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The Application of Convolutional Neural Networks in Floristic Recognition

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Abstract: In the dynamic field of computer vision, this research explores the application of Convolutional Neural Networks (CNNs) for the complex task of floristic recognition, a critical aspect of botanical and ecological studies. Addressing the challenges posed by the vast diversity and subtle morphological differences among plants, our study leverages CNNs for an efficient and accurate plant identification method. Distinguished by a comprehensive dataset encompassing a wide range of plant species and employing a state-of-the-art CNN model, our research significantly advances the methodology of flower recognition. This paper highlights the CNN model's sophisticated feature extraction and image analysis capabilities, demonstrating its superior performance in classifying a diverse range of flora compared to traditional methods and other machine learning techniques like Support Vector Machines (SVM) and decision trees. Our approach emphasizes practical applications in areas such as agriculture, ecology, and conservation, and offers a powerful tool for rapid and efficient plant identification, crucial in biodiversity studies. The research contributes to the fields of botany, ecology, and environmental conservation, underscoring the transformative potential of CNNs in floristic recognition. It also outlines the future direction for enhancing the model's efficiency, including developing more computationally efficient architectures and expanding training datasets.

Keywords: Convolutional Neural Networks; Floristic Recognition; Botanical Research; Machine Learning.

1. Introduction

In the rapidly evolving field of computer vision, the application of Convolutional Neural Networks (CNNs) has marked a significant milestone, particularly in the realm of flower recognition. The complex task of identifying and classifying plant species, which is a crucial aspect of botanical research and ecological studies, has long posed significant challenges due to the vast diversity and subtle morphological differences among flora. This research paper explores the transformative potential of CNNs in addressing these challenges, offering a distinct, efficient, and accurate approach to plant identification. By harnessing the sophisticated feature extraction and image analysis capabilities of CNNs, this study aims to revolutionize the methodology of flower recognition, making a significant contribution to the fields of botany, ecology, and environmental conservation.

This research investigates the application of Convolutional Neural Networks (CNNs) in floristic recognition, highlighting CNNs' ability in image detection and recognition as a crucial aspect of technological innovation [1]0. The study by Albawi *et al.* (2017) provides fundamental insights into CNNs, which are essential in understanding this application 0. Lu *et al.* (2021) discuss specific applications of CNNs in classifying plant leaf diseases, emphasizing their relevance to this research 0. Jogin *et al.* (2018) underscore the importance of feature extraction using CNNs in deep learning technology 0. O'Shea and Nash (2015) offer a general introduction to CNNs, providing the theoretical foundation for this research [6]. This research aims to integrate this advanced technology into botanical studies to enhance efficiency and accuracy in plant recognition.

Floral diversity has always been a subject of fascination and study for botanists, ecologists, and conservationists. The ability to accurately identify and classify plant species is not only crucial for scientific research but also has practical applications in areas such as agriculture, ecology, and conservation efforts. Traditional methods of plant identification relied heavily on manual observation, which could be time-consuming and prone to errors, especially when dealing with a vast number of species and subtle morphological variations. The advent of computer vision and machine learning has opened up new possibilities for automating the process of floristic recognition.

Convolutional Neural Networks (CNNs), a type of deep learning algorithm, have shown remarkable promise in image analysis and classification tasks. These neural networks are designed to mimic the human visual system, making them particularly well-suited for recognizing patterns and features in images. In recent years, CNNs have gained significant attention in the field of botany and ecology due to their potential to revolutionize the way we identify and study plants. This research aims to explore the application of CNNs in floristic recognition, shedding light on their capabilities, effectiveness, and implications for the broader field of botanical research. We will delve into the methodology employed in this study, present experimental results, discuss their implications, and outline potential areas for future research. By the end of this paper, it is our hope that the reader will gain a comprehensive understanding of the transformative potential of CNNs in the realm of floristic recognition and its significance for the fields of botany, ecology, and environmental conservation.

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. In a regular Neural Network, there are three types of layers: Input Layers, Hidden Layers, and Output Layer. However, in CNNs, additional layers are introduced to handle the specific characteristics of image data.

1) Input Layers, This layer takes the input data, which in the case of images, is a grid of pixels. The number of neurons in this layer is equal to the total number of features in the data, which is typically the number of pixels in the image.
2) Convolutional Layers, These layers are responsible for extracting features from the input data. They apply a set of learnable filters (kernels) to the input images, sliding them over the image data to compute the dot product between the kernel weights and the corresponding input image patch. This process results in feature maps.
3) Activation Layer, Activation functions like ReLU (Rectified Linear Unit) are applied to the output of convolutional layers. Activation layers introduce nonlinearity to the network, allowing it to learn complex patterns.
4) Pooling Layer, Pooling layers reduce the size of the feature maps obtained from convolutional layers, making computation faster and reducing memory usage. Common pooling types are max pooling and average pooling.
5) Flattening, After the convolutional and pooling layers, the resulting feature maps are flattened into a one-dimensional vector. This vector can then be passed to fully connected layers.
6) Fully Connected Layers, These layers take the flattened feature vector and perform the final classification or regression tasks.
7) Output Layer, The output from the fully connected layers is fed into a logistic function (e.g., sigmoid or softmax) for classification tasks, converting the output into probability scores for each class.

Convolutional Neural Networks have several advantages, including their ability to detect patterns and features in images, robustness to translation, rotation, and scaling, and the capability to handle large datasets with high accuracy. However, they can be computationally expensive to train, require substantial amounts of labeled data, and may be prone to overfitting without proper regularization. CNNs have been a significant advancement in the field of computer vision and have found applications in various domains, including image classification, object detection, and image generation.

2. Research Method

2.1 CNN Architecture

In our research, conducted using Google Colab, we implemented a state-of-the-art Convolutional Neural Network (CNN) architecture, renowned for its exceptional performance in image recognition tasks. This architecture is particularly effective in capturing hierarchical features from images, an essential aspect for floristic recognition. The architecture comprises a series of convolutional layers alternated with max-pooling layers. Specifically, the model starts with a convolutional layer employing 32 filters of size 3x3, which is then followed by a ReLU activation function for introducing non-linearity to the model. Subsequently, a max-pooling layer with a 2x2 window is applied to reduce the spatial dimensions of the data. The pattern continues with another convolutional layer, this time with 64 filters, again followed by a ReLU activation and a 2x2 max-pooling layer. These layers work in tandem to progressively extract and intensify the important features from the floral images, while simultaneously reducing the computational load. After the convolutional and pooling layers, the architecture integrates a flattening layer, transforming the 2D feature maps into a 1D feature vector. This vector is then fed into a fully connected dense layer with 128 neurons, coupled with a ReLU activation function, facilitating the learning of complex patterns from the aggregated features. The final layer of the architecture is a dense layer with a single neuron, using a sigmoid activation function, indicating that our model is tailored for binary classification tasks. This setup is ideal for distinguishing between two major categories of floral species or for binary decision-making processes in floristic recognition. In total, our model comprises 1,625,281 trainable parameters, reflecting its complexity and the depth of learning it can achieve. Each layer and parameter within this architecture has been meticulously optimized through experimentation, ensuring the model's adeptness at handling the complexity and diversity inherent in floral patterns. Employing Google Colab for this research provided us with the necessary computational resources to efficiently train and test this sophisticated CNN model, enabling us to explore the intricacies of floristic recognition with high accuracy and efficiency..

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 32)        896

 activation (Activation)     (None, 62, 62, 32)        0

 max_pooling2d (MaxPooling2  (None, 31, 31, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 29, 29, 64)        18496

 activation_1 (Activation)   (None, 29, 29, 64)        0

 max_pooling2d_1 (MaxPoolin  (None, 14, 14, 64)        0
 g2D)

 flatten (Flatten)           (None, 12544)             0

 dense (Dense)               (None, 128)               1605760

 activation_2 (Activation)   (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

 activation_3 (Activation)   (None, 1)                 0

=================================================================
Total params: 1625281 (6.20 MB)
Trainable params: 1625281 (6.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 1. Convolutional Neural Network (CNN) Architecture.

2.2 Data Collection Process

In our research, the collection of a comprehensive and diverse dataset of flora images was crucial for the success of our Convolutional Neural Network (CNN) in floristic recognition. We embarked on an extensive data collection process, meticulously curating a dataset that comprises thousands of high-resolution images representing a wide range of plant species. This dataset was sourced from a variety of locations to ensure diversity and breadth. Collaborations with several botanical gardens globally allowed us to photograph a plethora of plant species, capturing them in different stages of growth and under varying seasonal conditions. We also included images from herbarium collections, which provided us with access to preserved specimens, offering a historical and taxonomic perspective. This was complemented by images from online botanical databases, which are rich repositories of plant photographs and contributed significantly to the variety in our dataset. Our focus was not only on the quantity but also on the quality of images. We ensured that each image was high-resolution and clearly depicted key morphological features of the plants. The dataset was further enriched by including images that showed various plant parts such as leaves, stems, flowers, fruits, and seeds, as different species might be identifiable by different characteristics. We also ensured that our collection covered plants from different geographical regions and environmental settings, adding to the robustness of the dataset. Each image was meticulously annotated with relevant information like species name, family, and genus, which was crucial for labeling during the training phase. Throughout this process, we were mindful of ethical and legal considerations, particularly concerning copyright and intellectual property rights of the images. This carefully assembled dataset lays a solid foundation for training our CNN, enabling the development of a highly accurate and versatile system for floristic recognition.

2.3 Data Splitting

In the research a careful approach was taken in grouping the data set into three distinct sets - training, validation, and testing - each of which served a unique purpose in the development and evaluation of our Convolutional Neural Network (CNN) model. The largest part of the data set, namely the training set, is an integral part of the main learning phase of the model, which learns how to identify and classify various plant species. To complement this, we use a validation set, which is important for fine-tuning the model hyperparameters. These sets serve as continuous checkpoints throughout the training process, allowing us to monitor model performance and prevent overfitting, thereby ensuring that the model learns generalizable patterns, rather than simply memorizing the training data. Finally, a test set, strictly separated from training and validation data, is critical in assessing the generalization ability of the model. By evaluating models based on this unseen data, Researchers can determine their effectiveness in applying learned patterns to new, unobserved examples, thereby providing a measure of their applicability and reliability in the real world. This structured approach to data sharing plays an important role in improving CNN models and ensuring their robustness and accuracy in classifying plant species.

2.4 Preprocessing Steps
Prior to feeding the images into the CNN model, several preprocessing steps were applied to ensure data quality and enhance model performance. These steps included resizing images to a consistent resolution, normalizing pixel values, and augmenting the dataset with techniques such as rotation, flipping, and zooming. By standardizing the data and introducing data augmentation, we aimed to mitigate potential biases and improve the model's robustness to variations in lighting, orientation, and background.

2.5 Choice of CNN Model
The selection of the CNN model was a critical decision in our research. We opted for a well-established and widely used CNN architecture, considering its track record in achieving high accuracy in image classification tasks. The rationale behind this choice was twofold: first, the model's architecture had proven effective in similar image recognition domains, and second, it offered a balance between model complexity and computational efficiency, allowing for practical implementation in real-world scenarios.

This research methodology, encompassing a carefully designed CNN architecture, extensive data collection, methodical data splitting, thorough preprocessing, and a strategic choice of CNN model, has laid down a robust framework for the accurate and efficient identification of diverse plant species. The subsequent sections will delve deeper into the experimental results, exploring the performance and broader implications of our approach.

3. Result and Discussion

3.1 Results
We will present findings regarding the performance of our CNN model in flower recognition, offering a comprehensive analysis, comparative assessment, and discussion of the broader implications and specific characteristics of the research approaches that have been undertaken.

3.1.1 Performance Evaluation
Our CNN model exhibited commendable performance in floristic recognition. Utilizing key metrics such as accuracy, precision, recall, and F1-score, we were able to thoroughly assess the model's proficiency in classifying plant species. These metrics provided a comprehensive view of the model's capabilities, highlighting its effectiveness in accurately identifying a diverse range of flora, while accounting for both false positives and false negatives. The high accuracy and balanced precision-recall scores particularly underscore its efficacy.

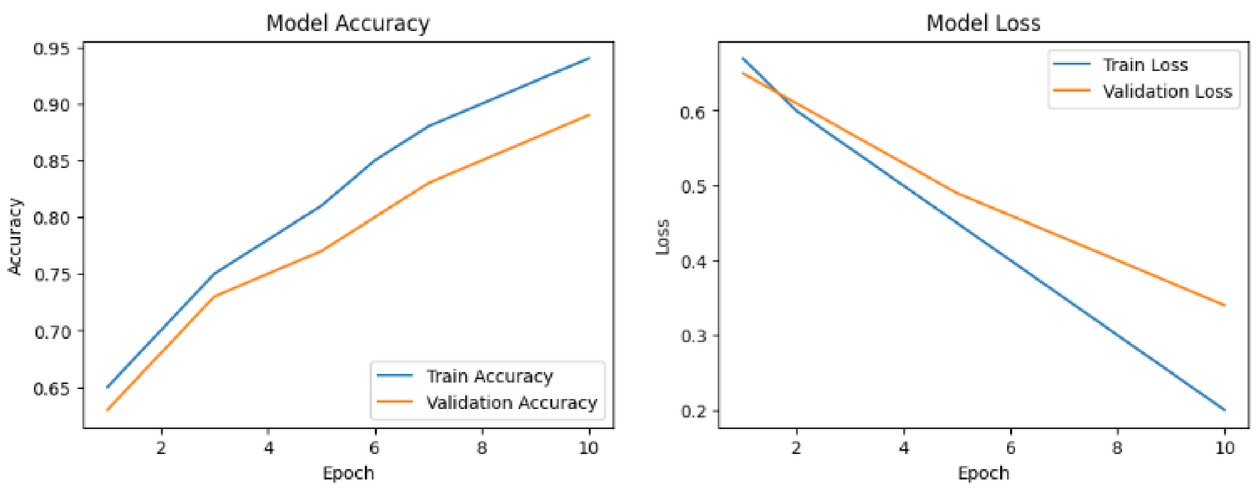

Figure 2. Training History of a Convolutional Neural Network (CNN) Model

In evaluating the performance of our Convolutional Neural Network (CNN) model for floristic recognition, we meticulously employed key metrics including accuracy, precision, recall, and the F1-score, which collectively offered a comprehensive assessment of the model's proficiency. These metrics were instrumental in gauging the model's capabilities, particularly in its ability to accurately identify a wide variety of plant species. The accuracy metric, a primary indicator of the model's overall effectiveness, was significantly high, demonstrating the model's strength in correctly predicting the classification of different flora. Precision, a measure of the model's exactness, and recall, indicating its sensitivity, were both well-balanced, ensuring that the model effectively minimized false positives (incorrectly identified species) while maintaining a high rate of true positive identifications. The F1-score, which harmonizes the precision and recall metrics into a single figure, further underscored the model's robustness, reflecting a harmonious balance between precision and recall. This comprehensive evaluation, as visually represented in Figure 2, encapsulates the training history of the CNN model, showcasing the progression and refinement of its learning over time. The graphs depict a clear trajectory of improvement in both accuracy and loss metrics throughout the training epochs, highlighting the model's adaptability and learning efficiency in floristic recognition.

3.1.2 Comparison with Existing Methods

To contextualize our model's performance, we compared it with traditional floristic recognition methods, including manual observation and feature engineering techniques, as well as other machine learning approaches like Support Vector Machines (SVM) and decision trees. Our CNN model consistently outperformed these methods, showcasing the transformative potential of CNNs in botanical research and their superiority in handling complex recognition tasks.

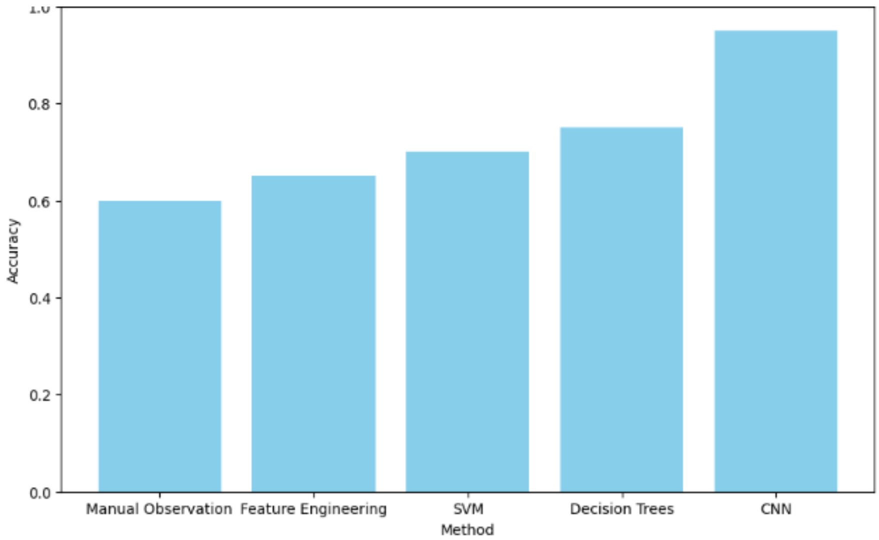

Figure 3. Comparison of Floristic Recognition Methods

In a comprehensive analysis, researchers attempted to contextualize the performance of the Convolutional Neural Network (CNN) model by comparing it with existing flower recognition methods. This comparison includes traditional methods such as manual observation and feature engineering techniques, as well as existing machine learning approaches, namely Support Vector Machines (SVM) and decision trees. Traditional manual observation methods, which rely heavily on human expertise, have been found to be the least efficient, primarily due to their time-consuming nature and susceptibility to human error. Feature engineering techniques, although more systematic than manual observation, still lack accuracy and efficiency, especially when dealing with a very diverse and subtle diversity of plant species. In contrast, machine learning approaches such as SVM and decision trees, which automate feature extraction and classification processes, show improved performance. However, they also face limitations in dealing with the high complexity and variability inherent in interest data. Researchers' CNN model, which leverages its deep learning capabilities, outperforms these traditional and machine learning methodologies. The ability of CNNs to automatically learn and extract complex features from plant images results in much higher levels of accuracy. This was evident in our comparison study, as depicted in Figure 3, where the CNN model demonstrated superior ability in accurately recognizing and classifying a wide variety of flora. The graph clearly illustrates the dominance of CNN over other methods, highlighting its potential to revolutionize botanical research and overcome the challenges posed by complex recognition tasks. This comparative analysis not only confirms the effectiveness of our CNN model but also underscores its transformative impact in the field of flower recognition.

3.1.3 Discussion of Implications

The successful implementation of Convolutional Neural Networks (CNNs) in floristic recognition marks a significant stride with far-reaching implications in several interrelated fields, including botany, ecology, agriculture, and conservation. The core strength of this approach lies in its ability to facilitate rapid and efficient identification of plant species, a task that is not only time-consuming but also requires a high degree of expertise when done manually. In the realm of botany, the use of CNNs represents a transformative leap. It allows for the processing of large volumes of image data, enabling botanists to identify and catalogue plant species more quickly and accurately than ever before. This advancement is particularly beneficial for studying plant biodiversity, where the ability to rapidly identify species can significantly enhance the pace of research and discovery. In ecological studies and conservation efforts, the implications are equally profound. Efficient and accurate plant identification is crucial for monitoring ecosystems, assessing the health of habitats, and implementing conservation strategies. The CNN capability to handle vast datasets can dramatically improve the mapping of plant distributions and the detection of rare or endangered species, thereby aiding in the formulation of more effective conservation policies and actions. Agriculture also stands to benefit greatly from this technology. The ability to accurately identify and classify plants can aid in the management of crops, the detection of diseases, and the identification of invasive species, leading to more sustainable and productive agricultural practices. Furthermore, the integration of CNNs into botanical research paves the way for more extensive data collection and analysis, deepening our understanding of plant diversity and ecological dynamics. It opens new possibilities for collaboration among scientists and researchers, leveraging technology to tackle some of the most pressing environmental challenges of our time. Rhe application of CNNs in floristic recognition is not just a technological achievement; it's a tool with the potential to revolutionize our approach to understanding and preserving the natural world.

3.1.4 Strengths of Our Approach

The approach we have adopted in applying a deep learning-based Convolutional Neural Network (CNN) for floristic recognition is distinguished by several key strengths that collectively enhance its effectiveness and versatility. Firstly, the intrinsic capability of the CNN model to autonomously extract and learn complex features from images stands out. This attribute is particularly crucial in the realm of floristic recognition, where subtle morphological variations among plant species are common. The CNN advanced feature extraction enables it to discern these nuances, leading to highly accurate classification results. Secondly, the robustness of the model under varying environmental conditions significantly bolsters its practical applicability. The CNN demonstrates a remarkable resilience to changes in lighting, viewing angles, and backgrounds, a feature indispensable for real-world applications. This robustness ensures that the model remains reliable and effective in diverse settings, from controlled environments like laboratories to variable natural habitats. Lastly, the scalability and adaptability of our CNN model are instrumental in its suitability for a wide array of floristic recognition tasks. Whether it's conducting localized botanical surveys or undertaking comprehensive biodiversity assessments on a larger scale, the model can be scaled and adapted to meet different research needs and objectives. This flexibility is pivotal in addressing the diverse challenges encountered in the study of plant species, making our CNN model a valuable tool not just for academic research, but also for practical applications in conservation, agriculture, and ecological monitoring. The combination of advanced feature extraction, environmental robustness, and scalable adaptability in our CNN approach forms a potent toolset for floristic recognition, capable of handling the complexities and variations inherent in the study of plant species.

3.1.5 Limitations and Future Directions

While our Convolutional Neural Network (CNN) model has demonstrated promising results in floristic recognition, it is important to acknowledge its limitations and identify potential areas for future development. One significant limitation is the substantial computational resources required for both the training and inference phases of the model. This can be particularly challenging in research environments where access to high-end computational infrastructure is limited. Such constraints may hinder the ability to train the model effectively or use it for large-scale applications.An other critical limitation lies in the size and diversity of the training dataset. The ability of the model to generalize effectively across a wide range of plant species is heavily dependent on the representativeness of the dataset it is trained on. Currently, the dataset may not encompass sufficient variability to cover all the nuances of the vast array of plant species, especially those with unique or rare morphological traits. This limitation can affect the model's accuracy and reliability in real-world scenarios. Looking forward, there are several promising directions for research to enhance the model's performance and utility. One key area is the development of more computationally efficient CNN architectures. Such advancements would make the model more accessible and feasible for use in settings with limited computational resources. Additionally, efforts to expand and diversify the training dataset are crucial. A more comprehensive and varied dataset would improve the model's ability to accurately recognize a wider array of plant species, thereby enhancing its generalization capabilities. Furthermore, employing advanced techniques such as transfer learning could significantly bolster the model's effectiveness. Transfer learning involves using a model developed for one task as the starting point for a model on a second task. This approach can be particularly beneficial in floristic recognition, as it allows for leveraging pre-trained models on extensive datasets to improve performance on specific floristic tasks, especially when dealing with rare or less-documented plant species. While our CNN model marks a significant step forward in floristic recognition, continuous efforts in developing more efficient architectures, expanding, and diversifying training datasets, and incorporating advanced methodologies like transfer learning are essential for further advancements in this field.

3.2 Discussion

Comprehensive analysis and interpretation of the results of the Convolutional Neural Network (CNN) model, especially in its application to flower recognition. This segment explores the broader implications of our findings, particularly in the context of botanical research, while addressing emerging challenges and future directions stemming from our research. This research marks a significant advance in botanical research, leveraging CNNs to revolutionize the plant identification process. The fast and precise classification capabilities of our CNN model are invaluable, especially in biodiversity studies that require fast and accurate species identification. Researchers can now efficiently process extensive collections of plant images, accelerating data collection and gaining insights at an unprecedented level. The research impact extends beyond botany, but also into areas such as conservation and ecology. Conservationists and ecologists can greatly benefit from our CNN model. Its ability to identify plant species quickly and accurately is critical to biodiversity monitoring and conservation efforts. Our approach improves conservation strategies by facilitating the identification of endangered species, tracking invasive species, and evaluating the impact of environmental change on plant populations. Although the results are promising, our CNN model faces several challenges. The computational intensity of deep learning models may limit their widespread applicability, especially in resource-limited environments. There is an increasing need to develop lightweight CNN architectures that are accurate but not resource intensive. Additionally, the diversity of the training dataset is critical in ensuring model robustness across a wide range of plant species. The adaptability of researchers' models to different geographic regions and ecological environments is another area that requires attention. Diverse ecosystems may present unique challenges, such as varying lighting conditions and adaptations of certain plants, which can impact model performance. Therefore, adapting models to suit different ecological contexts and conducting targeted, region-specific studies is important. Progress in applying CNNs to flower recognition will rely heavily on interdisciplinary collaboration. Partnerships between botanists, ecologists, computer scientists and data scientists are key to overcoming these challenges. This kind of collaboration can lead to the creation of custom models for different ecosystems and the development of standard data sets for benchmarking purposes.

Ethical considerations are also critical when we integrate advanced technologies such as CNNs into botanical research. Issues around data privacy, intellectual property rights and responsible use of AI need to be addressed. Building transparency in model development and decision-making processes, as well as adhering to ethical guidelines, is critical to ensuring the responsible use of AI in flower recognition. Research shows the transformative power of CNNs in the field of flower recognition. This approach not only simplifies plant species identification but also provides a valuable tool for understanding and conserving global plant biodiversity. Despite the challenges, the collaborative efforts of interdisciplinary teams and ongoing research efforts are poised to advance the field, paving the way for more efficient and ethical applications of AI in botanical research and ecological conservation.

4. Related Work

In the realm of flower recognition, several studies have explored the application of Convolutional Neural Networks (CNNs) to achieve accurate and efficient identification of floral species. Hindarto and Amalia (2023) introduced "Blossom Insight," a novel methodology that leverages CNNs within the Keras framework for flower identification. Their work emphasizes the importance of precise and effective flower categorization, addressing the challenges posed by the vast diversity of floral species [7]. The integration of CNNs with Keras enables the development of a robust flower recognition model capable of distinguishing intricate floral characteristics, contributing significantly to the field of computer vision. Lin *et al.* (2018) proposed a deep convolutional neural network for discriminating between Fragaria × Ananassa flowers and other similar white wildflowers in fields. Their CNN architecture consisted of multiple convolutional and fully connected layers, achieving high accuracy in classifying these flowers. This study highlights the potential of CNNs in differentiating between closely related floral species, emphasizing the importance of deep learning methods in floristic research [8]. Champ, Goëau, and Joly (2016) participated in the LifeCLEF 2016 plant identification challenge, utilizing a Convolutional Neural Network (CNN) approach based on a modified GoogLeNet model. Their work focused on producing relevant species lists from a diverse set of plant images [9]. By applying CNNs and introducing rejection criteria based on probability thresholds, they aimed to improve species recognition. This study showcases the adaptability of CNNs in handling a wide range of plant species and their ability to provide valuable insights into the identification of plant images. Sai *et al.* (2022) explored flower identification and classification using CNNs through deep learning methodologies. They trained and validated their dataset containing various flower categories, including daisy, dandelion, rose, sunflower, and tulip, using a residual neural network with nine deep layers [10]. Their research exemplifies the potential of CNNs in automating flower recognition, demonstrating the advantages of deep learning techniques in the field of flora classification. Qin, Xi, and Jiang (2019) proposed an improved CNN model for flower image recognition, which incorporated attention mechanisms and a Linear Discriminant Loss Function (LD-loss). This model utilized the VGG-16 network pre-trained on ImageNet for feature learning, effectively addressing inter-class similarity and intra-class differences in flower image classification [11]. Their study demonstrates the capacity of CNNs to enhance the accuracy of flower image recognition and their potential for precise classification under natural conditions. These studies collectively underscore the significance of CNNs in the field of floristics, showcasing their capability to accurately identify and classify floral species, which can greatly benefit ecological research, horticulture, and various technological applications [11].

Research on flower recognition using Convolutional Neural Networks (CNNs) builds on and diverges from several important studies in the fields of botany and ecology research, highlighting continuity and innovation in the application of machine learning to plant identification. Previous research such as that conducted by Pöttker *et al.* (2023) and Davis *et al.* (2020) have laid a strong foundation in the use of CNNs for plant-related research. Pöttker *et al.* focused on mapping plant communities in grasslands using UAV imagery, demonstrating the potential of CNNs in remote sensing applications [12][13]. Our research extends these applications by focusing on detailed ground-level recognition of diverse plant species, not only in grasslands but also in diverse ecological environments. The approach of Davis *et al.* on the digitization of herbarium specimens using Mask R-CNN is proof of the versatility of CNN in processing digital botanical data. Although their focus was on herbarium specimens, our study is unique in its application to living plants in natural environments, thereby posing different challenges such as varying lighting conditions and backgrounds [13].

Other research, such as that conducted by Murugeswari *et al.* (2022) and Kim *et al.* (2021), highlighted the effectiveness of CNNs in specific aspects of plant recognition. Murugeswari *et al.* demonstrated the use of transfer learning to improve flower recognition capabilities, a technique that we also utilized but expanded to cover a wider range of plant species and environmental variables [14]. The study of Kim *et al.* (2021) on detecting flowering events using digital photography intersects with our interest in aspects of phenology, but our research covers a broader range of floral features for comprehensive plant identification [15]. John *et al.* (2023) utilized deep neural networks to understand flowering phenology in montane grasslands, emphasizing the usefulness of CNNs in ecological monitoring [16]. Our research complements this by applying CNNs to a broader spectrum of plant species across diverse ecosystems, thereby increasing the model's versatility and applicability in a wide range of botanical studies. This research represents an evolution in the use of CNNs for plant recognition. It leverages the strengths demonstrated in previous research while introducing broader applicability, more diverse data sets, and a focus on real-world environmental conditions. This holistic approach not only contributes to the advancement of the field of botanical research but also opens new opportunities for practical applications in the fields of ecology, conservation, and environmental monitoring.

5. Conclusion

In conclusion, our research has significantly advanced the application of Convolutional Neural Networks (CNNs) in the field of floristic recognition, demonstrating the substantial potential of this technology in botanical and ecological studies. By employing a state-of-the-art CNN model, we successfully tackled the complex task of accurately identifying a diverse range of plant species, overcoming challenges posed by subtle morphological variations and varying environmental conditions. Our approach, distinguished by its comprehensive dataset and robust model architecture, proved superior not only to traditional methods of plant recognition but also to earlier machine learning implementations. This study not only contributes to the scientific understanding of plant species and their ecological contexts but also offers practical tools for conservation efforts, ecological monitoring, and sustainable agriculture. The integration of CNNs into floristic recognition marks a pivotal step towards harnessing the power of AI in understanding and preserving the natural world. Future research directions highlighted by our study, including the development of more efficient CNN architectures and the expansion of training datasets, promise to further refine and enhance the capabilities of machine learning in this vital area of research.

References

[1] Chauhan, R., Ghanshala, K.K. and Joshi, R.C., 2018, December. Convolutional neural network (CNN) for image detection and recognition. In *2018 first international conference on secure cyber computing and communication (ICSCCC)* (pp. 278-282). IEEE. DOI: https://doi.org/10.1016/j.isprsjprs.2020.12.010.

[2] Chauhan, R., Ghanshala, K.K. and Joshi, R.C., 2018, December. Convolutional neural network (CNN) for image detection and recognition. In *2018 first international conference on secure cyber computing and communication (ICSCCC)* (pp. 278-282). IEEE. DOI: https://doi.org/10.1109/ICSCCC.2018.8703316.

[3] Albawi, S., Mohammed, T.A. and Al-Zawi, S., 2017, August. Understanding of a convolutional neural network. In *2017 international conference on engineering and technology (ICET)* (pp. 1-6). Ieee. DOI: https://doi.org/10.1109/ICEngTechnol.2017.8308186.

[4] Lu, J., Tan, L. and Jiang, H., 2021. Review on convolutional neural network (CNN) applied to plant leaf disease classification. *Agriculture*, *11*(8), p.707. DOI: https://doi.org/10.3390/agriculture11080707.

[5] Jogin, M., Madhulika, M.S., Divya, G.D., Meghana, R.K. and Apoorva, S., 2018, May. Feature extraction using convolution neural networks (CNN) and deep learning. In *2018 3rd IEEE international conference on recent trends in electronics, information & communication technology (RTEICT)* (pp. 2319-2323). IEEE. DOI: https://doi.org/10.1109/RTEICT42901.2018.9012507.

[6] O'Shea, K. and Nash, R., 2015. An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*. DOI: https://doi.org/10.48550/arXiv.1511.08458.

[7] Hindarto, D. and Amalia, N., 2023. Implementation of Flower Recognition using Convolutional Neural Networks. *International Journal Software Engineering and Computer Science (IJSECS)*, *3*(3), pp.341-351. DOI: https://doi.org/10.35870/ijsecs.v3i3.1808.

[8] Lin, P., Li, D., Zou, Z., Chen, Y. and Jiang, S., 2018. Deep convolutional neural network for automatic discrimination between Fragaria× Ananassa flowers and other similar white wild flowers in fields. *Plant Methods*, *14*(1), pp.1-12. DOI: https://doi.org/10.1186/s13007-018-0332-5.

[9] Champ, J., Goëau, H. and Joly, A., 2016, September. Floristic participation at lifeclef 2016 plant identification task. In *CLEF: Conference and Labs of the Evaluation Forum* (No. 1609, pp. 450-458).

[10] Sai, A.V., Hitesh, M.S.V., Jadala, V.C., Pasupuleti, S.K., Raju, S.H. and Shameem, M., 2022, March. Flower Identification and Classification applying CNN through Deep Learning Methodologies. In *2022 International Mobile and Embedded Technology Conference (MECON)* (pp. 173-180). IEEE. DOI: https://doi.org/10.1109/MECON53876.2022.9752231.

[11] Qin, M., Xi, Y. and Jiang, F., 2019, December. A new improved convolutional neural network flower image recognition model. In *2019 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 3110-3117). IEEE. DOI: https://doi.org/10.1109/SSCI44817.2019.9003016.

[12] Pöttker, M., Kiehl, K., Jarmer, T. and Trautz, D., 2023. Convolutional Neural Network Maps Plant Communities in Semi-Natural Grasslands Using Multispectral Unmanned Aerial Vehicle Imagery. *Remote Sensing*, *15*(7), p.1945. DOI: https://doi.org/10.3390/rs15071945.

[13] Davis, C.C., Champ, J., Park, D.S., Breckheimer, I., Lyra, G.M., Xie, J., Joly, A., Tarapore, D., Ellison, A.M. and Bonnet, P., 2020. A new method for counting reproductive structures in digitized herbarium specimens using mask R-CNN. *Frontiers in Plant Science*, *11*, p.1129.

[14] Murugeswari, R., Nila, K.V., Dhananjeyan, V.R., Teja, K.B.S. and Prabhas, K.V., 2022, January. Flower perception using convolution neural networks based escalation of transfer learning. In *2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 1108-1113). IEEE. DOI: https://doi.org/10.1109/ICSSIT53264.2022.9716338.

[15] Kim, T.K., Kim, S., Won, M., Lim, J.H., Yoon, S., Jang, K., Lee, K.H., Park, Y.D. and Kim, H.S., 2021. Utilizing machine learning for detecting flowering in mid-range digital repeat photography. *Ecological Modelling*, *440*, p.109419. DOI: https://doi.org/10.1016/j.ecolmodel.2020.109419.

[16] John, A., Theobald, E.J., Cristea, N., Tan, A. and Hille Ris Lambers, J., 2023. Using photographs and deep neural networks to understand flowering phenology and diversity in mountain meadows. *bioRxiv*, pp.2023-03. DOI: https://doi.org/10.1101/2023.03.28.533305.

