International Journal of Data Science and Artificial Intelligence (IJDSAI)
Volume 02, Issue 06, November – December (2024)

RESEARCH ARTICLE

REVIEW ON ANIMAL SPECIES RECOGNITION USING TRANSFER LEARNING VGG-16 MODEL

Mayuri M. Vengurlekar[1, *], Ashish Pal[1], Pravin Parihar[1], Mustafa Nandervawala[1], Saahil Parmar[1], Shankar Amalraj [2]

[1] Department of Computer Engineering, KJ College of Engineering and Management Research, Pune, Maharashtra, India.

[2] Associate Professor, Department of Electrical Computer Engineering, K J College of Engineering and Management Research, Pune, India

*Corresponding e-mail: mayurivengurlekar.kjcoemr@kjei.edu.in

Abstract – This review highlights recent advancements in animal species recognition using transfer learning, with a focus on the VGG16 model. The use of deep learning methods, particularly convolutional neural networks (CNNs), has significantly enhanced the accuracy of classifying various animal species. By leveraging pre-trained models, researchers have been able to achieve remarkable results, even in scenarios where labelled data is limited. This paper synthesizes findings from various studies that utilized the VGG16 architecture across different datasets, including mammals, birds, and marine species, showcasing its efficacy in capturing intricate visual features essential for species differentiation. Despite the promising outcomes, significant challenges persist, such as the dependency on well-annotated datasets and the need for robust data augmentation techniques. Additionally, the review highlights gaps in current research, particularly regarding the adaptability of the VGG16 model across underrepresented species and ecological contexts. This synthesis of existing literature serves as a foundational resource for researchers pursuing advancements in automated species recognition methodologies.

Keywords *– Animal Species Recognition, Transfer Learning, Convolutional neural network, fine-tuning, VGG16.*

1. INTRODUCTION

Identifying animal species plays a crucial role in biodiversity conservation, ecological studies, and wildlife management. Traditionally, this task has relied on expert taxonomists, whose availability is often limited by time and geographic constraints. The advent of digital imaging technologies, combined with recent advances in artificial intelligence, has paved the way for automated species recognition systems [1]. Deep learning, especially convolutional neural networks (CNNs), has proven to be a highly effective tool for processing vast amounts of visual data with exceptional accuracy. [2][3][4][5]. Transfer learning, a technique that leverages pretrained models on large datasets, has become increasingly popular in the domain of animal species recognition. By fine-tuning established architectures, researchers can effectively address challenges associated with limited labelled data and improve classification performance [6][3][7]. Notably, the VGG16 model has gained prominence in recent studies for its deep architecture and success in image classification tasks, particularly across various animal taxa including birds, marine life, and mammals [8][7][9]. This review highlights recent advancements in animal species recognition using transfer learning, with a focus on the VGG16 model. By examining a range of studies that implement this approach, the paper highlights the effectiveness of the VGG16 architecture in capturing nuanced visual features essential for distinguishing closely related species [5][4][10]. Furthermore, it identifies existing gaps in the literature, including challenges related to data scarcity, model adaptability, and the need for innovative data augmentation techniques [7][8][11]. Ultimately, this review serves as a valuable resource for researchers and practitioners seeking to leverage deep learning methodologies for enhanced species identification and conservation strategies [12][13].

2. LITERATURE REVIEW

The use of deep learning, especially Convolutional Neural Networks (CNNs), in wildlife image classification has seen substantial growth, with transfer learning techniques playing a key role. One study discusses advancements in CNN architectures like ResNet50, NASNetMobile, and InceptionV3 for recognizing endangered species, achieving over 90% classification accuracy, and noting the emergence of mobile applications for real-time classification with a rapid turnaround time of approximately 460 milliseconds. Despite these successes, gaps persist in addressing species with high visual similarity and the reliance on general datasets like ImageNet, suggesting the necessity for domain-specific pretraining to improve performance in ecological tasks [2]. A pioneering study showcased the efficacy of transfer learning by achieving an impressive accuracy of 92.5% in classifying cat breeds using the Oxford-IIIT Pet dataset; however, this study was limited to cat breeds, and its results were not generalized to other animal categories, potentially limiting its broader applicability [3]. Another comparative study evaluated multiple deep learning architectures, concluding that VGG16 struck an optimal balance between complexity and accuracy, achieving 85.3% on a wildlife dataset while emphasizing the role of image augmentation techniques, such as rotation and cropping; nevertheless, the study had a limited focus on image augmentation, indicating that further exploration of advanced methods could enhance performance [4].

The literature reveals a growing focus on bird species identification through CNNs, with models such as ResNet152V2 achieving an impressive accuracy of 95.45%. However, many existing studies concentrate on small datasets, which limits the generalizability of their findings. Additionally, challenges in distinguishing species with similar characteristics are highlighted, pointing to the need for larger, more diverse datasets to improve biodiversity classification [5]. One study emphasizes the effectiveness of pretrained models VGG16 and ResNet50 in animal species recognition, achieving accuracies of 87% and 86%, respectively. This research underscores the benefits of fine-tuning these models, especially for recognizing smaller species; however, a critical gap identified is the limited availability of labelled datasets, particularly for small or geographically isolated species. Moreover, the study emphasizes the need for more precise labelling techniques, such as bounding box annotations, to enhance model performance in complex environments [6][14][15]. Another paper discusses the use of MobileNet-V2, a lightweight CNN optimized for animal recognition, which achieved a commendable accuracy of 95.16% through transfer learning. This model presents advantages in computational efficiency and real-time applications compared to traditional CNNs. Nevertheless, significant gaps remain, including the need for evaluation on larger, more diverse datasets and the exploration of integrating real-time video data for enhanced animal recognition systems [7].

In the underwater realm, researchers faced unique challenges due to data scarcity; yet they managed to achieve an accuracy of 86% by employing a pre-trained ResNet50 model. The findings underscored the potential of transfer learning to address obstacles posed by diverse environments; however, accuracy could be improved with better data diversity [8]. Another study explores the use of transfer learning with deep residual networks (ResNet) for animal activity recognition, specifically in sheep behaviour, achieving a high accuracy of 98.40% through knowledge transfer. While the results demonstrate transfer learning's effectiveness in handling sensor variability, the focus on sheep limits the generalizability of findings to other species [9]. The versatility of the VGG16 model is also highlighted in studies focused on birds and endangered species, achieving accuracies of 89% and 87.5%, respectively, through a hybrid approach that combined features from multiple architectures; however, the study did not thoroughly investigate the model's performance on imbalanced data, which is common in conservation datasets [10]. Additionally, one model achieved up to 96.79% accuracy on specialized datasets and 90.91% on broader datasets of 200 bird classes. Gaps remain, including a reliance on small, region-specific datasets that limit generalizability, challenges with species that have high visual similarity, and the need for improved dataset diversity and quality. Future research should explore advanced architectures and evaluation techniques to optimize classification performance [11].

Furthermore, investigations into EfficientNet architectures for classifying marine species revealed that EfficientNet-B5 outperformed other models, achieving a remarkable 93.4% accuracy, but this study was limited by computational resources, and deeper networks were not extensively evaluated for accuracy gains [12]. A comprehensive study on livestock species recognition using the InceptionResNetV2 model achieved an accuracy of 91.3%; however, the dataset was limited to livestock, and expanding the model to classify more species could enhance its robustness [13]. For instance, authors employed the VGG16 model in a study focusing on bird species classification, yielding an accuracy of 88.7%. While the model was accurate, it struggled with classifying very similar bird species, indicating a need for additional feature extraction techniques [16]. A study highlights the creation of an IoT-based Bird Species Classification and Object Detection system utilizing MobileNetV2, which achieved a training accuracy of 90.91% and a validation accuracy of 85%. Although the system improves bird-watching experiences in India, its scope is limited to 200 species, raising questions about its robustness and broader applicability. [17][18]. Finally, in exploring goat/sheep classification, a transfer learning approach with the Xception model achieved an accuracy of 88.6%, yet it faced high computational demand, and the effectiveness of data augmentation strategies was not thoroughly explored [19][20]. In exploring the classification of pistachio species using transfer learning models, specifically AlexNet, VGG16, ResNet50, and a novel Convolutional Neural Network (CNN), the proposed CNN achieved an impressive accuracy of 99%, outperforming AlexNet (90%), VGG16 (92%), and ResNet50 (94%). Evaluation metrics included accuracy (ACC), precision (P), recall (R), and F1-score, assessed over 20 epochs. However, the research identifies gaps such as potential overfitting, limited dataset diversity impacting generalizability, high computational requirements, and challenges in model interpretability. The findings emphasize the effectiveness of transfer learning in agricultural classification while highlighting the need for larger datasets and improved interpretability [21].

3. METHODOLOGY

3.1. Data gathering

The proposed methodology for this research utilizes the iNaturalist Wildlife Dataset, constructed from data collected through social media, camera traps, and citizen science platforms. This dataset aims to provide a global overview of wildlife and enable species monitoring, even in remote locations. It is instrumental for automated wildlife classification, a critical aspect of ecological studies, conservation efforts, and wildlife management, facilitating species population estimates, individual identification, and behavioral analysis. Traditional classification methods often face challenges such as harsh environments, variable image quality, and long-tail data distribution; however, the iNaturalist dataset addresses these issues through a unique spatiotemporal approach. The dataset consists of three primary components: observations, metadata, and images. Observations will be sourced from iNaturalist and will include a subset focused on the Felidae and Elephantidae families, comprising 2 taxonomic families, 16 genera, 48 species, and 67 subspecies. This selection is carefully curated to reflect common challenges encountered in wildlife classification. The spatiotemporal metadata, collected using the Open-Meteo Weather API, will enhance the dataset by providing environmental context, allowing classification methods that extend beyond image recognition to consider species' interactions with their habitats. The image component consists of photographs from camera traps and citizen-science contributions. These images will undergo pre-processing using the Mega-detector, a YOLO-based object detection model designed to recognize humans, vehicles, and wildlife. This process involves cropping, enhancing, and filtering the images to ensure quality, effectively excluding erroneous entries such as footprints or images containing multiple animals.

3.2. Preprocessing

Before training the VGG16 model, the collected images will undergo preprocessing to enhance their quality and ensure suitability for the deep learning pipeline. The process includes resizing images to 224x224 pixels to align with VGG16's input requirements and normalizing pixel values to a 0-1 range to accelerate convergence during training. Data augmentation techniques such as rotation, zoom, horizontal flipping, brightness adjustment, and shearing will be employed to enhance dataset variability and improve model robustness. These augmentations aim to help the model generalize effectively by simulating diverse orientations, scales, and lighting conditions typically observed in real-world wildlife images.

3.3. Transfer Learning with VGG16

The VGG16 model, pre-trained on the ImageNet dataset, will serve as the backbone for the transfer learning process. Initially, the convolutional layers of VGG16 will be used for feature extraction, leveraging pre-trained weights to enhance learning efficiency. The original architecture will be modified by removing the top fully connected layers and adding new custom layers designed for classifying various animal species. These modifications will include a dense layer, a dropout layer to mitigate overfitting, and an output layer with a softmax activation function. The model will undergo fine-tuning, where the new layers will be trained while keeping the lower layers frozen initially, followed by gradual unfreezing of the lower layers to allow the model to learn more specific features relevant to the dataset.

3.4. Model Training

The dataset will be divided into training, validation, and test sets, typically in an 80-10-10 ratio. The training process will utilize the Adam optimizer for weight adjustments and the cross-entropy loss function to evaluate model performance. Key hyperparameters, including learning rate, batch size, and the number of epochs, will be optimized using grid search. Early stopping will be applied to prevent overfitting by halting training when validation accuracy no longer improves. The model will be trained to convergence, with validation metrics closely monitored to ensure optimal performance.

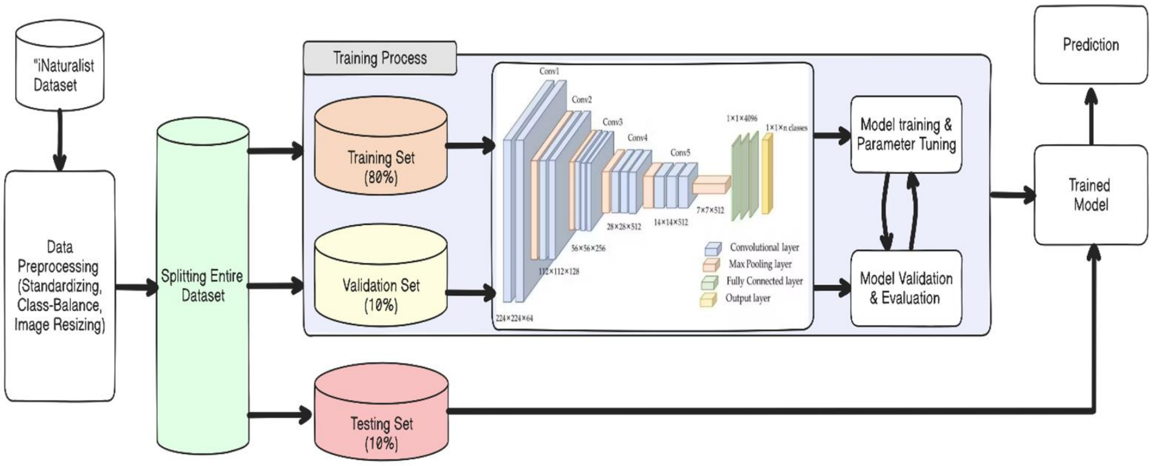

Figure 1. The image classification pipeline consists of several stages: preprocessing the raw dataset, training and validating the model architecture, and ultimately testing the finalized model using a range of diverse sample sets.

3.5. Evaluation

After completing the training process, the model's ability to accurately recognize animal species will be thoroughly evaluated using a range of performance metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of the model's effectiveness by measuring its overall performance, ability to correctly identify true positives, minimize false positives, and balance precision and recall. Additionally, a confusion matrix will be generated to analyze the classification performance for each species in detail. This matrix will highlight areas where the model performs well and pinpoint specific species or groups of species where misclassifications occur, offering valuable insights into potential shortcomings. Such an analysis can help refine the model by identifying challenging classes that may require additional training data or enhanced preprocessing techniques. The test dataset, containing unseen samples, will be used to evaluate the model's generalization capabilities. This step ensures that the model is not overfitting to the training data and can maintain high performance when applied to new, real-world scenarios. To gauge its competitiveness, the model's accuracy will be compared to benchmark results achieved by state-of-the-art approaches in animal species recognition.

Furthermore, visualization tools such as precision-recall curves, receiver operating characteristic (ROC) curves, and bar charts will be utilized to graphically present the evaluation results. These visual aids will help interpret the model's performance, making it easier to identify strengths and weaknesses. By highlighting areas for improvement, these tools can guide future iterations of the model, ultimately contributing to more robust and reliable species recognition capabilities.

3.5. Evaluation

VGG16, a widely used convolutional neural network for transfer learning, offers a simple and uniform architecture that is effective for feature extraction and general image classification tasks. However, compared to more advanced models like ResNet, Inception, MobileNet, and DenseNet, VGG16 has significant limitations in terms of computational efficiency and scalability. ResNet, with its residual connections, allows for much deeper architectures without performance degradation, often surpassing VGG16 in accuracy while requiring fewer parameters. Inception networks excel in efficiency and multi-scale feature extraction, making them more suitable for tasks demanding both accuracy and computational performance. MobileNet, on the other hand, is specifically designed for resource-constrained environments, leveraging depthwise separable convolutions to achieve lightweight and fast performance, though it may sacrifice accuracy on complex datasets. DenseNet, with its densely connected layers, enhances feature reuse and gradient flow, often outperforming VGG16 with fewer parameters. While VGG16 is still a solid choice for tasks prioritizing simplicity and interpretability, its higher computational demands and lower performance on complex tasks make it less competitive than these modern architectures for most transfer learning applications.

4. DISCUSSION

The advancements in animal species recognition using transfer learning underscore the effectiveness of deep learning architectures, particularly the VGG16 model. Numerous studies have demonstrated that transfer learning significantly enhances model performance, especially in scenarios with limited labelled data. For example, leveraging pre-trained models like VGG16 has resulted in remarkable accuracy rates in various species classification tasks, including marine species, cats, and birds [8][3][16]. Additionally, the VGG16 and ResNet50 models have shown strong performance, achieving accuracies of 87% and 86%, respectively, in animal species recognition, further validating the effectiveness of transfer learning in this domain [6]. While these promising results highlight the potential of transfer learning approaches, several limitations persist. Many models, despite achieving high accuracy, struggle with classifying underrepresented species due to imbalanced datasets [5][4]. This issue is exacerbated in conservation datasets, where certain species are significantly underrepresented, affecting the model's ability to generalize. Additionally, the reliance on specific architectures, such as VGG16 or ResNet, may limit generalizability across different datasets and species. This suggests a need for hybrid models that combine multiple architectures for improved performance [16][10]. Moreover, the computational requirements of deep learning models pose challenges, particularly in real-time applications or when deployed on resource-constrained devices. While lightweight models like MobileNet-V2 offer solutions for resource efficiency, they often require optimization techniques to maintain high accuracy [7][11]. Future research should focus on integrating these lightweight models and exploring optimization strategies to make species recognition systems more accessible and efficient in practical applications [7][17]. Overall, the ongoing exploration of transfer learning in animal species recognition reflects a dynamic field with substantial potential for practical applications in conservation, biodiversity monitoring, and ecological research. Continued innovation and collaboration among researchers will further enhance the effectiveness of these systems, paving the way for more accurate and robust species classification solutions [13][12].

5. CONCLUSION

This review underscores the progress made in animal species recognition through transfer learning, specifically utilizing the VGG16 model. The studies analyzed demonstrate the effectiveness of pre-trained deep learning architectures in achieving high accuracy with limited datasets. Techniques such as data augmentation and model fine-tuning are critical for improving performance and generalization. However, challenges such as dataset variability and overfitting still exist, hindering broader applications in real-world scenarios. Future research should aim to overcome these limitations and explore innovative approaches for more robust and adaptable models. Overall, the advancements in this field hold great promise for enhancing biodiversity monitoring and conservation effort.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

REFERENCES

[1] S. P. Deshmukh, D. Choudhari, S. Amalraj, and P. N. Matte, "Hybrid Deep Learning Method for Detection of Liver Cancer," *Comput. Assist. Methods Eng. Sci.*, vol. 30, no. 2, pp. 151–165, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] D. Choe, E. Choi, and D. K. Kim, "The Real-Time Mobile Application for Classifying of Endangered Parrot Species Using the CNN Models Based on Transfer Learning," *Mob. Inf. Syst.*, vol. 2020, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[3] D. Diffran Nur Cahyo, A. Sunyoto, and D. Ariatmanto, "Transfer Learning and Fine-tuning Effect Analysis on Classification of Cat Breeds using a Convolutional Neural Network," *in 2023 6th International Conference on Information and Communications Technology, ICOIACT 2023, Institute of Electrical and Electronics Engineers Inc.*, 2023, pp. 488–493. [CrossRef] [Google Scholar] [Publisher Link]

[4] M. M. Boukar, A. A. Mahamat, O. H. Djibrine, and U. B. Abubakar, "Improving the Accuracy of Animal Species Classification in Camera Trap Images Using Transfer Learning," *in International Conference on Artificial Intelligence, Computer, Data Sciences, and Applications, ACDSA 2024, Institute of Electrical and Electronics Engineers Inc.*, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] A. Manna, N. Upasani, S. Jadhav, R. Mane, R. Chaudhari, and V. Chatre, "Bird Image Classification using Convolutional Neural Network Transfer Learning Architectures," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 3, pp. 854–864, 2023, [CrossRef] [Google Scholar] [Publisher Link]

[6] S. Binta Islam, D. Valles, T. J. Hibbitts, W. A. Ryberg, D. K. Walkup, and M. R. J. Forstner, "Animal Species Recognition with Deep Convolutional Neural Networks from Ecological Camera Trap Images," *Animals*, vol. 13, no. 9, May 2023 [CrossRef] [Google Scholar] [Publisher Link]

[7] H. Liu, "Animal Image Classification Recognition based on Transfer Learning," *Int. Core J. Eng.*, vol. 7, p. 2021 [CrossRef] [Google Scholar] [Publisher Link]

[8] M. S. R. Oion et al., "Marine Animal Classification Using Deep Learning and Convolutional Neural Networks (CNN)," *in 2023 26th International Conference on Computer and Information Technology, ICCIT 2023, Institute of Electrical and Electronics Engineers Inc.*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] S. Mekruksavanich, P. Jantawong, and A. Jitpattanakul, "ResNet-based Deep Neural Network using Transfer Learning for Animal Activity Recognition," *in 6th International Conference on Information Technology, InCIT 2022, Institute of Electrical and Electronics Engineers Inc.*, 2022, pp. 445–449. [CrossRef] [Google Scholar] [Publisher Link]

[10] W. Yang and D. Cristina, "Recognition of Bird Species of Gaoligong Mountain using Transfer Learning Based on VGG-16," *in 2024 4th International Conference on Neural Networks, Information and Communication Engineering, NNICE 2024, Institute of Electrical and Electronics Engineers Inc.*, 2024, pp. 643–647. [CrossRef] [Google Scholar] [Publisher Link]

[11] H. K. Kondaveeti, S. V. N. S. V. Guturu, K. S. Jayan Praveen, and S. V. S. Kumar, "A Transfer Learning Approach to Bird Species Recognition using MobileNetV2," *in Proceedings of the 7th International Conference on Intelligent Computing and Control Systems, ICICCS 2023, Institute of Electrical and Electronics Engineers Inc.*, 2023, pp. 787–794. [CrossRef] [Google Scholar] [Publisher Link]

[12] S. Guo, S. Wang, J. Guo, and J. Xu, "Classification of Aquatic Animals by the Spherical Amphibian Robot based on Transfer Learning," *in 2021 IEEE International Conference on Mechatronics and Automation, ICMA 2021, Institute of Electrical and Electronics Engineers Inc*., Aug. 2021, pp. 1213–1218. [CrossRef] [Google Scholar] [Publisher Link]

[13] A. Ruchay, I. Akulshin, V. Kolpakov, K. Dzhulamanov, H. Guo, and A. Pezzuolo, "Cattle Face Recognition Using Deep Transfer Learning Techniques," *in 2023 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2023 - Proceedings, Institute of Electrical and Electronics Engineers Inc.*, pp. 569–574, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] P. Ramesh, S. Amalraj, P. Arunachalam, M. Gopiraman, A. M. Al-Mayouf, and S. Vasanthkumar, "Covalent intercalation of hydrazine derived graphene oxide as an efficient 2D material for supercapacitor application," *Synth. Met.*, vol. 272, no. November 2020, pp. 116656, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] V. B. Korde, S. Khot, D. B. Kamble, and S. Amalraj, "Review: Perovskite nanostructures materials versatile platform for advance biosensor applications," *Sensors and Actuators Reports*, vol. 7, pp. 100201, 2024. doi: 10.1016/j.snr.2024.100201[CrossRef] [Google Scholar] [Publisher Link]

[16] A. A. Biswas, M. M. Rahman, A. Rajbongshi, and A. Majumder, "Recognition of Local Birds using Different CNN Architectures with Transfer Learning," *in 2021 International Conference on Computer Communication and Informatics, ICCCI 2021, Institute of Electrical and Electronics Engineers Inc.*, Jan. 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] H. K. Kondaveeti, K. S. Sanjay, K. Shyam, R. Aniruth, S. C. Gopi, and S. V. S. Kumar, "Transfer Learning for Bird Species Identification," *in ICCSC 2023 - Proceedings of the 2nd International Conference on Computational Systems and Communication, Institute of Electrical and Electronics Engineers Inc., 2023.* [CrossRef] [Google Scholar] [Publisher Link]

[18] S. Amalraj, and P. A. Michael, "Synthesis and characterization of Al2O3 and CuO nanoparticles into nanofluids for solar panel applications," *Results Phys.*, vol. 15, pp. 102797, 2019. doi: 10.1016/j.rinp.2019.102797 [CrossRef] [Google Scholar] [Publisher Link]

[19] H. K. Ravikiran, L. S. Ravi, K. M. Madhu, K. Bindu, B. A. Farzana Praveen, and T. Tanuja, "Study on VGG16 Transfer learning Model for Goat/Sheep Image Classification," *in International Conference on Recent Advances in Science and Engineering Technology, ICRASET 2023, Institute of Electrical and Electronics Engineers Inc., 2023.* [CrossRef] [Google Scholar] [Publisher Link]

[20] A. Fredderics, K. Kumar, J. S. Renius, and R. Guru, "The FHA analysis of dual-bridge LLC type resonant converter," *Int. J. Power Electron. Drive Syst.*, vol. 4, no. 4, pp. 538–546, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[21] F. Patel, S. Mewada, S. Degadwala, and D. Vyas, "Recognition of Pistachio Species with Transfer Learning Models," *in International Conference on Self Sustainable Artificial Intelligence Systems, ICSSAS 2023 - Proceedings, Institute of Electrical and Electronics Engineers Inc., 2023*, pp. 250–255. [CrossRef] [Google Scholar] [Publisher Link]

AUTHORS

Mayuri M. Vengurlekar received her B.E. degree in Computer Engineering from Vishwakarma Institute of Information Technology, Pune, India. She obtained her M.E. in Computer Science from Savitribai Phule Pune University, Pune, India. Presently, she is working as an Assistant Professor at K J College of Engineering & Management Research, Pune, India, and pursuing her PhD degree at Savitribai Phule Pune University, Pune, India. Her current research focuses on machine learning techniques, with a particular emphasis on mitigating negative transfer in transfer learning.

Ashish Pal, an engineering student at KJ College of Engineering and Management Research, is passionate about exploring machine learning and its applications in image processing. His research interests lie in utilizing transfer learning techniques to enhance image classification and object detection tasks. Ashish is dedicated to bridging theory with real-world solutions and advancing the field of artificial intelligence.

Pravin Parihar is an aspiring engineer from KJ College of Engineering and Management Research, specializing in machine learning and computer vision. His focus is on developing innovative solutions using image processing and transfer learning to address complex challenges. He is committed to advancing technology through research and hands-on experimentation.

Mustafa Nandervawala, a student at KJ College of Engineering and Management Research, has a keen interest in artificial intelligence and deep learning. He is particularly fascinated by the role of transfer learning in optimizing image processing tasks and is driven to contribute to impactful technological advancements in this domain.

Saahil Parmar, an engineering enthusiast at KJ College of Engineering and Management Research, is focused on leveraging machine learning and transfer learning to tackle image processing challenges. He aspires to innovate practical solutions and contribute meaningfully to the rapidly evolving field of AI.

Shankar Amalraj received his B.E. degree in Electrical and Electronics Engineering from Anna University, Chennai, Tamil Nadu, India. He obtained his M.Tech degree in Power Systems from Kalasalingam University, Madurai, Tamilnadu. He earned his doctorate in Nanotechnology from the Karunya Institute of Technology and Sciences, Coimbatore. Currently, he is working as an Associate Professor at KJ College of Engineering and Management Research, Pune. He is actively engaged in the fields of Artificial Intelligence and Computational Sciences.

Arrived: 03.11.2024
Accepted: 05.12.2024