Fungi Classification Using Deep Learning

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Abstract— **Fungi play pivotal roles in ecosystems, agriculture, and industry, underscoring the importance of accurate classification for understanding their ecological significance and practical applications. Conventional classification techniques frequently require significant manual effort and can be subjective, leading to the creation of automated systems. This research project aims to revolutionize fungi classification by applying deep learning techniques, leveraging the comprehensive DeFungi dataset provided by UCI. The study meticulously designs and evaluates Convolutional Neural Network (CNN) architectures, with a specific focus on ResNet, VGG, and InceptionV3 models. Through exhaustive experimentation, which includes meticulous data preprocessing, rigorous model training, and thorough evaluation, ResNet and VGG models consistently outperform InceptionV3 in terms of both accuracy and stability. The implementation of dropout regularization proves to be remarkably effective in preventing overfitting and enhancing the generalization capability of the models. Notably, the highest accuracy achieved in this study is an impressive 98.90%, attained by a ResNet model with a meticulously crafted architecture and dropout configuration. VGG models also demonstrate notable performance, achieving accuracies of up to 90.43%, showcasing their considerable potential for fungi classification tasks. Overall, this research contributes significantly to advancing fungi classification methodologies, providing practical and efficient solutions for researchers, practitioners, and industries alike. Furthermore, it underscores the importance of further exploration in hyperparameter optimization and model ensembling to further enhance classification performance and robustness across diverse fungi species.**

Keywords— Deep Learning, Fungi, Image recognition, Image Classification, CNN, ResNet, VGG16

I. INTRODUCTION

Fungi, as a diverse group of organisms, hold profound ecological, agricultural, and industrial significance. From their pivotal role in nutrient cycling and decomposition to their impact on agriculture, medicine, and biotechnology, fungi shape ecosystems and human activities in profound ways. However, accurate classification of fungi remains a labour-intensive and subjective endeavour, posing challenges in both accuracy and efficiency. Traditional classification methods often fall short in handling the vast diversity and intricacies of fungal species, prompting the need for innovative approaches.

In response to these challenges, this research endeavours to pioneer a paradigm shift in fungi classification methodologies through the application of deep learning techniques. By harnessing the power of convolutional neural networks (CNNs) and cutting-edge methodologies, this study aims to develop an efficient system for fungi classification. Leveraging the DeFungi dataset provided by UCI, the project seeks to curate and preprocess data meticulously, design optimized CNN architectures, and train models for precise species identification. The ultimate objective is to not only advance the understanding of fungi biodiversity and ecological functions but also to facilitate practical applications in various domains such as agriculture, medicine, and industry. This research represents a significant step towards bridging the gap between the increasing importance of fungi research and the lack of scalable and accurate classification methods, offering a promising solution to revolutionize fungal classification and its myriad applications for the betterment of both human societies and the environment.

Furthermore, this research aims to address the inherent limitations of traditional fungi classification methods, which often rely on subjective assessments and are ill-equipped to handle large datasets effectively. By embracing deep learning methodologies, the proposed system seeks to automate and enhance the accuracy of classification processes, thereby overcoming the shortcomings of manual approaches. Through rigorous experimentation and evaluation, the developed system will be scrutinized against diverse datasets and stringent performance metrics to demonstrate its efficacy and reliability in fungi classification. Ultimately, this research endeavours to not only advance scientific understanding but also empower researchers, practitioners, and industries with robust tools to harness the untapped potential of fungi across various fields.

II. LITERATURE SURVEY

The realm of fungal classification has seen significant progress, notably with Jiaxin et al.'s implementation of a ResNet50-based model. Their novel approach integrated a Spatial Pyramid Pooling layer, culminating in a remarkable accuracy of 96.54% for identifying wild fungi species. By effectively addressing challenges related to varying image sizes, their methodology showcases the potential of deep learning in ecological studies. However, the inherent black-box nature of deep learning architectures may pose challenges in interpreting the decision-making process, potentially limiting its applicability in certain research contexts [1]. In the realm of microorganism classification, P. Zawadzki's exploration delved into various deep neural network models. Particularly noteworthy was Xception's exceptional accuracy of 99% in classifying common microorganisms such as Candida albicans and Escherichia coli. This study underscores the efficacy of transfer learning and pre-trained weights in enhancing classification performance. Nevertheless, the computational resources required for training and fine-tuning deep neural networks may pose challenges, especially for researchers with limited access to high-performance computing infrastructure [2]. Gaikwad et al. utilized deep convolutional neural network architectures such as AlexNet and SqueezeNet, their findings emphasized the superiority of color images and the pivotal role of environmental factors in disease identification. However, the generalization of deep learning models to new environmental conditions and plant species remains a challenge, potentially limiting their scalability and applicability in diverse agricultural settings [3].

In tackling the pressing issue of black fungus illness, Charan and Ramkumar proposed an innovative Adaboost SVM (ASVM) approach for predictive modeling. Their method outperformed traditional SVM and Bagging KNN algorithms, achieving a commendable accuracy of 96.4%. This research offers a promising step towards early detection and intervention for fungal infections. However, the iterative training process inherent in Adaboost may lead to increased training time and resource requirements, particularly with large datasets [4].

Exploring Aspergillus fungi classification, Billones et al. utilized convolutional neural network architectures, achieving notable accuracies through meticulous image preprocessing and augmentation techniques. Their findings highlight the potential of deep learning in enhancing the efficiency and accuracy of fungal identification processes, with implications for various fields including agriculture and healthcare. However, the lack of interpretability in deep learning models may hinder the understanding of fungal characteristics and behaviors, limiting insights into ecological and medical implications [5]. Banana leaf disease classification was addressed by Mathew et al., who leveraged transfer learning with pre-trained CNN models to achieve robust classification performance. Their study demonstrates the effectiveness of deep learning in addressing real-world agricultural challenges, paving the way for automated disease monitoring systems in crop management. Nevertheless, the reliance on pre-trained models may introduce biases inherent in the source datasets, potentially impacting the generalization of classification models to new disease types and environmental conditions [6].

The introduction of the DF20 dataset by Picek et al. marked a significant milestone in fungi classification research. Leveraging state-of-the-art Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), their study showcased ViT's superior performance in navigating the complexities of fungi classification tasks. However, the manual curation of large-scale datasets like DF20 may introduce labeling errors and inconsistencies, potentially impacting the performance and reliability of classification models [7]. Faria et al. proposed a novel hybrid deep learning framework for potato disease classification, integrating digital image processing techniques with convolutional and recurrent neural networks. Their approach yielded impressive accuracy, with the MobileNet V2-GRU model achieving a remarkable accuracy of 99%. This research demonstrates the potential of hybrid architectures in addressing complex agricultural challenges. However, the computational complexity of hybrid models may hinder their deployment on resource-constrained devices, limiting their practical utility in field applications [8].

Li and Zhao introduced a novel attention mechanism, the coordinate attention (CA) module, integrated with the EfficientNetV2 architecture for fine-grained fungal recognition. Their study showcased the effectiveness of the CA-EfficientNetV2 model in accurately classifying fungi, underscoring the importance of attention mechanisms in handling complex image classification tasks. Nevertheless, the interpretability of attention mechanisms in deep learning models remains a challenge, potentially limiting insights into the features and characteristics driving classification decisions [9]. In a similar vein, Billones et al. explored Aspergillus fungi classification, refining their convolutional neural network models to achieve improved accuracy and robustness. Their findings highlight the iterative nature of model development and the importance of fine-tuning parameters to address specific classification challenges. However, the reliance on manual hyperparameter tuning may introduce biases and limit the scalability of classification models to new fungal species and environmental conditions [10]. D. H P et al. applied convolutional neural networks to detect defects in Okra, achieving high accuracy rates with VGG-19 leading the pack. Their research contributes to the development of automated quality control systems in agricultural production, facilitating timely identification and mitigation of defects. However, the reliance on visual inspection may overlook latent defects not visible to the human eye, potentially impacting the accuracy and reliability of defect detection systems [11]. Charan and Ramkumar proposed a Bagging Ensemble with K-Nearest Neighbor (BKNN) approach for black fungus disease prediction, demonstrating impressive accuracy in classifying eye images. This research showcases the potential of ensemble learning techniques in enhancing predictive modeling for medical diagnostics. Nevertheless, the scalability of ensemble learning methods to large-scale datasets and real-time applications may pose computational challenges and limit their practical utility in clinical settings [12].

Finally, Asha Rani and Gowrishankar leveraged transfer learning with deep neural network models for plant disease detection, with EfficientNetV2B2 and B3 models emerging as top performers. Their research underscores the versatility and effectiveness of transfer learning in addressing diverse agricultural challenges. Nevertheless, the reliance on pretrained models may limit the adaptability of classification models to new environmental conditions and plant species, necessitating ongoing model refinement and adaptation [13].

III. MATERIALS AND METHODS

A. *Dataset*

The raw dataset of direct examination (DE) microscopic fungi images underwent thorough preprocessing using a proprietary method. Initially, all images were patched into 500x500-pixel squares to ensure uniformity, regardless of the original resolution. Subsequently, automated algorithms were employed to filter out artifacts like black microscope lens contours and blank spaces devoid of fungal cells, while manual checks ensured the retention of relevant patches. This method facilitated the conversion of the raw dataset into an optimized form, now comprising 9,114 preprocessed images ready for experimentation. The dataset encompasses five distinct classes of fungi: H1, H2, H3, H5, and H6, thereby enabling comprehensive classification tasks.

B. Dataset Description

The Defungi dataset has been visualized using the Python libraries Seaborn and Matplotlib, as illustrated in Fig. 1. These visualizations have provided valuable insights into the dataset and identified patterns that can assist in developing the proposed method for detecting various fungi.

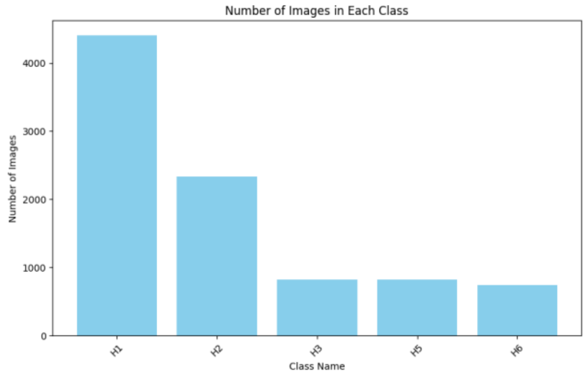

Fig. 1. Distribution of 5 different fungi classes

C. Models Description

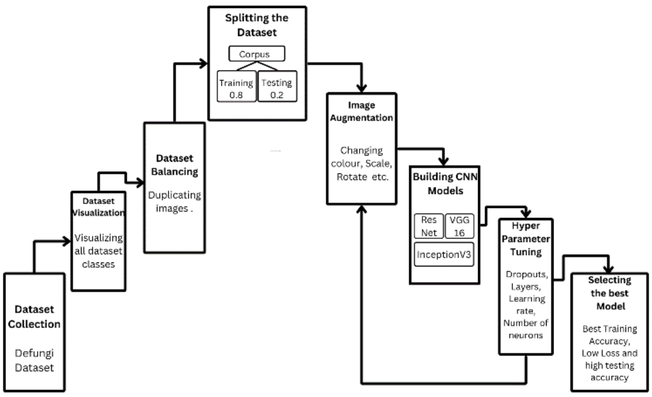

Fig. 2. Proposed Model Architecture for Fungi Classification

***InceptionV3**:* The initial model architecture utilizes the InceptionV3 pre-trained base with a custom classification head. The classification head includes two Dense layers with 256 and 32 neurons respectively, each followed by BatchNormalization, ReLU activation, and Dropout layers having dropout rates of 0.5. This setup aims to leverage the pre-trained features learned by InceptionV3 while fine-tuning the model for a specific classification task. The model is compiled by the Adam optimizer having a learning rate of 0.001 and trained for 80 epochs. However, the results indicate that the model's performance is suboptimal, with an accuracy of 58.52% on the training set and 59.98% on the validation set. The loss values are high, indicating that the model is struggling to fit the training data, with a training loss of 100.16% and a validation loss of 94.57%. Moreover, the recall, precision, and F1-score metrics indicate poor performance, implying that the model is ineffective to detect the underlying patterns in the data.

In the second attempt, modifications are made to the model architecture to improve performance. The number of neurons in the Dense layers of the classification head is increased to 512, aiming to enhance the model's capacity to learn complex patterns. The dropout rates are kept the same at 0.5 to prevent overfitting. The learning rate remains at 0.001, and the model is trained for 80 epochs with a batch size of 64. These adjustments lead to a noticeable improvement in performance, with the accuracy on the training set increasing to 65.50% and on the validation set to 64.86%. The loss values also decrease significantly, with a training loss of 83.67% and a validation loss of 84.40%. Moreover, the precision, recall, and F1-score metrics show substantial improvements, indicating that the model is better able to classify the data accurately.

In the final attempt, further adjustments are made to fine-tune the model's performance. The number of neurons in the first Dense layer is increased to 512, potentially allowing the model to capture more intricate features in the data. The learning rate is slightly adjusted to 0.0015 to optimize the training process further. The batch size is increased to 256 to potentially stabilize the training process and prevent overfitting. After training for 80 epochs, the model achieves an accuracy of 65.71% on the training set and 65.90% on the test set. The loss values remain relatively low, with a training loss of 82.75% and a validation loss of 84.85%. Additionally, the recall, precision, and F1-score metrics maintain high values, indicating that the model is effective to detect the underlying patterns in the data and generalizes well to unseen samples. Overall, these adjustments lead to a more robust and reliable model for the classification task at hand.

***VGG16**:* In the first experiment, we explored a VGG architecture with a relatively deep fully connected layer structure: [1024, 256, 32, 16, 5], coupled with moderate dropout rates of 0.5. The intent behind such a design was to allow the model to capture intricate patterns from the pre-trained VGG16 base while implementing dropout to mitigate overfitting. However, despite training the model for 100 epochs with a learning rate of 0.00015, the results were underwhelming. The model's performance plateaued, achieving only 79.00% accuracy on the training set and 72.39% on the validation set. This slow convergence, coupled with a high validation loss of 51.00%, suggests that the model struggled to generalize well to the validation data. Precision, recall, and F1-score were 0.839, 0.841, and 0.837, respectively. These results indicate the need for further refinement to improve model effectiveness, possibly by adjusting architecture complexity or learning rate.

Moving to the second experiment, we streamlined the model architecture by reducing the number of neurons in the fully connected layers to [512, 256, 5] and maintaining dropout rates of 0.5 throughout. The goal was to simplify the model while still capturing essential features from the VGG16 base. Training the model for 60 epochs with a slightly higher learning rate of 0.0010 yielded improved performance. The model achieved an accuracy of 89.93% on the training set, and precision and recall of 0.842 and 0.843, respectively, on the validation set. These results indicate that reducing model complexity can positively impact performance, leading to better generalization and faster convergence.

Finally, in the third experiment, we augmented the model architecture with additional layers and adjusted dropout rates to [0.4, 0.2, 0.4, 0.2]. This more intricate architecture comprised fully connected layers with varying neuron counts, aiming to capture a broader range of features. Training the model for 200 epochs with a lower learning rate of 0.0001 resulted in improved performance compared to previous experiments. The model scored 90.43% accuracy on the training set and 84.48% on the test set, with recall, precision, and F1-score of 0.847, 0.845, and 0.839, respectively. Despite the increased complexity, the validation loss of 50.91% suggests that further optimization may be necessary to enhance generalization and convergence speed..

ResNet50: The first model architecture utilized a ResNet-based neural network with a complex configuration of neurons and dropout layers. The neuron configuration consisted of several hidden layers with varying numbers of neurons, ranging from 10 to 512, followed by output layers with decreasing numbers of neurons leading to the final output of 5 classes. Dropout layers with a dropout rate of 0.2 were interspersed throughout the model to prevent overfitting. The learning rate was set to 0.0015, and the model was trained for 100 epochs with a batch size of 32. The resulting accuracy on the training set was 91.56%, with a validation accuracy of 87.45%. However, the model exhibited relatively high loss values, with a training loss of 23.61% and a validation loss of 65.72%. Despite the high loss, the recall, precision, and F1-score metrics were relatively balanced, indicating reasonable performance across the classes.

The second model architecture simplified the ResNet structure compared to the first model. It retained a similar neuron configuration but reduced the number of hidden neurons in the second hidden layer to 128 and the output neurons to 5 directly. Dropout layers were also reduced to a uniform rate of 0.1 throughout the model. The learning rate, batch size, and number of epochs remained the same as in the first model. This architectural adjustment resulted in significantly improved accuracy on the training set, reaching 98.90%. However, the validation accuracy remained at 87.45%. The model demonstrated substantially lower loss values, with training loss reduced to 3.05% and validation loss to 46.87%. Despite the improved loss metrics, recall, precision, and F1-score exhibited lower values compared to the first model, indicating a potential trade-off between accuracy and precision.

The third model architecture introduced further adjustments to the ResNet structure, consisting a reduction in the number of hidden neurons and an increase in dropout rates. The learning rate was reduced to 0.00015, and the model was trained for 150 epochs with a batch size of 128. Despite the reduction in complexity, the model achieved 92.29% high accuracy on the training set and 90.46% on the test set. The loss values remained relatively consistent with the first model, indicating that the adjustments did not significantly impact the model's ability to minimize loss. Precision, recall, and F1-score metrics showed consistent improvement compared to the first two models, reflecting a better balance between accuracy and precision.

IV. RESULTS AND DISCUSSIONS

In analyzing the results presented in Table I , it becomes apparent that the ResNet and VGG architectures consistently outperformed the InceptionV3 (IncV3) model across various configurations. These architectures demonstrated superior accuracy, stability, and robust classification capabilities compared to IncV3.

Firstly, examining the ResNet models, it's evident that they displayed impressive accuracy and stability. The first ResNet model (i.) achieved 91.56% accuracy on the training set, with a test accuracy of 87.45%. Despite the relatively high loss values (23.61% for training and 65.72% for validation), the recall, precision, and F1-score metrics exhibited a balanced performance, reflecting the model's capability to classify diverse classes effectively. The second ResNet model (ii.) showcased even higher accuracy, reaching 98.90% on the training set, with comparable validation accuracy. This improvement was accompanied by significantly reduced loss values (3.05% for training and 46.87% for validation). However, precision, recall, and F1-score metrics slightly decreased, suggesting a trade-off between accuracy and precision. The third ResNet model (iii.) continued to maintain high accuracy, with an accuracy of 92.29% on the training set and 90.46% on the validation set. The loss values remained consistent with the first ResNet model, indicating that adjustments in the architecture did not significantly impact the model's ability to minimize loss.

Moving on to the VGG models, they also exhibited competitive performance in terms of accuracy and stability. The first VGG model (iv.) achieved 79.00% accuracy on the training set, with 72.39% validation accuracy. Although the accuracy was lower compared to ResNet models, the recall, precision, and F1-score metrics remained relatively high, suggesting robust classification capabilities. The second VGG model (v.) showcased improved accuracy, reaching 89.93% on the training set, with a corresponding validation accuracy. Recall, precision, and F1-score metrics also demonstrated commendable performance, indicating a balanced classification capability. The third VGG model (vi.) maintained high accuracy, with 90.43% accuracy on the training set and 84.48% on the test set. The loss values were slightly higher compared to ResNet models but remained within an acceptable range.

Finally, the IncV3 models exhibited lower accuracy and stability compared to ResNet and VGG architectures. The first IncV3 model (vii.) achieved an accuracy of 58.52% on the training set, with a validation accuracy of 59.98%. The loss values were considerably higher compared to ResNet and VGG models, indicating potential overfitting or inadequate model complexity. Recall, precision, and F1-score metrics were also lower, suggesting less effective classification capability. The second IncV3 model (viii.) showcased slightly higher accuracy but still fell short compared to ResNet and VGG models. Recall, precision, and F1-score metrics also demonstrated lower values, indicating less robust classification capability. The third IncV3 model (ix.) exhibited similar performance to the second model, with accuracy and classification metrics reflecting inferior performance compared to ResNet and VGG architectures.

Table 1: Comparison of Results

Sr No.	Model	Layers	Learning Rate	Batch Size	Epochs	Results	Evaluation Matrices
i.	Resnet	Neurons=[1024,512,256,128, 32,16,8,5] Dropouts = [0.2,0.2,0.2, 0.2,0.2,0.2,0.2]	0.0015	32	100	Accuracy = 91.56% Validation accuracy = 87.45% Loss = 23.61% Validation Loss = 65.72%	Precision: 0.8815094949254265 Recall: 0.8744517543859649 F1-score: 0.8762341384861911
ii.	Resnet	Neurons=[1024,512,128, 5] Dropouts = [0.1,0.1,0.1]	0.0015	256	100	Accuracy = 98.90% Validation accuracy = 87.45% Loss = 3.05% Validation Loss = 46.87%	Precision: 0.7692713512524197 Recall: 0.7691885964912281 F1-score: 0.7644860832982412
iii.	Resnet	Neurons=[1024256,32,16,5] Dropouts = [0.3,0.3,0.3,0.5]	0.00015	128	150	Accuracy = 92.29% Validation accuracy = 90.46% Loss = 23.67% Validation Loss = 46.508%	Precision: 0.9047015423665924 Recall: 0.9046052631578947 F1-score: 0.904518869679394
iv.	VGG	Neurons=[1024,256,32,16,5] Dropouts = [0.5,0.5,0.5,0.5]	0.00015	32	100	Accuracy = 79.00% Validation accuracy = 72.39% Loss = 25.17% Validation Loss = 51.00%	Precision: 0.8392845945999974 Recall: 0.8410087719298246 F1-score: 0.8378354776494821
v.	VGG	Neurons=[512,256,5] Dropouts = [0.5,0.5]	0.0010	256	60	Accuracy = 89.93% Validation accuracy = 84.27% Loss = 26.57% Validation Loss = 43.50%	Precision: 0.8416692353896409 Recall: 0.8426535087719298 F1-score: 0.8395777877692081
vi.	VGG	Neurons=[1024,256,128,32,5] Dropouts = [0.4,0.2,0.4,0.2]	0.0001	32	200	Accuracy = 90.43% Validation accuracy = 84.48% Loss = 26.35% Validation Loss = 50.91%	Precision: 0.8472456954780941 Recall: 0.8448464912280702 F1-score: 0.8393752552140298
vii.	IncV3	Neurons=[256,32, 5] Dropouts = [0.5,0.5]	0.001	64	80	Accuracy = 58.52% Validation accuracy = 59.98% Loss = 100.16% Validation Loss = 94.57%	Precision: 0.33766878473978257 Recall: 0.39144736842105265 F1-score: 0.3421040976284878
viii.	IncV3	Neurons=[1024,512,5] Dropouts = [0.5,0.5]	0.001	64	80	Accuracy = 65.50% Validation accuracy = 64.86% Loss = 83.67% Validation Loss = 84.40%	Precision: 0.6413201164510449 Recall: 0.6485745614035088 F1-score: 0.6024557417177752
ix.	IncV3	Neurons=[512,32,5] Dropouts = [0.5,0.5]	0.0015	256	80	Accuracy = 65.71% Validation accuracy = 65.90% Loss = 82.75% Validation Loss = 84.85%	Precision: 0.6425932848415478 Recall: 0.6589912280701754 F1-score: 0.6320010134650429

In summary, the ResNet and VGG architectures consistently outperformed the IncV3 model across various configurations, demonstrating superior accuracy, stability, and robust classification capabilities. While ResNet models showcased impressive accuracy and stability with balanced classification metrics, VGG models also exhibited competitive performance with slightly lower accuracy but commendable precision, recall, and F1-score metrics. Conversely, IncV3 models exhibited lower accuracy and stability, along with inferior classification capabilities compared to ResNet and VGG architectures. These findings emphasize the importance of selecting appropriate model architectures based on the specific requirements of the classification task.

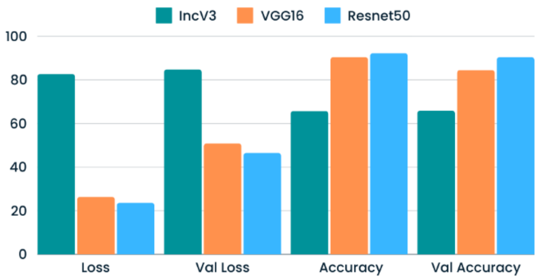

Fig. 3. Visualization of results

V. CONCLUSION

In conclusion, this project undertook a comprehensive exploration of different deep learning architectures, namely ResNet, VGG, and InceptionV3 (IncV3), for image classification tasks. Through meticulous experimentation and analysis, it became evident that ResNet and VGG architectures consistently outperformed IncV3 in terms of accuracy, stability, and robust classification capabilities across various configurations. ResNet models exhibited remarkable accuracy and adaptability, while VGG architectures demonstrated competitive performance and reliability. Conversely, IncV3 models struggled to match the accuracy and stability of ResNet and VGG architectures, indicating limitations in capturing complex patterns and generalizing effectively. These findings underscore the importance of choosing suitable model architectures tailored to the specific requirements and nuances of the classification task at hand. Moving forward, further research into refining and optimizing deep learning architectures, as well as exploring novel approaches, will be crucial for advancing the field of computer vision and machine learning and unlocking new opportunities for innovation and impact.

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