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CRAB SPECIES CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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Abstract : Crabs are an important part of marine ecosystems and are also widely used in fisheries and food industries. Identification of crab species can be difficult and time-consuming, especially if there are similar physical characteristics between species. Our research presents a deep learning-based system for automatic classification of crab species from images. The data consists of 1,921 images of 10 crab species, which are collected from the Roboflow Universe. The images are preprocessed and augmented prior to model training. MobileNetV2 with Transfer Learning is used to create the classification model. 80% of the data is used for training while the remaining 20% is used for model validation. The trained model is evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. In addition, the model is used to predict a unique crab image to show its classification. The presented system provides an image-based approach that can aid in faster crab species identification.

IndexTerms **- Crab Species Classification, Deep Learning, Image Classification, MobileNetV2, Transfer Learning, Convolutional Neural Network, Image Recognition.**

I. INTRODUCTION

Crabs are important organisms in marine ecosystems as well as in fisheries and the food industry. There are many crab species that have different physical characteristics such as their body shape, shell structure, colour, and size. Correct identification of these species is important for studying marine biodiversity and managing aquatic resources.

Traditional identification of crab species is largely based on observation of their physical characteristics, which can be difficult and time-consuming, especially when there are similar appearances between species. It can also require expert knowledge and experience. Hence, an automatic image-based classification system can help to reduce the effort that is needed for identifying crab species.

II. LITERATURE REVIEW

Deep learning has become an important approach for image classification as it can learn useful features from the images themselves. Convolutional Neural Networks (CNNs) are commonly used techniques for image recognition tasks as they can learn visual patterns like edges, shapes, textures, and object structures [1]. These capabilities make CNN-based methods suitable for classifying biological species from images.

Traditional species identification typically depends on physical observation and expert knowledge. Image-based deep learning can provide an alternative by learning the difference between species from labelled image datasets. Such systems have been used to various biological classification problems where the model learns the visual characteristics from the training images and uses them to classify new images [1].

Transfer Learning is another common technique that is used in deep learning-based image classification. Rather than training a model from scratch, a model that has already learned general visual features from a large image dataset can be adapted to a new classification task [2]. This can reduce the required training data and is useful when the available data is comparatively limited.

MobileNet is a lightweight CNN architecture that is designed for efficient image processing with less computation than many larger deep learning models [3]. MobileNetV2 improves upon this architecture using inverted residual connections and linear bottlenecks [4]. Its relatively lightweight nature makes it suitable for image classification applications where computing resources and training time are important.

Deep learning-based image classification can be used for identifying species from their visual characteristics. However, the performance of such systems depends on the quality and diversity of the dataset, preprocessing procedures, model architecture, and training procedure. For crab species classification, an image-based system using Transfer Learning can provide a practical approach for distinguishing between multiple crab species.

In our research, MobileNetV2 with Transfer Learning is applied to a dataset containing 10 crab species. We focus on developing a simple image classification system that can learn species-specific visual features and classify a new crab image into the appropriate category.

III. METHODOLOGY

The proposed system used a deep learning algorithm that involved dataset collection, image preprocessing, data augmentation, model development, model training, and performance evaluation.

A. Dataset Collection

The data used for this research was taken from the Roboflow Universe. It consists of 1921 images of ten different species of crabs. All images are divided into ten subfolders with respect to the species of a crab, so that the dataset can be used for image classification tasks in a supervised setting. The list of crab species represented in this dataset is given below: Asian Paddle, Blue Crab, Curry Puff, Devil Crab, Floral Egg, Mud Crab, Purple Shore, Red Eye, Scorpion, and Sentinel Crab.

B. Image Preprocessing

The collected images were prepared for the deep learning model. All of them were resized to 224 × 224 to match the size requirement of MobileNetV2. The MobileNetV2 model requires preprocessing step, which is applied to the images so that they can be compatible with the pretrained network. Finally, the data was split into 80% training set and 20% validation set.

C. Data Augmentation

Data augmentation was applied to the training images to diversify the data set. The following operations were applied: rotation, width shifting, height shifting, zooming, and horizontal flipping. These transformations allow the model to generalize better from different transformations of crab images and avoid overfitting to a particular image arrangement.

D. MobileNetV2-Based Model

MobileNetV2 architecture was selected as the main classification model with Transfer Learning. The pretrained MobileNetV2 network was loaded with ImageNet weights, while the base layers were frozen

during the main training process. Additional layers were added on top of the model to adapt it to the crab classification task.

The extracted features were piped into a Global Average Pooling layer, followed by a Dense layer of 128 neurons and a Dropout layer. The output layer was a Softmax classifier with 10 classes that predicted the final species of the crab.

E. Model Training

The model was trained on the prepared training dataset for 20 epochs. Adam optimizer with a learning rate of 0.0001 was used, and categorical cross-entropy was chosen as the loss function. The validation data was employed to evaluate the model's performance, and early stopping and learning-rate adjustment were applied during the training process.

F. Model Evaluation

After training, the model was tested on the validation set by calculating such metrics as accuracy, precision, recall, and F1-Score. These metrics helped measure the model's performance in classifying different crab species.

In addition, a new crab image was input into the trained model to demonstrate how it predicts the species of a crab.

IV. RESULTS AND DISCUSSION

The MobileNetV2-based model was trained on the prepared dataset for crab species classification. The validation set of images of 10 different crab species was used to evaluate the model performance. The accuracy, precision, recall, and F1-score metrics were calculated.

The model achieved a high score of 91.51% accuracy on the validation set. This means that more than 90% of the images were classified correctly by the trained model. Using the Transfer Learning approach allowed avoiding training the model from scratch while achieving a good result.

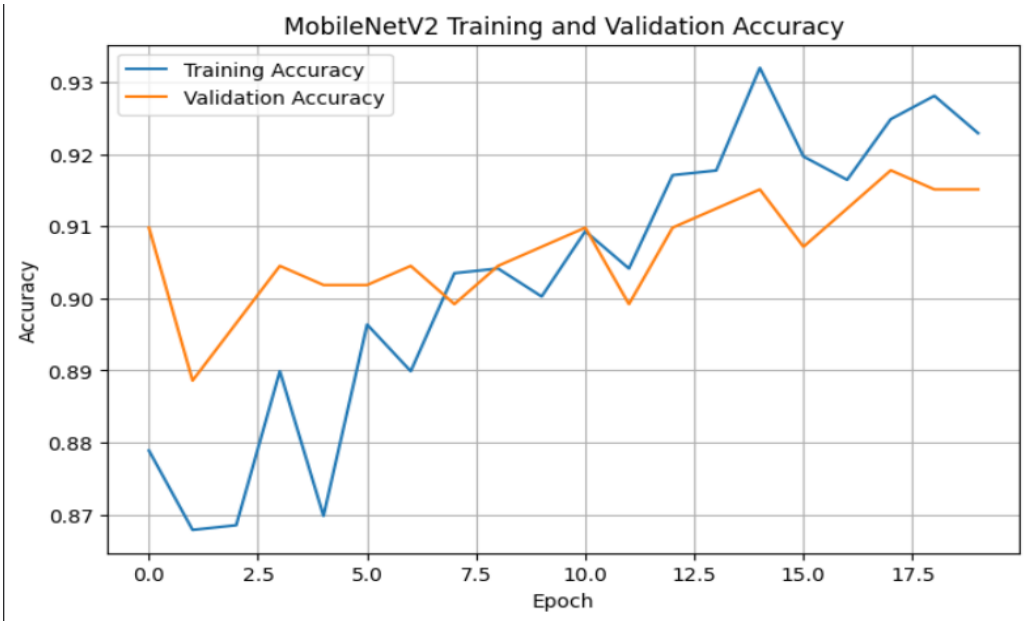


fig. 1. Training and validation accuracy

The training and validation loss curves demonstrate how the loss of the model changed during training. This gives an understanding of how the model has learnt from the training data across each epoch.

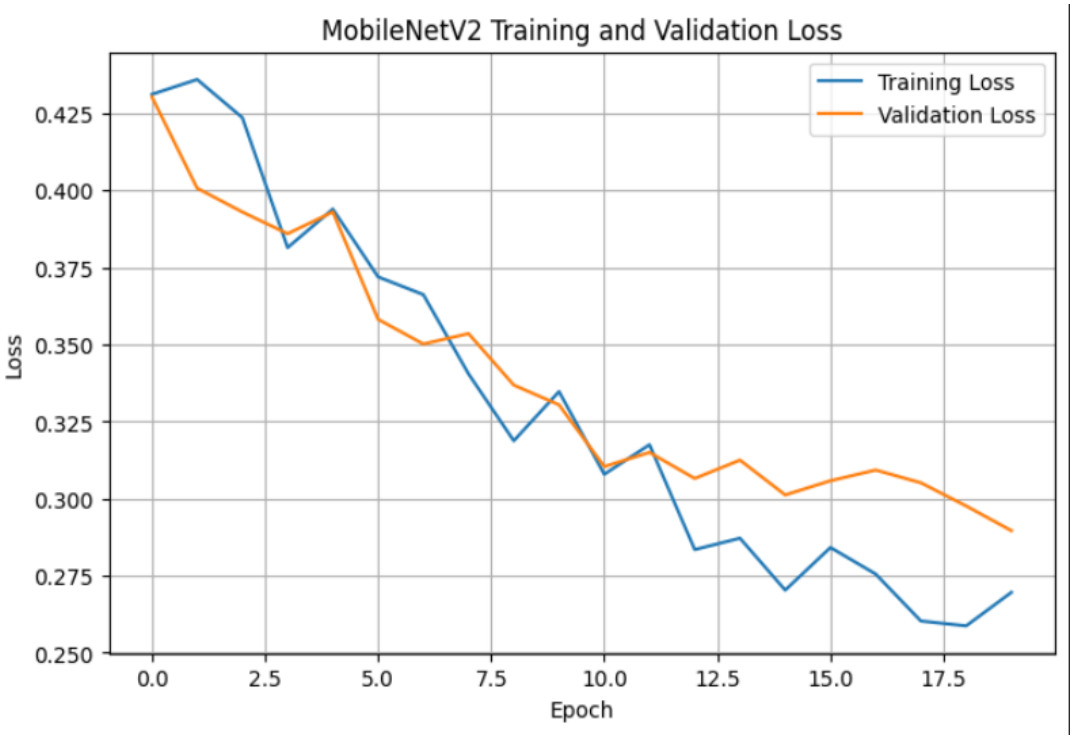


fig. 2. Training and validation loss

A new image of a crab was inputted into the model, and the model predicted the species of the crab with a certain confidence score. As a result, it can be seen that the model can be used to classify new images after the training.

V. CONCLUSION

The research provided an insight into a deep learning-based approach used for the classification of crab species from images. The system employed MobileNetV2 and Transfer Learning to classify 10 different crab species found in the image set used for the research. Resized, preprocessed, and augmented images were used to train the model.

The accuracy recorded using the validation set was 91.51%. The result proved the effectiveness of the approach used, as it was possible to classify the majority of the images within the set. Additionally, the classification report and confusion matrix were utilized to evaluate the performance of the trained model. Finally, an image of a crab was predicted using a trained model to predict its species.
It can thus be concluded that deep learning approaches can be used as image-based classifiers for crab species recognition. The approach used is recommended due to the ability of MobileNetV2 to provide a relatively lightweight solution to image classification tasks. However, the performance of the model relies on the quality and variety of images used for training. As future work, more images and species should be considered in addition to improving the model to improve the performance.

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