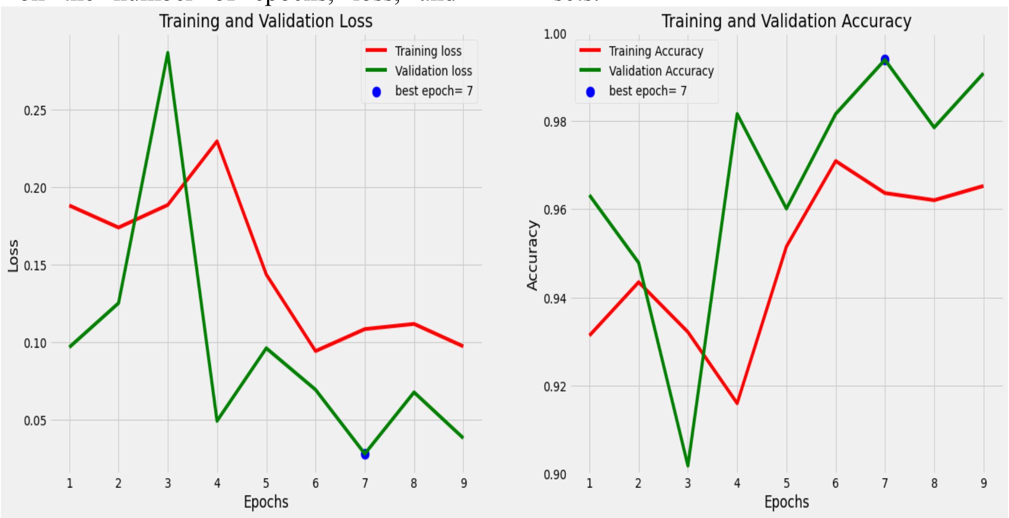


Fig. 7. Model accuracy for animal species

V. CONCLUSION

Our study's objective was to create a method for accurately classifying animal species from input images that contain complex and cluttered scenes. To assess the input photos, we used a deep neural network that was particularly trained for animal classifications. Our experimental findings showed that our suggested method performed better than existing methods and achieved a high accuracy rate of 98% for species classification. Going forward, we plan to develop an application that leverages computer vision and AI techniques to predict animal movements. By training the application with diverse datasets and testing it with real-time images captured by cameras in forest and residential areas, we anticipate improved accuracy in classifying animal images. Furthermore, by issuing alerts to relevant parties, our application can help save lives. While our current web application can accept image inputs and generate predictions, our future plans will make the project even more valuable.

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