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A PYTHONIC ELEGANCE: UNRAVELING IRIS CLASSIFICATION THROUGH CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Horticulturists and hobbyists appreciate the unique characteristics of irises, particularly their distinctive floral structure with three upward-pointing standards and three downward-drooping falls, contributing to their aesthetic appeal. The petal and sepal arrangement serves as a crucial identifier, forming the recognizable iris blossom. Despite a wide range of iris cultivars and hybrids, botanists and horticulturists find it hard to distinguish iris; they use specific traits like bloom size, petal features, and scent to distinguish closely related species. The image classification has undergone transformative advancements, with Convolutional Neural Networks (CNNs) playing a central role in enhancing accuracy and efficiency. This paper reviews the evolution of image classification methodologies, emphasizing the hierarchical feature extraction capabilities of CNNs. It also highlights the promising trajectory of image classification, fueled by innovations in regularization techniques, interpretability methods, and fine-tuning strategies using different models such as DenseNet, Xception, ResNet50, MobileNet, and InceptionV3. The DenseNet achieved an impressive accuracy of 92.40%, demonstrating its effectiveness in the given task. InceptionV3 followed closely with an accuracy of 89.96%and Xception has 83.54%, showcasing its robust performance. MobileNet outperformed the others, boasting an accuracy of 93.23%, suggesting its suitability for the specific application. However, ResNet50 displayed a significantly lower accuracy of 16.46%, indicating potential challenges or limitations for this model in the given context.

Keywords: iris flower, convolutional neural networks, python.

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1. INTRODUCTION

The iris flower represents grace and intricacy in the wide fabric of botanical wonders. This perennial plant, which is widely recognized for its remarkable beauty, is a member of the Iris genus, which has a wide variety of species and cultivars. In addition to being aesthetically pleasing, iris flowers are fascinating to study for botanists, horticulturists, and hobbyists.

The iris is a member of the iridaceous family and is distinguished by its distinct floral structure. The iris has a unique symmetry that adds to its beauty. It is distinguished by having three upward-pointing petals, known as standards, and three downward-drooping petals, known as falls. These petals' elaborate designs and range of colors add even more distinctiveness to each species of iris.

The form and arrangement of the petals and sepals are distinctive characteristics of iris flowers. The distinctive "falls" or lower petals that dangle downward and the upward-arching standards or top petals make iris blossoms identifiable. Iris species can also differ in terms of the color and pattern of their petals.[1]

There is a large range of iris cultivars and hybrids with slight variances, yet some iris species have characteristics that make them easily distinguished. To distinguish between closely related species, botanists and horticulturists frequently depend on distinct traits, such as the size and form of the blooms, the color and pattern of the petals, and even the scent.

Heterostyly, a unique reproductive strategy that distinguishes the iris from its floral counterparts, manifests in variations in the lengths of the style and stamen within the same species. This intricacy becomes a formidable hurdle for botanists engaged in the classification and categorization of iris varieties, particularly when dealing with closely related species or varieties that share similar external traits.

The difficulty amplifies as conventional botanical classification methods may struggle to capture the subtle nuances of heterostyly accurately. Relying solely on visual inspection may prove inadequate, prompting botanists to explore innovative approaches leveraging technological advancements to enhance their taxonomic efforts.

In this context, one such invaluable technological advancement is the application of Convolutional Neural Networks (CNNs). Tailored for image recognition tasks, these deep learning models exhibit a remarkable ability to discern intricate patterns within visual data. By training CNNs on a diverse dataset containing iris flower images, botanists empower these algorithms to unravel the complexities of heterostyly. [2]

Another is dealing with produced or hybridized irises; identification can become more difficult. Because hybridization can produce a wide range of variants, it might be more difficult to identify particular species only from their visual traits. [3]

The wide variety of iris cultivars and hybrids may make iris identification difficult for the general public or those who have a background in botany, even though professionals may find it simple. Furthermore, automated techniques for accurate and effective identification in various applications, such as machine learning models built on iris datasets, might be useful tools. [4]

Pythonic examination of the iris flower emerges as a marvel of botanical magnificence combined with computational power. The flexible language Python, which is well-known for its grace and effectiveness, serves as the prism through which to examine the unique characteristics of the iris. This study lays the groundwork for an extraordinary trip that reveals the subtle details that characterize the appeal of the iris flower-a journey where the beauty of nature and the accuracy of Python come together.

Python assumes the role of a digital botanist as it sets out to explore the iris flower. Lines of code become tools for analyzing the botanical subtleties of the iris thanks to its expressive syntax and robust ecosystem of libraries. Python serves as a link between the data science analytical lens and the organic beauty of the iris in this computational garden [5]

In the pursuit of botanical knowledge, the integration of technological advancements like CNNs becomes a crucial ally for botanists grappling with the intricate features of the iris flower. The synergy of traditional expertise and cutting-edge technology exemplifies the interdisciplinary nature of modern botanical research, where the fusion of biology and artificial intelligence contributes to a deeper understanding of the natural world.

The complex features of the iris flower, notably heterostyly, present a challenge for botanists in their quest for accurate species differentiation. However, with the incorporation of advanced technologies such as Convolutional Neural Networks, the botanical community is poised to surmount these challenges, unveiling the secrets hidden within the intricate reproductive structures of the iris and enriching our comprehension of the diverse wonders within the plant kingdom. [6]

2. REVIEW RELATED LITERATURE

Flower classification is a challenging task due to the wide range of flower species, which have a similar shape, appearance, or surrounding objects such as leaves and grass. Due to this, many studies have shown different strategies in deep learning of CNN to deal with this intricacy. Because of their capacity to automatically extract hierarchical characteristics from picture input, convolutional neural networks, or CNNs, have become highly effective tools for classifying flowers. Several tactics have been investigated by researchers to improve CNN performance in flower classification tasks.

Based on the study of Hiarty et al, entitled - Flower classification using deep convolutional neural network. A novel two-step deep learning classifier for flower classification, segmenting flower regions, and building a robust convolutional neural network classifier. The method is tested on three flower datasets, achieving classification results, surpass state-of-the-art methods in this field. [7]

According to Carnegie's research study, it discusses the widespread application of machine learning, particularly in image classification, which has diverse uses such as sorting and detection. The focus of the work is on creating a customized Convolutional Neural Network (CNN) using Transfer Learning methods with the Xception Model. This CNN is specifically designed for classifying images of essential oil plants. The model demonstrates effectiveness in accurately identifying and classifying essential oil plant images, with the results presented in a confusion matrix table. The article suggests that CNN's concept and methodology can be extended to perform image classification tasks for other types of plants as well. [8]

According to the study of Solanki, Arun, and Singh, Tarana, entitled Flower Species Detection System using Convolutional Neural Network, an efficient deep learning flower classifier using the Oxford-102 flower dataset, which includes 8189 images of 102 flower species. The method involves segmenting the images and feeding them to a convolutional neural network. The classifier uses various pre-trained models, with DenseNet achieving the highest classification accuracy when trained on a GPU. The classifier can be integrated with a mobile application for real-time flower species prediction. [9]

Based on the study of Anand, Suresh *et al*., the rapid development of computer technology is crucial for the fast and accurate identification of flower species through image processing on mobile devices. This paper develops an enhanced ensemble deep learning-based flower classification model, using CNN variants for dynamic ensemble selection. The model uses contrast-limited adaptive Histogram Equalization and filtering techniques for pre-processing, and the Improved Rat Swarm Optimizer algorithm for optimal hybrid pattern extraction. The experimental results show improved efficacy of the developed framework.

Based on the study of Ahmed, Mohammad *et al,* it discusses the prevalence of malware, highlighting its widespread use for illicit purposes and the constant emergence of new variants. The focus of the research is on utilizing machine learning in network security, an area that has experienced significant growth in the last decade. The study introduces a novel approach by representing malware signatures as 2D image representations and employing deep learning techniques to characterize these signatures within the BIG15 dataset, encompassing nine classes of malware. The research evaluates the performance of various machine learning and deep learning technologies, including Logistic Regression (LR), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), transfer learning on CNN, and Long Short-Term Memory (LSTM). The results indicate that transfer learning using InceptionV3 outperformed other models, achieving a high classification accuracy on the test dataset on the train dataset, showcasing its effectiveness in malware classification.

3. METHODOLOGY

3.1 Data Set

The images are collected from Shutter shock, Unsplash, and iStock images. These images consist of the classification of iris flowers, namely: Bearded Iris, Wall Iris, Iris Sanguine, Japanese Iris, and Douglas Iris.

Figure-1. Bearded Iris.

Figure-2. Wall Iris.

Figure-3. Iris Sanguine.

Figure-4. Japanese Iris.

Figure-5. Douglas Iris.

The dataset consists of raw, colored images, specifically focusing on iris flowers. Each distinct classification within the image dataset encompasses hundreds of images, contributing to a total of 4, 994 images across five different classes of the iris. The dataset is divided, with 80% going to training and 20% going to validation. As a result, the validation set has 929, while the training sets have 4,065. This comprehensive dataset serves as the foundation for the process of the research study, enabling a detailed exploration and analysis of iris flower characteristics for classification.

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Table-1. No. of Data sets.

Iris Flower	No. Of Images	Train	Test	Validation
Bearded Iris	1, 112	909	203	203
Wall Iris	913	756	157	157
Iris Sanguine	1, 011	804	207	207
Japanese Iris	1, 027	831	196	196
Douglas Iris	931	765	166	166
TOTAL	4, 994	4 ,065	929	929

3.2 Image Processing

The Google Colab will be used as a database platform to execute Python code. The methods that deal with manipulating digital images are as follows: DensNet, VGG16, MobileNet, InceptionV3, and ResNet50.

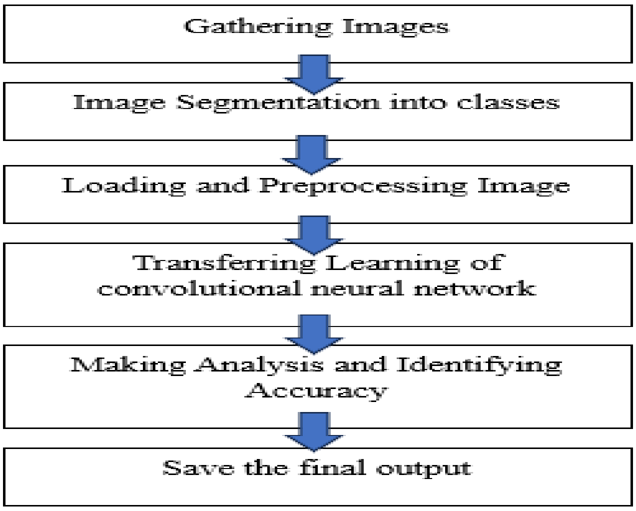

Figure-6. Process in image classification.

The initial phase in setting up the setting is to gather images of 5 different types of iris flowers. Afterwards, segmentation of images into their classes (Bearded, Iris Sanguine, Japanese Iris, and Douglas Iris.

Subsequently, creating a Python 3 notebook on Google Colab and configuring the runtime to take advantage of GPU capabilities for quicker and more effective model training. TensorFlow and Keras are two important libraries that are easily included in the Colab notebook environment.

Following by Loading of images. The management of visual data is the core function of image processing. The loading and preparation of photos are made easier with Keras. Preprocessing functions ensure that the images are compatible with the pre-trained CNNs, and they resize the images to fit the model's input specifications.

Processing the test set in batches to ascertain the number of steps is the next stage in assessing the model's performance on the test set. In the end, the evaluation produces test accuracy and test loss numbers. Followed by the confusion matrix, which provides a visual assessment of the effectiveness of the classification model. This entails creating and displaying the confusion matrix after first evaluating the model on the validation set. The following step is to determine its accuracy and conduct an analysis of the data's findings.

4. RESULTS AND DISCUSSIONS

In order to pre-train each convolutional neural network's efficacy in the classification of Iris Flower, the confusion matrix was used to evaluate the performance of a classification mode.

The figure below illustrates the confusion matrices for different models across the Classification of Iris flowers.

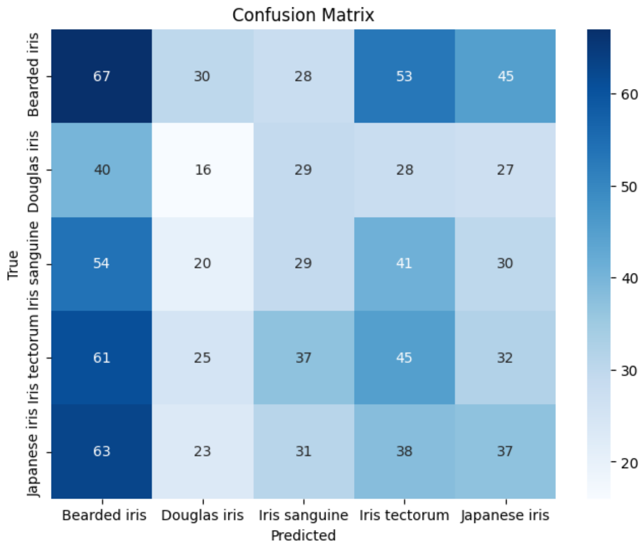

Figure-7. Dense Net.

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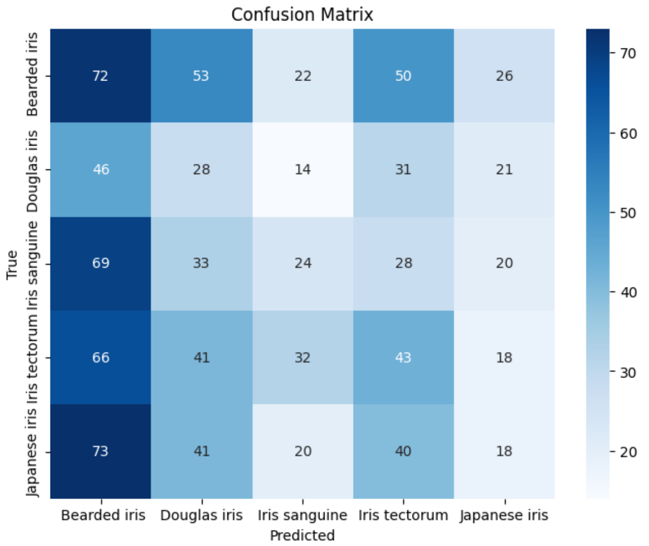

Figure-8. InceptionV3.

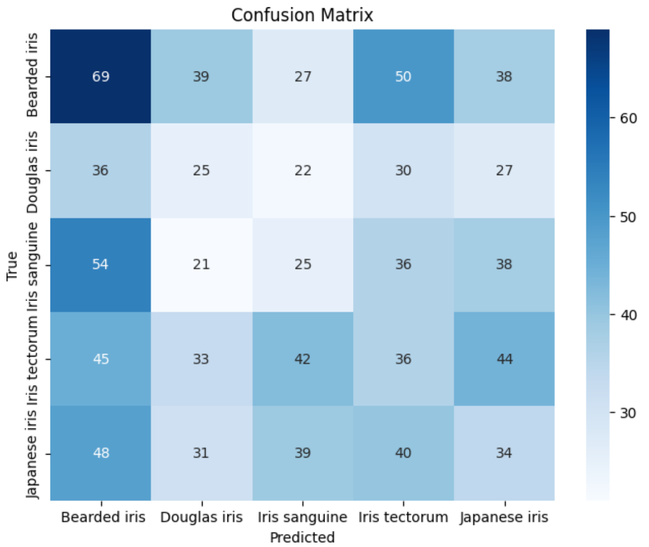

Figure-9. MobileNet.

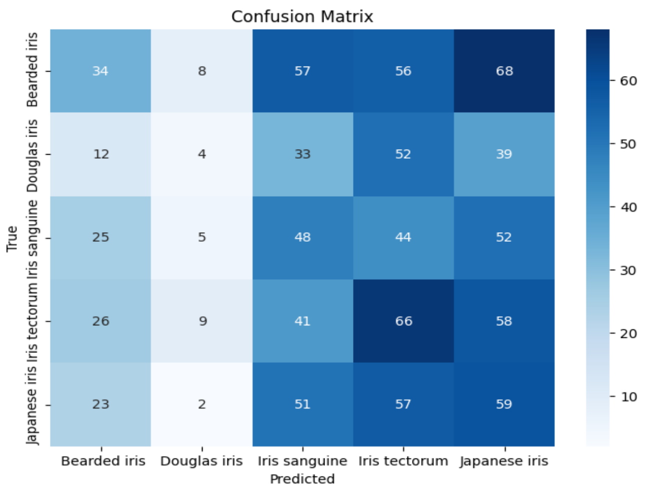

Figure-10. ResNet.

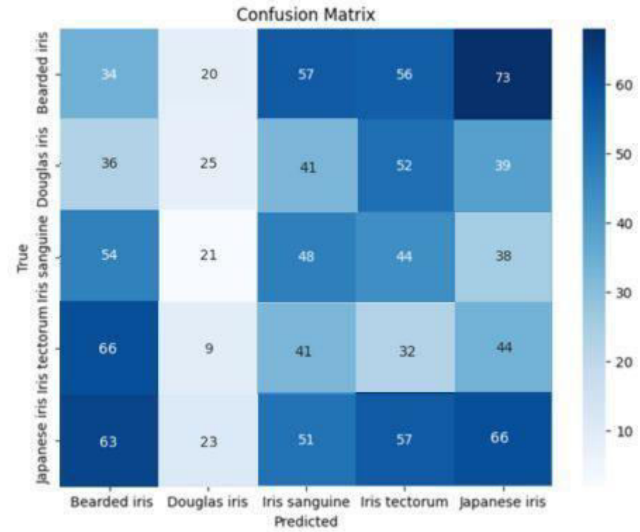

Figure-11. Xception.

Table-2. Accuracy percentage.

Model	Loading Time (Seconds)	Weight Size	Accuracy
DenseNet	176.6	27.85 MB	92.40%,
InceptionV3	222. 8	85.18 MB	89. 96%,
MobileNet	55.2	13.32 MB	93.23%
ResNet50	187.6	91.99 MB	16.46%
Xception	167.8	81.59 MB	83.54%

The table presents the accuracy percentages of various models. DenseNet achieved an impressive accuracy of 92.40%, demonstrating its effectiveness in the given task. InceptionV3 followed closely with an accuracy of 89.96% and Xception has 83.54%, showcasing its robust performance. MobileNet outperformed the others, boasting an accuracy of 93.23%, suggesting its suitability for the specific application. However, ResNet50 displayed a significantly lower accuracy of 16.46%, indicating potential challenges or limitations for this model in the given context. These accuracy percentages provide valuable insights into the relative performance of each model, aiding in the selection of the most suitable one for the intended use case.

5. CONCLUSIONS

In conclusion, Convolutional Neural Networks (CNNs) have showcased remarkable effectiveness in image classification. Its innate capacity to autonomously extract hierarchical features from images, leveraging convolutional layers, has markedly improved the precision and efficacy of image recognition systems.

From the gathered data, the InceptionV3 showcases an 89. 96%, on the other hand, the DenseNet has the accuracy of 92.40%, while the MobileNet has 93.23%. The VGG16 has the accuracy, and lastly, the ResNet50 has the accuracy recorded at 16.46% emphasizing the variation in performance metrics across different CNNs, underscoring the crucial need to select models tailored to specific task datasets.

Furthermore, ongoing research endeavors targeting challenges such as overfitting and interpretability illustrate the dynamic evolution of CNNs. Advances in regularization techniques, interpretability methods, and fine-tuning strategies hold the promise of enhancing the precision and robustness of image classification sys.

REFERENCES

[1] Iris - Biology Teaching Greenhouse. (n.d.). https://sites.berry.edu/cborer/inventory/iris/

[2] Heterostyly | botany. (n.d.). Encyclopedia Britannica. https://www.britannica.com/scienceeterostyly

[3] Iris - Biology Teaching Greenhouse. (n.d.). https://sites.berry.edu/cborer/inventory/iris/

[4] IRis germanica - Plant Finder. (n.d.). https://www.missouribotanicalgarden.org/PlantFinder/PlantFinderDetails.aspx?kempercode=f471

[5] Deepanshi. 2023, August 4. Beginner's Guide to Convolutional Neural Network with Implementation in Python. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2021/08/beginners-guide-to-convolutional-neural-network-with-implementation-in-python/

[6] Iris Flowers Species and their Classification - 2341 words | Research Paper example. 2022, November 2. IvyPanda. https://ivypanda.com/essays/iris-flowers-species-and-their-classification/

[7] Hiary H., Saadeh H., Saadeh M. and Yaqub M. 2018. Flower classification using deep convolutional neural networks. IET Computer Vision, 12(6), 855-862. https://doi.org/10.1049/iet-cvi.2017.0155

[8] Carnagie J. O., Prabowo A. R., Budiana E. P. and Singgih I. K. 2022. Essential oil plants Image classification using Xception model. Procedia Computer Science, 204, 395-402. https://doi.org/10.1016/j.procs.2022.08.048

[9] Solanki A. and Singh T. 2022. Flower Species Detection System Using Deep Convolutional Neural Networks. Lecture Notes in Electrical Engineering, 217-231. https://doi.org/10.1007/978-981-19-0284-0_17

[10] Ahmed M., Afreen N., Ahmed M., Sameer M. and Ahamed J. 2023. An inception V3 approach for malware classification using machine learning and transfer learning. International Journal of Intelligent Networks, 4, 11-18. https://doi.org/10.1016/j.ijin.2022.11.005

[11] The Editors of Encyclopaedia Britannica. 2023 December 14. Iris | Description, Species, and Facts. Encyclopedia Britannica. https://www.britannica.com/plant/Iris-plant-gen