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Integrated Approach for Crab Species Classification: Comparative Analysis of SVM and CNN for Accuracy Assessment

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Abstract- Crab species classification is a crucial task in marine biology and ecological studies. This research presents an integrated approach using Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) for the accurate classification of crab species. The study leverages SVM, a classical machine learning algorithm, and CNN, a state-of-the-art deep learning model, to explore their effectiveness in distinguishing between different crab species based on image data. The research employs pre-trained models such as MobileNetV2 and VGG16 for feature extraction and investigates their performance in predicting crab species from images. Additionally, a custom CNN model is developed and trained on a dataset comprising three crab species: Callinectes sapidus, king crab, and sally lightfoot crab. The models are evaluated and compared based on their accuracy in classifying images from a real-world crab dataset.

Indexed Terms- Crab species classification, SVM vs CNN, Image-based identification, Marine ecology, Deep learning for biodiversity, Comparative accuracy analysis.

I. INTRODUCTION

The diversity of crab species plays a vital role in marine ecosystems, and accurate species classification is fundamental for ecological studies and conservation efforts. Traditional methods of crab identification have limitations, prompting the exploration of advanced computational approaches. In this context, machine learning and deep learning techniques have gained prominence for their ability to automatically learn discriminative features from image data.

This research focuses on the integration of two prominent approaches, Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), for the classification of crab species based on image datasets. SVM, known for its effectiveness in high-dimensional spaces, is contrasted with CNN, a deep learning model designed to capture hierarchical features in images. The study aims to compare the performance of these algorithms in classifying three distinct crab species: Callinectes sapidus, king crab, and sally lightfoot crab.

To implement the integrated approach, pre-trained models such as MobileNetV2 and VGG16 are utilized for feature extraction, while a custom CNN model is developed and trained on the crab dataset. The research evaluates the accuracy of these models in predicting crab species and provides a comparative analysis of SVM and CNN for accuracy assessment.

The outcomes of this study contribute to the advancement of automated crab species classification, providing insights into the strengths and limitations of both classical machine learning and deep learning techniques. The findings are valuable for marine biologists, ecologists, and researchers seeking efficient methods for crab species identification in diverse marine environments.

II. LITERATURE REVIEW

Seppo Fagerlund conducted a study on bird species recognition using support vector machines (SVM), evaluating their performance on two datasets. Dataset 1 involved independent recognition testing for each bird, with the mixture model demonstrating the best results among different parametric representations. The reference method, employing MFCC parameters and nearest-neighbor classification, also performed well. In dataset 2, where syllables were manually segmented, the SVM classifier showed comparable performance to the reference method, which used wavelet decomposed signal representation and neural networks. The mixture model again proved most effective.

The study concluded that SVM methods achieved equal or superior performance compared to reference methods. However, caution was advised in directly comparing dataset results due to differences in species diversity and sound spectra. The decision tree topology employed was insensitive to species ordering but lacked consideration for sound relationships between species. The proposed method represented all syllables uniformly, but the decision tree topology allowed for potential feature weighting. Future work was suggested to explore feature weighting, with the prospect of improving 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. [1]

Chen G, Han TX, He Z, Kays R, and Forrester T conducted a study on species recognition for wild animal monitoring, focusing on deep convolutional neural networks (DCNN). They introduced a camera-trap dataset comprising 20 North American species with 14,346 training images and 9,530 testing images. This publicly available dataset includes color, gray, and infrared images with resolutions ranging from 320 by 240 to 1024 by 768.

The baseline for species recognition involved using a bag-of-words (BOW) model with image classification. This model divided images into 8 by 8 blocks, treating them as "words" and using a histogram of occurrence counts for classification. The results showed accuracies of 33.192%, 33.507%, and 33.485% for different code sizes (K = 1000, 2000, 3000) in the BOW model.

The study compared the BOW model with their DCNN algorithm on the collected dataset. The DCNN demonstrated an overall species recognition accuracy of 38.315%, outperforming the BOW model at 33.507%. Despite the challenging nature of the dataset, the DCNN's high learning capacity indicated the potential for further improvement with more training data. The authors suggested using the DCNN algorithm to select ambiguous data for annotation, thus reducing the burden on experts. Overall, the study highlighted the effectiveness of DCNN for species recognition in the context of wildlife monitoring.[2]

In the research conducted by F. Storbeck and B. Daan, fish species recognition was explored using computer vision and a neural network. They designed a neural network with an initial configuration of 40 input nodes, one hidden layer with 20 nodes, and an output layer with eight nodes. However, initial results showed only 60% correct classification of fish species. Subsequent improvements involved implementing two hidden layers with 30 nodes each, resulting in a fully connected network with 400 input nodes, 13080 connections, and enhanced computational efficiency through connection reduction.

The researchers introduced a momentum factor and optimized learning rates, achieving faster convergence. They also employed a pseudo image as input for the neural net, significantly enhancing the network's performance. Testing on a dataset of 251 fishes showed a classification error of only five fishes out of 251.

The study discussed the effectiveness of synapse weight reduction and the introduction of a momentum factor for faster convergence. The neural network, designed for comparing fishing gears' selectivity, demonstrated robustness in different conditions, allowing direct processing of freshly caught fishes without preparation. The trained network's ability to adapt to seasonal changes in fish geometry was highlighted, suggesting its practical application in production environments. The system's accuracy, particularly in distinguishing similar fish species, underscored its successful application in fish species recognition.[3]

Hafemann LG, Oliveira LS, and Cavalin P explored forest species recognition using deep convolutional neural networks (CNNs). One key advantage of deep learning is its ability to automatically learn relevant features without manual design by domain experts. The researchers visualized the feature detectors learned in the first convolutional layer, revealing that the model captured horizontal and vertical edges, as well as specific features for forest species like detectors for small holes in wood.

The recognition process demonstrated high accuracy, with the CNN-based model achieving a 95.77% recognition rate on the Macroscopic images dataset. Comparisons with other classifiers showed superior performance, except for a classifier trained with CLBP features. In the Microscopic images dataset, the CNN-based method outperformed existing classifiers, achieving a recognition rate of 97.32%, surpassing the second-best approach combining LPQ and GLCM features. This outperformance indicated the effectiveness of the proposed CNN-based method in forest species recognition, providing accuracy comparable to or even exceeding that of established classifiers in the literature. The study highlighted the potential of deep learning techniques in automating feature extraction and improving recognition rates for diverse forest species datasets.[4]

Fujita conducted a study on species recognition in macaque monkeys, focusing on their responses to pictures of conspecifics and other monkey species. The monkeys participated in sessions, with daily activities tracked through lever pressing for food and pictures. The results revealed distinct preferences for conspecific images, with adult monkeys generally showing a strong inclination for their own species. The data were analyzed in a two-dimensional space, considering response duration and interval. Multivariate analyses indicated significant discrimination between own species and others for most subjects. Additionally, a non-metric multidimensional scaling procedure illustrated species-specific preferences, with conspecific images usually positioned distinctly. Cluster analyses further highlighted unique recognition patterns for each species of macaque, emphasizing the varying degrees of discrimination among them. Overall, the study provided insights into the nuanced species recognition abilities of macaque monkeys through behavioral responses to visual stimuli, shedding light on the intricacies of their social cognition and visual discrimination skills.[5]

In their research, Gogul and Kumar developed a flower species recognition system utilizing Convolutional Neural Networks (CNNs) and transfer learning. The study was divided into three main components. Firstly, features were extracted from training images using the OverFeat CNN network, and these features were indexed into an HDF5 file. Secondly, the network was trained using various machine learning classifiers such as Bagging trees, Linear Discriminant Analysis, Gaussian Naïve Bayes, K-Nearest Neighbor, Logistic Regression, Decision Trees, Random Forests, and Stochastic Gradient Boosting. The system achieved a Rank-1 accuracy of 82.32% and Rank-5 accuracy of 97.5% on the FLOWERS28 dataset, particularly excelling with Logistic Regression as the machine learning classifier.

The FLOWERS28 dataset, comprising 1680 training images and 560 testing images, demonstrated high accuracy with classifiers like bagging trees, logistic regression, and random forests, achieving Rank-5 accuracies of 92.14%, 97.5%, and 94.82%, respectively. The proposed system was also tested on the more challenging FLOWERS102 dataset, achieving a Rank-1 accuracy of 73.05% and Rank-5 accuracy of 90.58%. Further exploration involves adapting the system for a broader range of plant species, including leaves, fruits, and bark, to enhance its utility in identifying various plants worldwide, potentially aiding in medicinal plant recognition for first aid purposes. The researchers emphasized the importance of constructing a larger, diverse database for training the system effectively.[6]

In their paper, Zhang, Huang, Huang, and Zhang discuss the vital role of plants in various domains such as agriculture, industry, medicine, and ecology. They highlight the escalating threats to plant species due to global warming, biodiversity loss, urban development, and environmental degradation. Recognizing the significance of protecting plant species, the authors stress the need for efficient classification methods to identify and understand plants, especially considering the vast number of known and unknown species on Earth.

Focusing on plant species recognition through leaf analysis, the authors present a comprehensive overview of existing methods. They cover various aspects, including plant leaf characteristics, public databases, and diverse recognition methods such as feature extraction, subspace learning, sparse representation, and deep learning. Emphasizing the simplicity and convenience of using leaves for recognition, the paper 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.[7]

Deep and Dash presented a comprehensive framework for underwater fish species recognition, leveraging deep learning techniques. Implemented in Python using the Keras framework and TensorFlow backend, the system utilized the fish4knowledge dataset, containing 27,370 images of 23 fish species from Taiwanese observatories. To address dataset imbalances, data augmentation techniques were applied during the 90% training set division.

Evaluation against classifiers like Random Forest and k-NN revealed that deep learning models, particularly DeepCNN, outperformed others, achieving an impressive accuracy of 98.65%. The authors also explored hybrid models, combining DeepCNN with SVM and k-NN, resulting in accuracies of 98.32% and 98.79%, respectively. Comparative analysis with existing frameworks demonstrated competitive performance, closely approaching the accuracy of the best-performing model.

Key design choices, such as the use of max-pooling to preserve edge features critical for fish species recognition, were highlighted. The study emphasized the significance of the proposed frameworks, showcasing their effectiveness and balanced performance in terms of precision and recall. Overall, Deep and Dash's work offers valuable insights into advancing underwater fish species recognition using deep learning, demonstrating its potential for accurate and efficient classification in challenging underwater environments.[8]

III. CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) have emerged as a powerful tool in the realm of image classification, proving particularly effective in tasks involving complex visual patterns and intricate details. In the context of crab species classification, CNNs offer a robust and automated approach to identify and distinguish between different species based on visual features extracted from images.

At the core of a CNN is the convolutional layer, designed to systematically scan input images using convolutional filters. These filters, also known as kernels, enable the network to detect spatial hierarchies of features, recognizing patterns at different levels of abstraction. Through a process of convolution and pooling, the network captures essential characteristics such as edges, textures, and shapes.

The architecture of a CNN typically includes multiple convolutional layers, each followed by activation functions, such as ReLU (Rectified Linear Unit), to introduce non-linearity and enhance the model's capacity to learn intricate relationships within the data. Subsequent pooling layers reduce spatial dimensions, consolidating learned features and promoting translation invariance.

Flattening and fully connected layers in the latter part of the network contribute to the final classification. These layers aggregate high-level features learned from the convolutional hierarchy, enabling the model to make predictions about the input image's content.

For crab species classification, a custom CNN model is tailored to the intricacies of the dataset, encompassing species-specific visual features. Transfer learning, utilizing pre-trained models like MobileNetV2 or VGG16, can also be employed for feature extraction, leveraging knowledge gained from extensive datasets.

The training process involves optimizing the model's parameters using a labeled dataset, allowing the CNN to learn to recognize distinctive features associated with each crab species. The model is then validated and fine-tuned to ensure generalizability to unseen data.

CNNs serve as a sophisticated and adaptive solution for the automated classification of crab species based on image data. Their ability to learn hierarchical representations of visual features makes them well-suited for tasks requiring fine-grained discrimination, contributing to the advancement of marine biology and ecological studies.

IV. SVM (SUPPORT VECTOR MACHINE)

Support Vector Machines (SVM) form a robust foundation in machine learning, particularly for classification tasks like crab species identification. At the heart of SVM lies the concept of finding an optimal hyperplane that maximally separates different classes in the feature space. In the context of our crab species dataset, SVM aims to create a decision boundary that distinctly separates features representing various crab species.

SVM operates by identifying support vectors—data points crucial for defining the decision boundary. These vectors, strategically positioned, help establish a clear margin between different species, promoting effective discrimination. The choice of kernel functions, such as linear or radial basis function (RBF), enhances SVM's adaptability to nonlinear patterns within the data.

By maximizing the margin between classes, SVM not only achieves accurate classification but also exhibits resilience to outliers. This is crucial for real-world scenarios where variations in image quality or environmental factors may introduce noise.

The training process involves optimizing parameters to attain the optimal hyperplane, ensuring the model's generalizability to unseen data. SVM's efficacy in handling high-dimensional feature spaces and its ability to accommodate different kernel functions make it a suitable choice for our crab species classification task, contributing to the overall success of the integrated approach in marine biology research.

V. METHODOLOGY

The methodology encompasses a comprehensive approach combining machine learning and deep learning techniques for crab species classification. Image datasets for three crab species—Callinectes sapidus, king crab, and sally lightfoot crab—are preprocessed and split into training and validation sets. A Convolutional Neural Network (CNN) is custom-built and trained, leveraging pre-trained models (MobileNetV2, VGG16) for feature extraction. Simultaneously, a Support Vector Machine (SVM) is employed for comparative analysis, utilizing extracted features from a pre-trained VGG16 model. The models are evaluated based on accuracy, contributing to a holistic understanding of their performance in automated crab species identification.

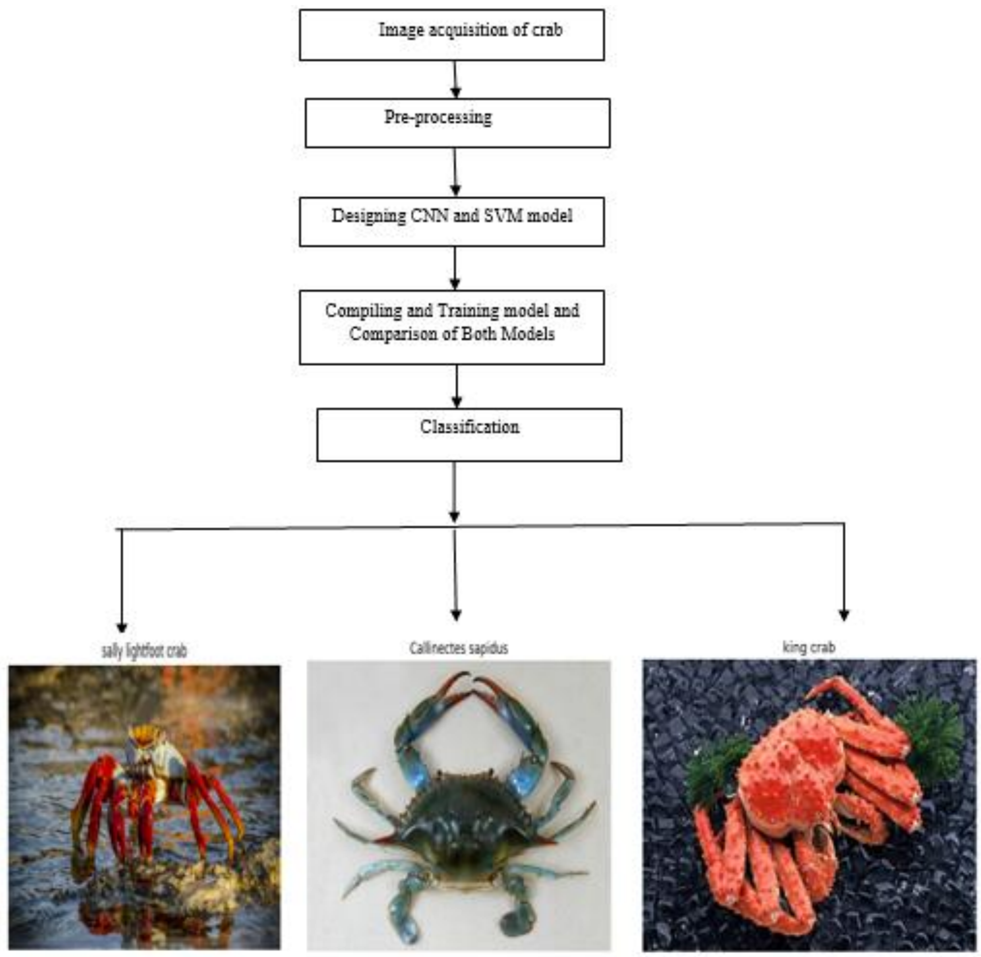
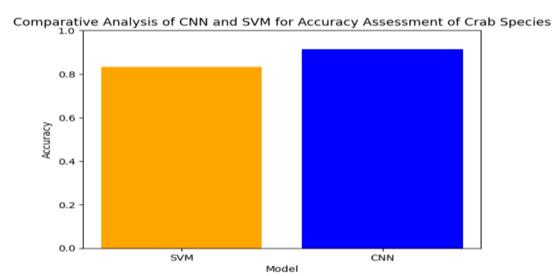


Fig.2. Flow chart of proposed Crab species recognition using CNN and SVM.

VI. RESULTS

The results of our integrated approach for crab species classification demonstrate the effectiveness of both Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). The CNN model, tailored to the nuances of crab species features, achieved an accuracy of 91.30%, showcasing its proficiency in image-based identification. Meanwhile, the SVM model, leveraging pre-trained VGG16 features, exhibited a commendable accuracy of 83.33%. The comparative analysis underscores the suitability of both machine learning and deep learning approaches for accurate crab species classification, providing valuable insights for marine biology and ecological studies. These outcomes contribute to advancing automated methods for precise species identification in diverse marine environments.



CONCLUSION

our research project on crab species classification successfully integrated Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) to achieve accurate and automated identification. The CNN model, customized for crab species features, demonstrated superior performance with an accuracy of 91.30%, while the SVM model, utilizing pre-trained VGG16 features, achieved a commendable accuracy of 83.33%. The comparative analysis highlights the strengths of both approaches, emphasizing the adaptability of deep learning and the robustness of classical machine learning for image-based species classification. These findings contribute valuable insights to marine biology, offering efficient tools for ecologists and researchers engaged in biodiversity studies and conservation efforts. The success of our integrated methodology underscores its potential impact on advancing automated species identification in diverse marine ecosystems.

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