Crab Species Classification using deep learning techniques

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Abstract - Crab species classification is based on the deep learning model. Crab species play an important role in undertaking environmental and biological marine research. This helps in the accurate categorization of crab species, this study offers a combined approach of convolutional neural networks (CNN) and artificial neural networks (ANN). Finding the model with the best accuracy in detecting photos of crabs is our main goal. To prepare pictures for input into CNN models, we first pre-process them by removing frames from the dataset. The study examines the efficiency of CNN, a cutting-edge deep learning model, and ANN, a traditional machine learning algorithm, in differentiating between several crab species based on visual data. Utilizing feature extraction, the study looks at how well they do in classifying crab species from photos. Furthermore, the CNN model is created and trained using a dataset that includes the coconut crab and vampire crab. The models are assessed and contrasted according to how well they can categorize photos from a dataset of actual crabs. Then, using the prepared data, we build and train each CNN architecture, including strategies like data augmentation that boost the prediction and strength of the model. Performance assessment makes use of criteria like correctness.

Index Terms - Image Classification, Crab Species, Convolutional Neural Network, Artificial Neural Network, Comparative analysis.

I. INTRODUCTION :

The multiplicity of crab species plays a vital role in marine ecosystems and has applications in marine biology, ecology, and fisheries management since it will offer a more accurate and efficient way to categorize different species of crabs (which include vampire crab and coconut crab). However, traditional methods of species identification are often time-consuming and subject to human error. In this study, machine learning and deep learning techniques have gained prominence for their ability to learn discriminative features from image data automatically. we propose a novel automated crab species classification approach using deep learning techniques. We leverage convolutional neural networks (CNNs) to analyze high-resolution images of crab species and extract discriminative features for species classification and Artificial Neural Network(ANN), is known to replicate the working of the human brain.
This work aims to reliably identify and categorize crab species from picture data by utilizing the power of deep learning algorithms in classifying two distinct crab species:

Fig.1 Coconut Crab **Fig.2 Vampire Crab**

Coconut crab and Vampire crab. The research evaluates the accuracy of these models in predicting crab species and provides a comparative analysis of CNN and ANN for accuracy assessment. The study's outcomes offer valuable insights into the capabilities and constraints of the methods. The findings are particularly relevant to marine biologists, ecologists, and researchers involved in the identification of crab species across various marine habitats. By providing efficient and accurate methods for automated crab species identification, the research contributes to the broader understanding and management of marine ecosystems.

II. LITERATURE SURVEY

The first research reference used was research from Yonatan Adiwinata et al., which discussed the research *using the Faster R-CNN method* with Inception-v2 architecture. Single Shot Detector (SSD) is also used in this research as a compliment. *The dataset they used in the research reference was the QUT FISH Dataset.* The research aimed to know the performance of the Faster R-CNN method against other object detection methods like SSD in fish species detection. *The accuracy of the Faster R-CNN reached 80.4%, far above the accuracy of the Single Shot Detector (SSD) Model with an accuracy of 49.2%.* The result of this research was a comparison of performance in fish species recognition between Faster R-CNN and SSD object detection methods [1]

Zhang, Huang, Huang, and Zhang discuss the crucial role played by plants in various domains such as agriculture, industry, medicine, and ecology. They emphasize the increasing threats to plant species brought about by global warming, biodiversity loss, urban development, and environmental degradation. Recognizing the importance of protecting plant species, the authors emphasize the need for efficient classification methods to identify and understand plants, particularly considering the vast number of both known and unknown species on Earth. The authors of the paper focus on plant species recognition through leaf analysis. They provide a comprehensive overview of existing methods, covering various aspects including plant leaf characteristics, public databases, and diverse recognition methods such as feature extraction, subspace learning, sparse representation, and deep learning. The paper emphasizes the simplicity and convenience of using leaves for recognition and aims to raise awareness about the importance of plant species identification. It serves as a valuable resource for beginners in the field, offering guidance and insights to foster a deeper understanding of plant species and contribute to their preservation.[2]

Jayashree Deka, Shakuntala Laskar, and Vikramaditya Baklial conducted a study on automated freshwater fish species classification using CNN**.** The major advantages of the deep CNN architecture over the manual supervised method are its self-learning and self-organized characteristics. The first layer in the CNN architecture is the image input primary layer that takes up 2-D and 3-D images as input.

Deep-learning architectures, AlexNet and Resnet-50, to classify 20 indigenous freshwater fish species from the Northeastern parts of India. It incorporates 60 million parameters and 650,000 neurons. The architecture consists of 5 convolution layers, max-pooling layers, and 3 consecutive fully connected layers. The two models are fine-tuned for training and validation of the collected fish data. Performed networks are evaluated based on overall accuracy, precision, and recall rate. They reported the best overall classification accuracy, precision, and recall rate of 100% at a learning rate of 0.001 by the Resnet-50 model on their dataset and benchmark Fish-Pak dataset.[3]

The study by Seppo Fagerlund discussed the use of support vector machines (SVM) for bird species recognition. This evaluated the performance of SVM on two different datasets. In the first dataset, where recognition testing was performed independently for each bird, the mixture model showed the best results among various generative representations, while the reference method employing MFCC parameters and nearest-neighbour classification also performed well. In the second dataset, where syllables were manually segmented, the SVM classifier demonstrated comparable performance to the reference method. Once again, the mixture model proved to be the most effective.

The study concluded that SVM methods achieved equal or superior performance compared to reference methods. However, the study advised caution in directly comparing dataset results due to differences in species diversity and sound spectra. While the proposed method represented all syllables uniformly, the decision tree topology employed lacked consideration for sound relationships between species. Future work was suggested to explore feature weighting, which could improve accuracy, as seen in the Pygmy Owl case. Overall, the study highlighted SVM's potential for bird species recognition and suggested avenues for further refinement.[4]

Chen G, Han TX, He Z, Kays R, and Forrester T performed a study on species recognition for monitoring wild animals. They focused on deep convolutional neural networks (DCNN) and introduced a camera-trap dataset that comprises 20 North American species. This publicly available dataset includes 14,346 training images and 9,530 testing images, with color, gray, and infrared images of resolutions ranging from 320 by 240 to 1024 by 768. To recognize different species, a bag-of-words model was used with image classification. This model divided images into blocks of 8 by 8, and treated them as "words". A histogram of occurrence counts for classification was used in this process. The code sizes (K) used in the BOW model were 1000, 2000, and 3000, which produced accuracies of 33.192%, 33.507%, and 33.485% respectively.

It contrasted the BOW model and the DCNN algorithm on a dataset. The DCNN algorithm showed better species recognition accuracy of 38.315% compared to 33.507% for the BOW model. The DCNN algorithm could improve with more training data, despite the dataset's challenging nature. The DCNN algorithm could also identify ambiguous data for annotation, which would help reduce the burden on experts. Overall, the study demonstrated the effectiveness of the DCNN algorithm for species recognition in wildlife monitoring.[5]

Vilches E, Escobar IA, Vallejo EE, Taylor CE. They investigated the utilization of data mining methodologies in addressing the issue of acoustic recognition of avian species. A substantial quantity of spectral and temporal attributes are typically generated by most tools used for the analysis of bird songs. introduced a new representation for bird syllables which was based on the average spectrum over time and classification was based on template matching.[6]

Marques TP, Rezvanifar A, Cote M, Albu AB, Ersahin K, Mudge T, Gauthier S. This article presents an extensive comparative examination of conventional, hybrid, and deep learning techniques for the detection of marine species in echograms. Marine biologists typically interpret acoustic backscatter data, visualized as echograms, through manual or semi-automatic means, which can be time-consuming. The automatic interpretation of echograms poses challenges due to the varying size and acoustic properties of marine life, as well as significant similarities between different classes. The study examines and contrasts three different approaches that encompass the full spectrum of machine learning methods. Our experimental results lead us to conclude that an end-to-end deep learning-based framework, which can easily accommodate new species, is generally more advantageous than other learning approaches for the interpretation of echograms, even when only a limited number of annotated training samples are available.[7]

Yang CH, Wu KC, Chuang LY, and Chang HW conducted this chapter DNA barcodes with short sequences are used for species identification. advances in sequencing technologies are the reason, DNA barcodes have step by step. DNA sequences from different organisms are easily and rapidly acquired. Therefore, DNA sequence analysis tools play an increasingly critical role in species identification. This study suggests deep barcoding, a deep learning framework for species classification utilizing DNA barcodes. Deep barcoding leverages the raw sequence data as the input to represent one-hot encoding as a one-dimensional image and employs a deep convolutional neural network alongside a fully connected deep neural network for sequence analysis. It can achieve an average accuracy of >90% for both simulation and real datasets. Although deep learning has proven to be highly effective in species classification using DNA sequences, its application remains challenging. The deep barcoding model can be a valuable tool for species classification and can contribute to DNA barcode-based species identification.[8]

Wei Tan J, Chang SW, Abdul-Kareem S, Yap HJ, and Yong KT performed the D-Leaf automatic plant species identification system is a cutting-edge CNN-based technique that uses three different types of Convolutional Neural Network (CNN) models—pre-trained AlexNet, fine-tuned AlexNet, and D-Leaf—to extract features from leaf photos. The five machine learning techniques Support Vector Machine (SVM), Artificial Neural Network (ANN), k-nearest-neighbour (k-NN), Naïve Bayes (NB), and CNN are then used to classify these attributes. The D-Leaf model outperformed conventional morphometric measurements (66.55%) and attained a comparable testing accuracy of 94.88% compared to AlexNet (93.26%) and fine-tuned AlexNet (95.54%) models. It was discovered that the CNN features fit the ANN classifier effectively, demonstrating the efficacy of D-Leaf as an automated method for identifying plant species.[9]

III. Convolutional Neural network

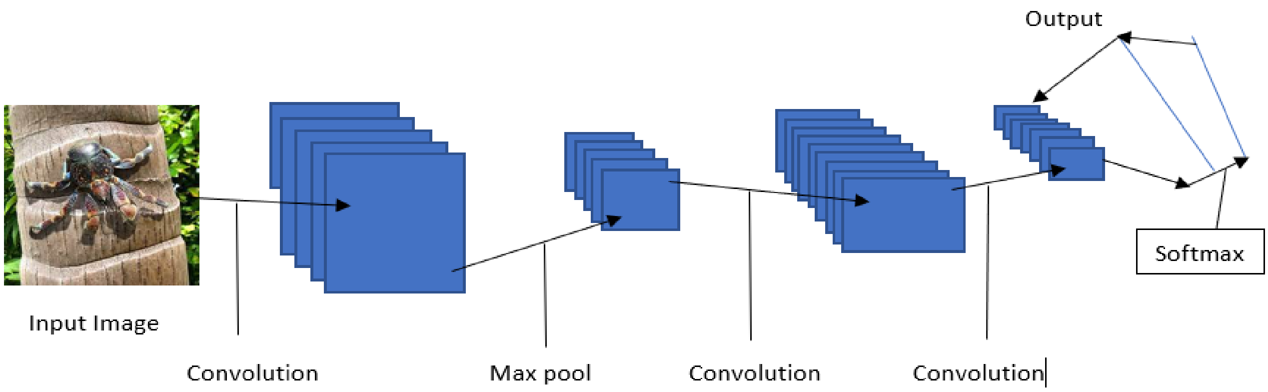


Fig.3 Overview of CNN model

Convolutional Neural Networks(CNNs) are for image classification tasks due to which their automatic learning and feature extraction capabilities make them an ideal choice for crab species images. In the above diagram, we can see the convolutional layers create feature maps from input images and capture by filters. Max pooling layers down-sample these maps, aids in reducing overfitting and computational complexity.
The flattened layer converts multi-dimensional feature maps into a one-dimensional vector, which is then passed to dense layers for classification, using the activation function, ReLU (Rectified Linear Unit), The CNN classifies vampire and coconut crab images using the softmax activation function, which generates predictions based on relevant aspects from input images. The activation function used in convolutional layers is ReLU (Rectified Linear Unit), and in the output layer, it is softmax which is suitable for multi-class classification problems The training process includes optimizing the model's parameters using a labeled dataset which allows the CNN to understand and recognize the distinctive features associated with each crab species.

IV. Artificial Neural network

The (ANN) Artificial Neural Network, is something that contains the artificial neurons called units. These are arranged in a series of layers that together form an Artificial Neural Network in a system. ANN has an input layer, an output layer as well a hidden layer. The ANN model is defined using Keras Sequential API, (Conv2D) convolutional layers, Max-pooling layers(MaxPooling2D), Dense, Flatten.
Before providing the input images to the model, the images are pre-processed. Data augmentation is applied to all the image datasets. This includes two types of augmentation which are performed on images, Spatial Augmentation and Pixel Augmentation. Spatial augmentation includes (Scaling, Flipping, and Cropping) whereas pixel augmentation includes (Contrast, Saturation, Brightness).

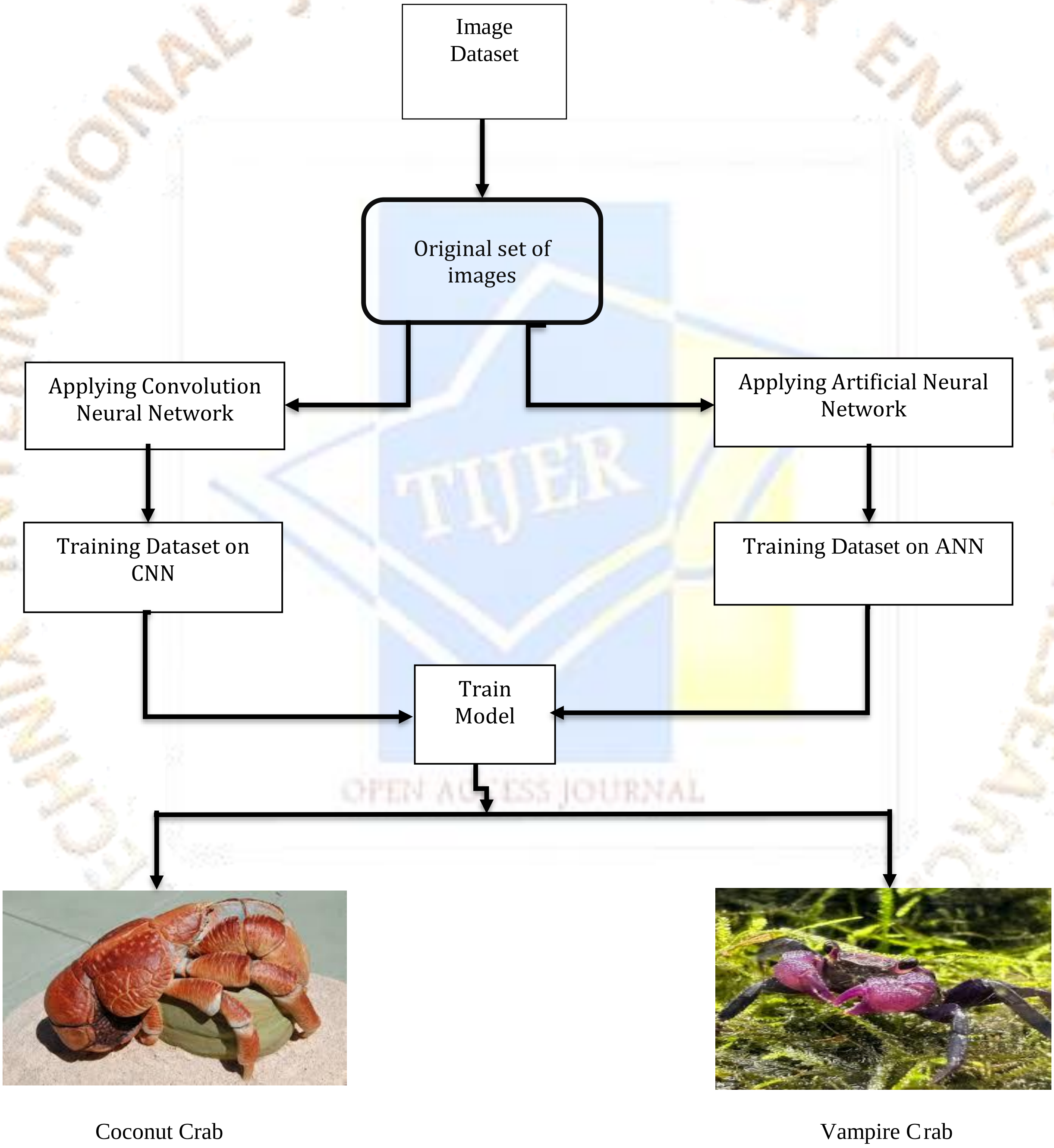
The activation function in convolutional layers is ReLU, while softmax is used in the output layer for multi-class classification problems. After all this, the model is compiled using the Adam optimizer and categorical cross-entropy loss function. Additionally, accuracy is specified as a metric to monitor during training.

The fit method is called to train the model using data from the train generator, and the steps per epoch and validation step parameters are set based on the number of samples and batch size to ensure that the model sees all the training and validation data during each epoch. Finally, the model is evaluated on the validation data using the evaluation method. The accuracy of the model on the validation set is printed.

V. METHODOLOGY

The methodology for classifying crab species features a complete approach that combines deep learning and machine learning approaches. The dataset is used for training the model, Crab Species Datasets which is publicly available on Kaggle. The Crab Species Dataset contains image datasets for Two different species of crabs which are divided into testing and training sets: Coconut crabs and Vampire crabs. For feature extraction, a Convolutional Neural Network (CNN) and Artificial Neural Network(ANN) architecture uses the Keras library for image classification tasks. The model consists of many convolutional layers namely, max-pooling layers, and fully connected layers. Figure 3. Describes the flow of crab species classification using CNN and ANN.

Fig 4. Flowchart of Crab Species Classification using CNN & ANN



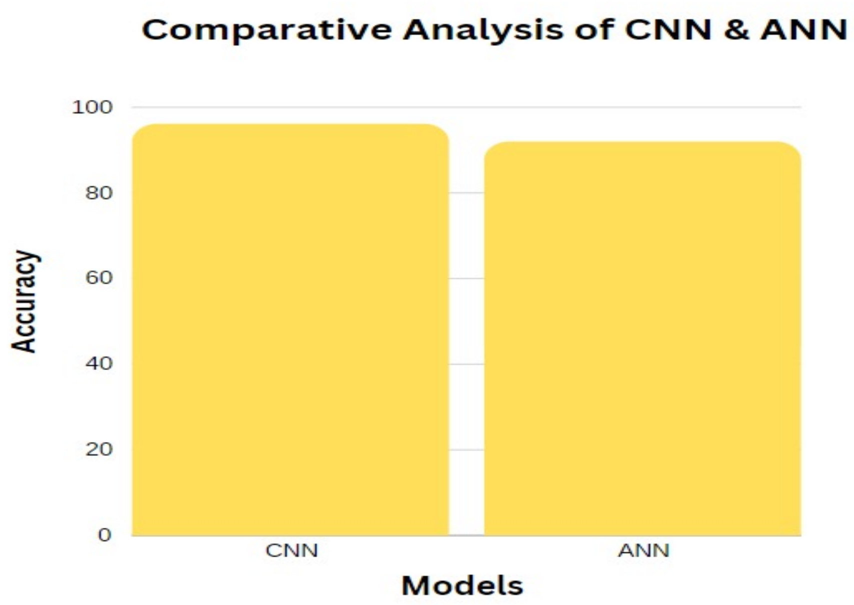
VI. RESULTS

We succeed in proposing a novel approach for crab species classification using deep learning techniques. The outcomes of our combined method for classifying crab species with Two types of crab which include vampire crab and coconut crab.

Epoch	Loss	Training Accuracy	Validation Accuracy
1/25	0.7370	0.4778	0.5000
2/25	0.6744	0.6042	0.6875
3/25	0.6149	0.7000	0.8125
4/25	0.5192	0.7661	0.8125
5/25	0.4414	0.8000	0.9375
6/25	0.3651	0.8778	0.8750
7/25	0.3499	0.8222	0.6975
8/25	0.4052	0.8333	0.9375
9/25	0.2975	0.8854	0.9375
10/25	0.2083	0.9111	0.9375

Fig4. Performance of CNN throughout 25 epochs

show how useful Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANN) are. The CNN model shows its ability to succeed in image-based identification with an accuracy of 96.15%. whereas the ANN model demonstrated an impressive 92.31% accuracy. The comparative study highlights the applicability of deep learning techniques for precise crab species categorization, offering insightful information for ecological and marine biology research. These results further the development of automated techniques for the accurate identification of species in various habitats in the ocean.



VII. CONCLUSION

Our deep learning-based crab species classification project utilized CNNs and ANNs for accurate and automated identification. The CNN model performed better for crab species features, with an accuracy of 96.15%, compared to the ANN model's accuracy of 92.31 %. The comparison analysis shows the advantages of both approaches, stressing deep learning's flexibility and classical machine learning's robustness for image-based species categorization. These discoveries add vital insights to marine biology and provide useful tools for ecologists. The successful performance of our methodology indicates its possible effect on the progression of automated crab classification of species in a wide range of maritime environments.

VIII. REFERENCE

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