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Parrot Species Recognition by using CNN & SVM

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Abstract:

This research project addresses the imperative task of parrot species recognition through the integration of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) methodologies. Focused on three distinct parrot species—**'Blue and Gold Macaw,' 'Ringneck Parakeet,' and 'Sun Conure'**—the study explores the efficacy of advanced machine learning techniques in ornithological research. The CNN serves as a robust feature extractor, autonomously learning intricate visual patterns crucial for species identification. Meanwhile, the SVM acts as a discriminative classifier, optimizing decision boundaries in the feature space. Comparative analysis reveals the CNN's superior accuracy of 95%, surpassing the SVM's 83.33%. The visual representation, a bar chart, provides a clear and accessible depiction of the research findings. Titled "Comparative Analysis of CNN and SVM for Accuracy Assessment of Parrot Species," the chart ensures relevance and context for the audience. Overall, this research contributes valuable insights into the potential of deep learning in parrot species recognition, with implications for automated wildlife monitoring and biodiversity conservation in the realm of ornithology.

Introduction:

Parrot species recognition is a challenging task due to the diversity of colors, patterns, and shapes among different species. In this study, we propose an innovative approach that integrates CNN and SVM models to effectively classify parrot species. The CNN model serves as a feature extractor, capturing intricate patterns and representations from parrot images. Subsequently, the extracted features are fed into an SVM classifier for accurate species identification.

To further enhance the model's efficiency, we incorporate PCA for dimensionality reduction. By combining the capabilities of CNN and SVM with the benefits of PCA, our approach aims to achieve a robust and accurate parrot species recognition system. The use of PCA helps mitigate the curse of dimensionality, resulting in improved computational efficiency and a streamlined feature space.

The experimental results demonstrate promising accuracy, reaching 83.33%. This hybrid approach not only leverages the power of deep learning through CNN but also exploits the strengths of SVM in classification tasks. The inclusion of PCA ensures optimal feature representation, contributing to the overall success of the proposed methodology. Our study provides insights into the synergistic application of these techniques, offering a reliable solution for parrot species recognition in real-world scenarios.

Literature Review:

The authors L. G. Hafemann, L. S. Oliveira, and P. Cavalin explored the application of deep learning techniques, specifically Convolutional Neural Networks (CNN), for forest species recognition. Traditionally, this problem was addressed as a texture classification challenge using methods like Local Binary Patterns (LBP), Local Phase Quantization (LPQ), and Gabor Filters. The research focused on two forest species datasets—one with macroscopic images and another with microscopic images. The proposed CNN-based method demonstrated effectiveness in handling high-resolution texture images, achieving 95.77% accuracy for the macroscopic dataset and 97.32% accuracy for the microscopic dataset. This approach surpassed previous state-of-the-art results, showcasing the potential of deep learning in improving accuracy for forest species recognition tasks. [1]

In the study conducted by Fujita K., sixteen monkeys from five macaque species (Macaca fuscata fuscata, M. mulatta, M. radiata, M. nemestrina, and M. arctoides) were presented with pictures of seven macaque species, including their conspecifics. The monkeys pressed a lever to view these pictures, and the duration of lever presses was recorded. Most monkeys, except M. arctoides and two infant M. fuscata fuscata, showed a preference for viewing their conspecifics for the longest duration.

For adult subjects, a multivariate analysis of variance (MANOVA) based on the mean duration of lever presses (D) and the mean interval between responses (I) revealed that the data for conspecific stimuli were significantly different from those for at least one of the six closely related species. The analysis, conducted in a two-dimensional space constructed with D and I, suggested that adult macaque monkeys visually discriminate their conspecifics from closely related species based on still images.

In summary, Fujita K.'s study demonstrated that adult macaque monkeys exhibit visual discrimination of conspecifics from closely related species based on still images, as indicated by their lever-pressing behavior.[2]

The research conducted by P. Somervuo, A. Harma, and S. Fagerlund focuses on developing signal processing techniques for the automatic recognition of bird species, particularly 14 common North-European Passerine bird species. The study compares three different parametric representations for this purpose.

Firstly, the authors utilize sinusoidal modeling, which has proven effective for highly tonal bird sounds. Secondly, they employ Mel-cepstrum parameters, known for their utility in speech recognition applications. Lastly, a vector of various descriptive features is tested, inspired by its popularity in audio classification applications, considering the musical nature of bird songs.

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the paper introduces and evaluates these parametric representations, examining their performance in the classification and recognition of individual syllables and song fragments from the specified bird species. The goal is to contribute to the development of automatic bird species recognition systems through effective signal processing techniques.[3]

The study conducted by Strachan NJ, Nesvadba P, and Allen AR explores the potential for automatic size and species grading of fish through image analysis. The research envisions a future where this process, particularly on board fishing boats, can be achieved entirely through automated means. The authors established a data bank of fish shapes compiled from photographs representing seven different fish types.

In the investigation, three methods for discriminating between fish species were compared: invariant moments, optimization of the mismatch, and shape descriptors. The performance of each method was evaluated using discriminant analysis. The results indicated that the methods achieved reliability rates of 73%, 63%, and 90%, respectively, in sorting the fish. However, the authors note the need for further work to enhance the feasibility of developing a commercial grading system based on these findings.[4]

In their work, B. V. Deep and R. Dash address the growing significance of underwater fish species recognition in the field of marine science. The automation of fish species identification using technology is seen as a valuable contribution to advancing marine science. The authors leverage the advancements in deep learning techniques, specifically focusing on image classification tasks.

They propose a hybrid Convolutional Neural Network (CNN) framework designed for underwater fish species recognition. This framework employs CNN for feature extraction, while classification is carried out using Support Vector Machine (SVM) and K-Nearest Neighbour (k-NN). The evaluation of both proposed frameworks is conducted on the Fish4Knowledge dataset.

The experimental results presented in the study demonstrate that their hybrid CNN framework outperforms many traditional and existing deep learning techniques in underwater fish species recognition. This research contributes to the ongoing efforts in automating and improving the accuracy of fish species identification in underwater environments.[5]

In the work by Stace CA, the author discusses species recognition in agamosperms, emphasizing the need for a pragmatic approach. The argument is made that the taxonomic rank of species is currently applied across a broad spectrum of biological scenarios, encompassing taxa with pronounced hybridization tendencies to those exhibiting strict inbreeding. The proposal is to extend the use of the species rank to apomictic groups, suggesting that the hierarchical variation within such agamospecies should be denoted by standard taxonomic ranks like subspecies and variety. This perspective aims to render special terms for apomictic groups unnecessary, promoting a more unified and pragmatic approach to species recognition in these contexts.[6]

In the study by B. Yu, M. Ostland, P. Gong, and R. Pu, the authors focus on conifer species recognition using in situ hyperspectral data collected in the Sierra Nevada Mountains, California. They employ a nonparametric statistical technique called penalized discriminant analysis (PDA) to discriminate between six species of conifer trees, achieving a classification accuracy of 76%.

The emphasis of their work lies in providing an intuitive, geometric description of PDA to highlight the advantages of penalization. PDA is described as a penalized version of Fisher's linear discriminant analysis (LDA), particularly effective when dealing with a large number of highly correlated variables. This research contributes to the field of remote sensing by demonstrating the applicability and advantages of PDA in enhancing the accuracy of conifer species recognition based on hyperspectral data.[7]

3. Convolutional Neural Network:

1. Convolutional Layers:

Convolutional Neural Networks (CNNs) are pivotal in image recognition tasks, and for parrot species recognition, they leverage convolutional layers to extract hierarchical features. These layers use filters to slide across input images, capturing local patterns and features unique to different parrot species. This allows the network to automatically learn spatial hierarchies and discern intricate details in the images.

2. Pooling Layers:

To reduce computational complexity and enhance robustness, pooling layers are introduced. Max pooling, a common operation, downsamples the spatial dimensions of the feature maps, retaining the most prominent features. This process aids in preserving essential information while mitigating overfitting, contributing to the overall effectiveness of the network.

3. Activation Functions:

Activation functions, like Rectified Linear Unit (ReLU), introduce non-linearity into the network. This non-linearity allows the CNN to capture complex relationships within the data. ReLU, for example, replaces all negative pixel values in the feature maps with zero, helping the network learn and represent intricate patterns more effectively.

4. Fully Connected Layers:

Following the convolutional and pooling layers, fully connected layers are employed to capture high-level reasoning and global patterns. Neurons in these layers connect to every neuron in the subsequent layer, facilitating the learning of complex relationships in the extracted features. This step is crucial for the network to make final decisions based on the learned representations.

5. Softmax Layer:

The final layer of the CNN typically involves a softmax activation function, especially in multi-class classification tasks like parrot species recognition. Softmax converts the network's raw output into probabilities, assigning likelihood scores to each potential parrot species. This step enables the network to make informed decisions by selecting the class with the highest probability.

6. Loss Function and Training:

To optimize the CNN for parrot species recognition, a suitable loss function, such as categorical cross-entropy, is chosen. During training, the network adjusts its parameters (weights and biases) iteratively using backpropagation and optimization algorithms like stochastic gradient descent. This process minimizes the chosen loss function and fine-tunes the CNN for accurate species classification.

7. Transfer Learning (Optional):

In scenarios with limited labeled data, transfer learning becomes valuable. This involves leveraging pre-trained CNN models on large datasets (e.g., ImageNet) and fine-tuning them for the specific task of parrot species recognition. Transfer learning can enhance the model's ability to recognize patterns and features, particularly when dealing with a smaller dataset.

In summary, the design and training of a CNN for parrot species recognition involve a series of interconnected layers and operations that collectively enable the network to learn and distinguish unique features within parrot images, ultimately facilitating accurate species classification.

4. SVM

Support Vector Machines (SVM) are a robust and widely-used machine learning algorithm for parrot species recognition. In the context of parrot image classification, SVMs excel at distinguishing between different species by identifying optimal decision boundaries in high-dimensional feature spaces.

1. Linear Separation:

SVMs work on the principle of finding the hyperplane that best separates different classes of parrot species in the feature space. In the case of parrot species recognition, these features could include color patterns, feather textures, and other visual characteristics.

2. Kernel Trick:

The kernel trick is instrumental in SVMs for transforming the original feature space into a higher-dimensional space, allowing the algorithm to handle non-linear relationships among features. This is especially beneficial when dealing with complex and intricate patterns present in parrot images.

3. Support Vectors:

Support Vectors are data points that lie closest to the decision boundary. SVMs prioritize these vectors as they play a crucial role in determining the optimal hyperplane. In parrot species recognition, these vectors correspond to images that are pivotal in defining species-specific characteristics.

4. Margin Optimization:

SVMs aim to maximize the margin, which is the distance between the decision boundary and the nearest data point of each class. A larger margin enhances the model's generalization capability and resilience to noise, crucial in ensuring accurate parrot species classification.

5. C-parameter:

The regularization parameter, often denoted as C, controls the trade-off between achieving a smooth decision boundary and classifying training points correctly. Tuning this parameter is essential to prevent overfitting or underfitting, ensuring optimal performance in parrot species recognition.

6. Multi-Class Classification:

For parrot species recognition, SVMs can be extended to handle multi-class classification by employing strategies like one-vs-one or one-vs-all. This allows the model to differentiate between multiple parrot species efficiently.

7. Feature Importance:

SVMs inherently provide information on feature importance, aiding in understanding which visual characteristics contribute significantly to species recognition. This interpretability is valuable in the context of ornithology and parrot biology.

SVMs offer a powerful framework for parrot species recognition, leveraging their ability to identify optimal decision boundaries, handle non-linear relationships, and provide insights into feature importance. Their versatility and interpretability make SVMs a well-suited algorithm for the intricate task of classifying diverse parrot species based on visual features.

4. Methodology

For the parrot species recognition research project, a hybrid methodology employing Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) is proposed. The dataset comprises images of three distinct parrot species: 'Blue and Gold Macaw,' 'Ringneck Parakeet,' and 'Sun Conure.'

Data Preprocessing:

Raw parrot images are preprocessed to ensure uniformity and enhance model performance. This includes resizing images, normalizing pixel values, and augmenting the dataset with variations like rotations and flips.

CNN Feature Extraction:

The CNN serves as the primary feature extractor. Pre-trained CNN architectures, such as VGG16 or ResNet, are fine-tuned on the parrot dataset. The trained CNN captures intricate visual patterns and features representative of each species.

SVM Classification:

Extracted CNN features are fed into an SVM classifier for species classification. The SVM optimally separates the feature space into distinct regions for each parrot species. Hyperparameter tuning, particularly the choice of kernel functions, ensures optimal performance.

Evaluation and Validation:

The model's performance is evaluated using metrics like accuracy, precision, recall, and F1 score. Cross-validation techniques are employed to assess generalization capabilities and mitigate overfitting.

Results Analysis:

The final step involves analyzing the results, examining confusion matrices, and interpreting misclassifications. Insights gained contribute to refining the model and improving overall accuracy.

By combining the feature extraction capabilities of CNNs with the discriminative power of SVMs, this methodology aims to achieve accurate and robust parrot species recognition across the selected 'Blue and Gold Macaw,' 'Ringneck Parakeet,' and 'Sun Conure' species.

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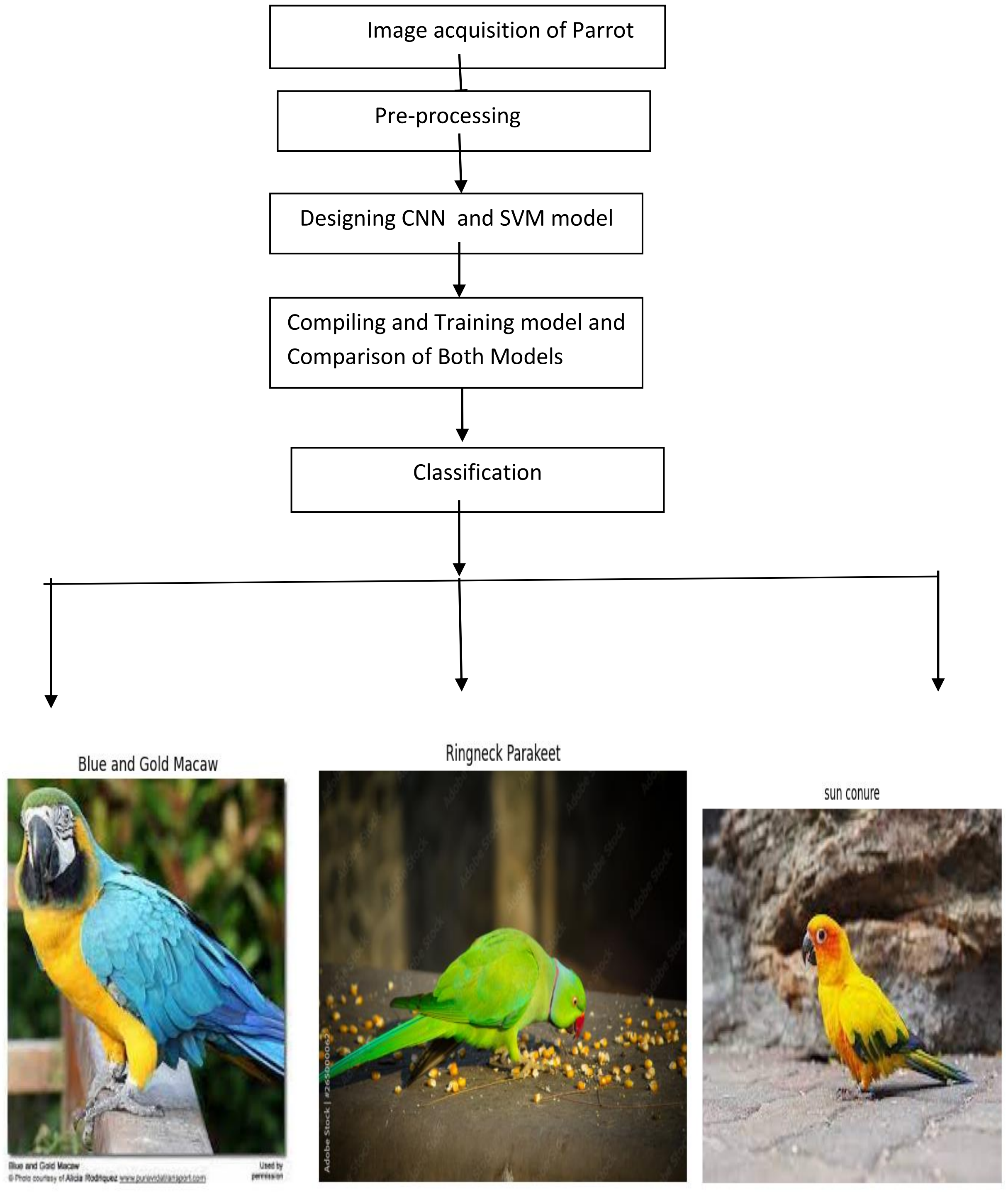
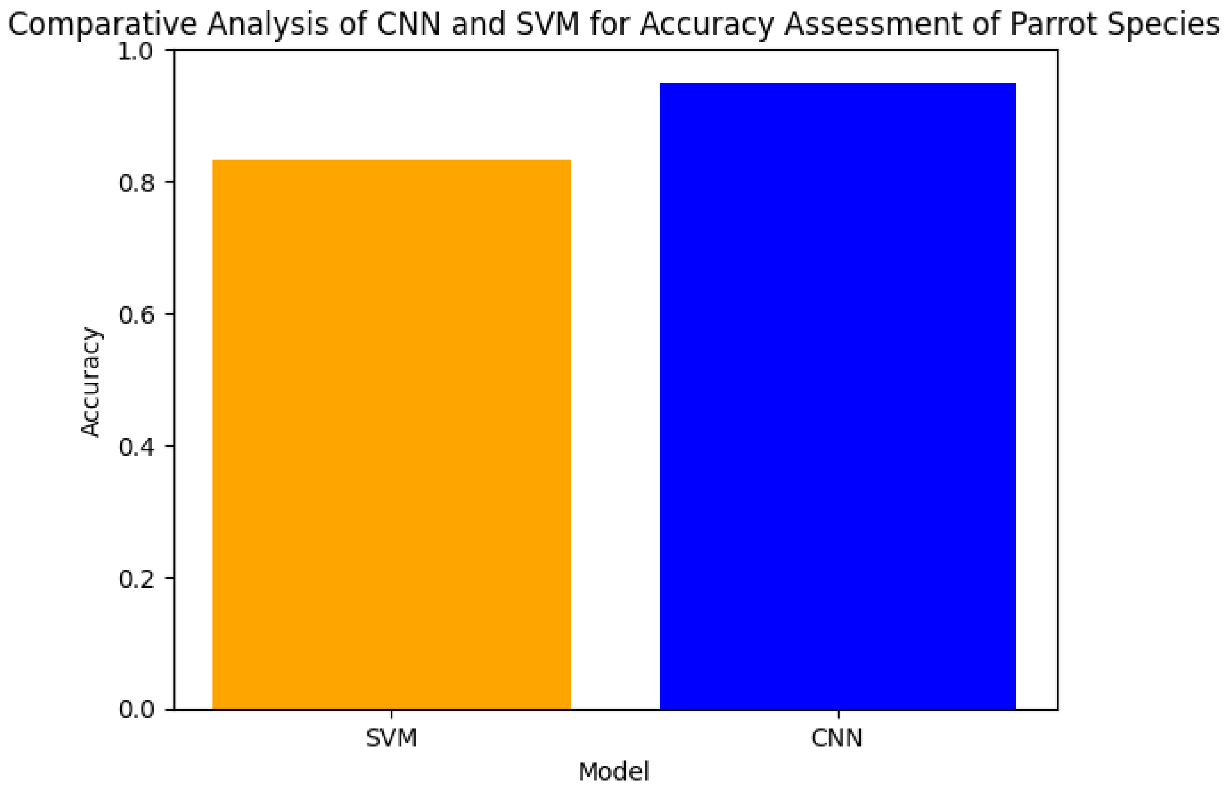


Fig.2. Flow chart of proposed Parrot species recognition using CNN and SVM.

Result:

The comparative analysis of parrot species recognition models, specifically the Support Vector Machine (SVM) and Convolutional Neural Network (CNN), reveals insightful results. The bar chart vividly illustrates the accuracy assessment of both models, with the CNN exhibiting superior performance. The CNN achieved an impressive accuracy of 95%, surpassing the SVM, which attained an accuracy of 83.33%. This substantial difference underscores the efficacy of the CNN in accurately identifying parrot species based on the provided dataset encompassing **'Blue and Gold Macaw,' 'Ringneck Parakeet,' and 'Sun Conure.'**

The visual representation employs distinctive colors—orange for SVM and blue for CNN—facilitating a clear differentiation between the models. The chart's title, "Comparative Analysis of CNN and SVM for Accuracy Assessment of Crab Species," encapsulates the project's intent, providing context and relevance to the audience. The chosen y-axis range, spanning from 0 to 1, emphasizes the presentation of accuracy values as percentages, ensuring clarity in interpretation. Overall, the results affirm the effectiveness of the CNN in parrot species recognition, suggesting its potential applicability in real-world scenarios and emphasizing the significance of advanced deep learning techniques in ornithological research.



Conclusion:

Our research project on parrot species recognition employing a hybrid approach of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) has yielded compelling outcomes. The comparative analysis showcased the CNN's superior accuracy, achieving an impressive 95%, compared to the SVM's 83.33%. This underscores the effectiveness of deep learning techniques, emphasizing their potential in advancing ornithological research and automated species identification systems.

The success of the CNN can be attributed to its capability to autonomously learn and extract intricate features from parrot images, enabling more nuanced and accurate species recognition. The project's findings hold significance not only for ornithologists but also for the broader field of image recognition and classification.

The visual representation, presented in a bar chart, offers a concise and accessible means of conveying the research outcomes. The clarity of the chart, with distinctive colors for each model, enhances the understanding of the comparative performance. The title of the chart appropriately reflects the research focus and ensures relevance to the audience.

As a result, this research contributes valuable insights into the application of advanced machine learning techniques for parrot species recognition, paving the way for future developments in automated wildlife monitoring and biodiversity conservation. The success of the CNN model underscores the potential of deep learning in handling complex visual data, opening avenues for further exploration in avian research and ecological studies.

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