Comparative analysis of convolutional neural network architectures for poultry meat classification

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ABSTRACT

The increasing demand for standardized food quality assurance, particularly in regions like Morocco, emphasizes the need for accurate classification of poultry meat. This study evaluates and compares ten convolutional neural network (CNN) architectures—VGG19, VGG16, ResNet50, GoogleNet, MobileNetV1, MobileNetV2, DenseNet, NasNet, EfficientNet, and AlexNet—for classifying commonly consumed poultry meat types in Moroccan markets, including chicken, turkey, fayoumi, and farmer's chicken. A labeled image dataset was used to train and test each model, with performance assessed using metrics such as accuracy, precision, recall, training time, and computational complexity. Additionally, the study investigates how dataset size influences model performance, addressing challenges like limited data availability and scalability. The results highlight DenseNet as the top-performing architecture, achieving 98% classification accuracy while also demonstrating superior computational efficiency. These findings are valuable for improving food quality control, offering data-driven support for stakeholders in poultry production, distribution, and regulatory bodies. By identifying optimal deep learning models for poultry meat classification, the study contributes to enhancing food authentication and safety in Morocco and similar regions. It also encourages the integration of AI-driven systems in food inspection processes, providing scalable, accurate, and efficient solutions for ensuring standardized quality in the poultry supply chain.

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1. INTRODUCTION

Poultry meat constitutes a cornerstone of global food security, providing a rich source of protein and essential nutrients. In Morocco, poultry production is particularly vital, contributing significantly to both national dietary needs and the agricultural economy. As consumer demand for high-quality poultry products intensifies, accurate and efficient classification of poultry meat becomes paramount for maintaining consumer trust, ensuring food safety, and supporting fair market practices. This necessitates the adoption of advanced technologies capable of automating and standardizing the classification process. Convolutional neural networks (CNNs), a highly effective category of deep learning models specialized in image processing, have proven to be a compelling approach to addressing this challenge. Their ability to discern intricate patterns and features from image data with minimal pre-processing makes them ideally suited for complex classification tasks in the food industry. The application of CNNs in food classification has gained considerable traction in recent years, with successful implementations in areas such as fruit and vegetable sorting, meat quality assessment, and species identification. Several studies have explored the potential of CNNs for poultry meat classification specifically. For example, our previous work [1] demonstrated the effectiveness of the MobileNetV2 pre-trained model for this task. Other research in [2] has employed CNNs to classify chicken breasts based on visual characteristics like color, texture, and fat distribution, while further studies in [3] have investigated their use in authenticating poultry meat products to detect adulteration and ensure product integrity. Despite these advancements, a comprehensive comparative analysis of various CNN architectures tailored to the specific context of Moroccan poultry meat classification remains lacking. Such an analysis is crucial for understanding the strengths and limitations of different models and for developing robust classification systems that accommodate regional variations in poultry breeds, processing methods, and consumer preferences.

This study addresses this gap in our research team [4]–[7] by presenting a comparative analysis of ten distinct CNN architectures for poultry meat classification in Morocco. Utilizing a diverse dataset of poultry meat images representative of the Moroccan market, we evaluate the performance of these architectures in accurately distinguishing between different poultry types and cuts. Through rigorous testing and comparison of key performance metrics, we aim to identify the optimal CNN architectures for maximizing classification accuracy and efficiency in the Moroccan poultry industry. The findings of this research aid in the progression of advanced tools for quality control, traceability, and consumer protection within the Moroccan poultry sector, with broader implications for food security and economic development.

2. RELATED WORK

In the realm of food classification, particularly concerning the categorization of poultry meat, a wealth of prior investigations has laid the groundwork for the comparative analysis expounded within this study. Over time, researchers have delved into an array of methodological approaches, spanning from conventional machine learning techniques to the more intricate realms of deep learning methodologies. For instance, numerous studies have delved into the efficacy of support vector machines (SVMs), random forests, and k-nearest neighbors (k-NN) algorithms in discerning and classifying poultry meat based on a diverse array of visual attributes and features [8], [9]. Moreover, the advent and subsequent maturation of deep learning methodologies, notably CNNs, have sparked considerable interest within the research community. CNN architectures such as VGG, ResNet, and Inception have emerged as stalwarts in the classification of various food items, including poultry meat, showcasing remarkable performance and accuracy in discerning intricate patterns and features within visual data [10], [11]. It is within this context that our study endeavors to contribute significantly. By systematically comparing ten widely employed CNN architectures on a standardized and rigorously curated poultry meat dataset, our analysis aims to shed light on their respective strengths, weaknesses, and applicability in real-world scenarios. Through this endeavor, we aim not only to advance the understanding of poultry meat classification but also to provide practitioners and researchers alike with valuable insights into the optimal selection and deployment of CNN models for similar tasks.

3. MATERIALS AND METHODS

This method focuses on classifying four specific poultry categories-chicken, turkey, Fayoumi, and chicken farmer-using various pre-trained CNN architectures. In this study, we exploit the capabilities of ten diverse CNN architectures, including VGG19, VGG16, ResNet50, GoogleNet, MobileNetV1, MobileNetV2, DenseNet, NasNet, EfficientNet, and AlexNet. Unlike conventional methods that often require training large models from scratch on extensive datasets, by utilizing pre-trained feature maps, we circumvent the need to start training from the ground up, thereby saving computational resources and time. Through this approach, the resulting models demonstrate a remarkable ability to visually differentiate between chicken, turkey, Fayoumi, and chicken farmers with a high level of accuracy across the various CNN architectures tested.

4. IMAGES ACQUISITION

This study on poultry meat classification concentrated on chicken, turkey, and chicken farmers, acknowledging that Moroccans are among the highest consumers of meat globally, averaging 30 kilograms consumed per person each year. In Morocco, as in many other countries, meat holds significant social value and is considered a highly esteemed component of the diet [12]. Poultry constitutes the majority of meat consumption in Morocco, because of its lower price [13]. To enhance accuracy, we included Fayoumi as well, resulting in a dataset covering four poultry types. The dataset was compiled by purchasing various cuts of turkey, chicken, Fayoumi, and chicken farmer from a market in Meknes, Morocco. We used a 16-megapixel digital camera phone (Huawei Y9 Prime) along with a photography LED box, as shown in Figure 1, to capture high-quality images. Additionally, we employed a program for image cropping to augment the dataset. Images were taken of different parts of the bird, including the thigh, drumstick, wing, breast, and neck. This approach allowed us to capture detailed attributes and textures crucial for classification. The images were captured over a period of 20 days, ensuring diversity in the dataset. The original image dimensions were 4608×3456 pixels, which were resized to 408×306 pixels to ensure compatibility with the model and accommodate storage limitations on Google Drive. We focused on preserving color and texture details, crucial for accurate classification [14], [15], and zoomed in on features and attributes of the images. Sample images from our dataset are depicted in Figure 2.

Figure 1. Photography LED box

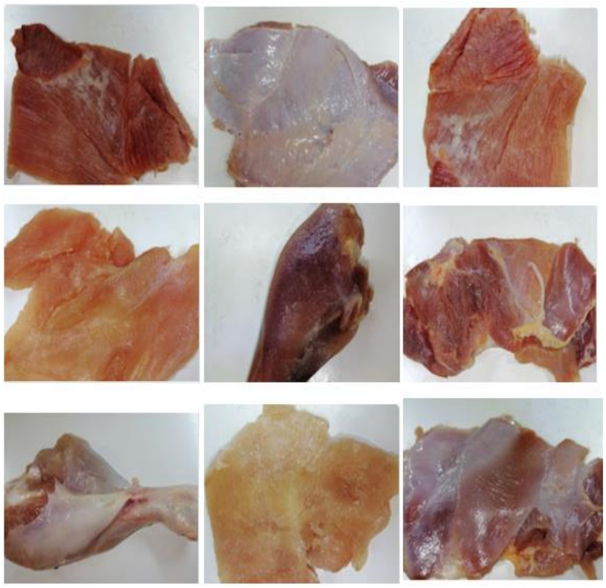


Figure 2. Dataset samples [1]

5. DATASET AUGMENTATION

The training dataset constitutes a pivotal component, comprising a total of 746 images that have been categorized into four distinct classes. Recognizing the significance of data augmentation in enhancing model generalization and performance, we took measures to enrich the dataset further. Leveraging a coding program developed, we implemented augmentation techniques to diversify the dataset. Through this augmentation process, each original image was transformed into eight variations, including rotations and horizontal mirroring. This augmentation strategy significantly bolstered the dataset, expanding it to a total of 7614 images, as visually depicted in Figure 3. This augmentation not only amplifies the dataset's volume but also enriches its diversity, empowering our models with a more comprehensive understanding of the variability within the dataset, thereby enhancing their robustness and classification accuracy.

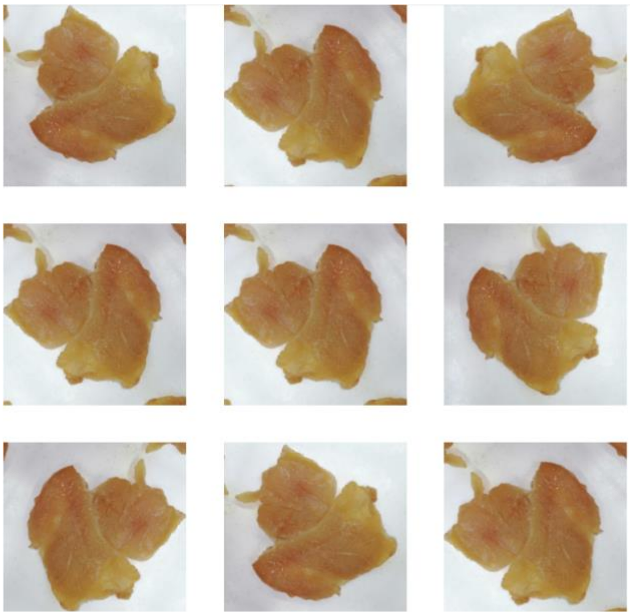


Figure 3. Example of an image augmentation

6. THE MODELS

The study utilized a diverse array of pre-trained CNN models to preprocess and classify the poultry meat dataset. in Figure 4, an overview of CNN architecture is specified. These models encompassed a wide range of architectures and characteristics, including VGG19, VGG16, ResNet50, GoogleNet, MobileNetV1, MobileNetV2, DenseNet, NasNet, EfficientNet, and AlexNet. Each of these models has been pretrained on large-scale image datasets like ImageNet, enabling them to learn rich representations of visual features, which can be effectively transferred to our poultry meat classification task.

VGG19, VGG16, and ResNet50 are renowned for their deep architectures and superior performance in image classification tasks [16]–[18]. NasNet, on the other hand, is designed to be compact, making it suitable for deployment on resource-constrained devices without compromising accuracy. NasNet architectures often achieve state-of-the-art performance but require significant computational resources for their design [19]. MobileNetV2 and MobileNetV1 are optimized for mobile and embedded applications, offering lightweight architectures while maintaining competitive accuracy [20]–[22]. DenseNet stands out for its densely connected layers, promoting feature reuse and facilitating efficient training [23].

EfficientNet is part of a family of models that scale up in complexity and accuracy by balancing network depth, width, and resolution [24]. AlexNet, one of the pioneering CNN architectures, introduced key concepts such as convolutional layers and rectified linear units (ReLU), paving the way for modern deep learning research [25]. GoogleNet, with its inception modules and global average pooling, emphasizes both depth and computational efficiency [26].

By leveraging pre-trained models, we capitalized on the wealth of knowledge these models have accumulated during their training on diverse image datasets. This approach significantly reduced the computational overhead and time required for training, allowing us to focus on fine-tuning the models for poultry meat classification. Moreover, by evaluating the performance of these diverse models across various metrics such as accuracy, precision, recall, and F1-score, we gained valuable insights into their effectiveness and suitability for poultry meat classification tasks.

Through this comprehensive analysis, we aimed to identify the most effective CNN architecture for poultry meat classification, considering factors such as accuracy, efficiency, and scalability. By evaluating the ten prominent architectures-VGG19, VGG16, ResNet50, GoogleNet, MobileNetV1, MobileNetV2, DenseNet, NasNet, EfficientNet, and AlexNet-we sought to determine which model performs best in distinguishing between chicken, turkey, fayoumi, and chicken farmer meat. Our findings reveal that certain architectures, such as DenseNet and VGG16, demonstrated superior accuracy and computational efficiency, making them well-suited for real-world applications in poultry meat classification. These results contribute to the advancement of research in leveraging deep learning techniques for food quality assessment and authentication, with potential applications in industries involved in poultry meat production and distribution.

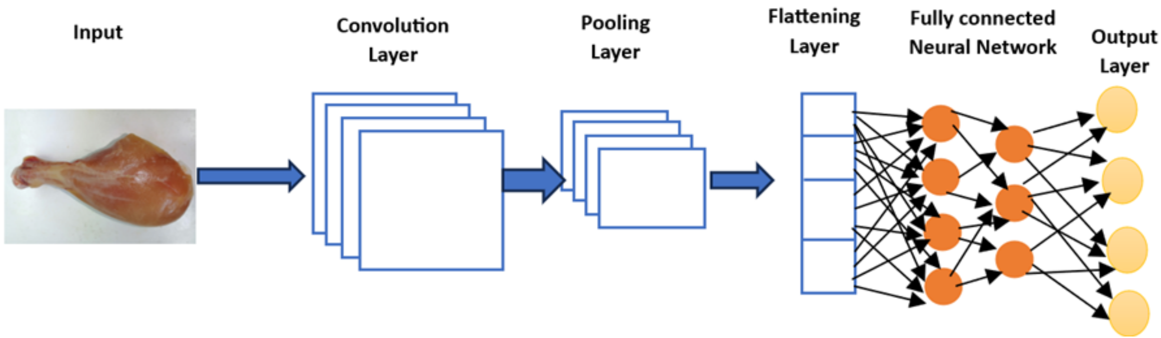


Figure 4. High level design of convolution architecture

7. RESULTS AND DISCUSSION

In this section, we present and discuss the results of our comparative analysis of ten CNN models for poultry meat classification. The models evaluated include VGG19, VGG16, ResNet50, GoogleNet, MobileNetV1, MobileNetV2, DenseNet, NasNet, EfficientNet, and AlexNet. We analysed their performance based on accuracy and loss metrics to determine their suitability for classifying poultry meat.

7.1. Performance comparison

The results in Table 1 present a nuanced balance between computational efficiency and classification accuracy across the evaluated CNN models. DenseNet emerges as a frontrunner, showcasing an outstanding accuracy of 98% with an exceptionally low loss of 0.03. This remarkable performance can be attributed to DenseNet's dense connectivity pattern, which promotes feature reuse and gradient flow, as highlighted by [27]. This finding underscores the importance of intricate network architectures in achieving high accuracy in image classification tasks.

Traditional architectures such as VGG19, VGG16, and ResNet50 exhibit competitive performance, with accuracies of 95%, 97% and 91%. These models, renowned for their deep architectures and residual connections, excel in capturing intricate features within poultry meat images [28]. However, their deeper structures may entail higher computational overheads during both training and inference phases, necessitating careful consideration in resource-constrained environments.

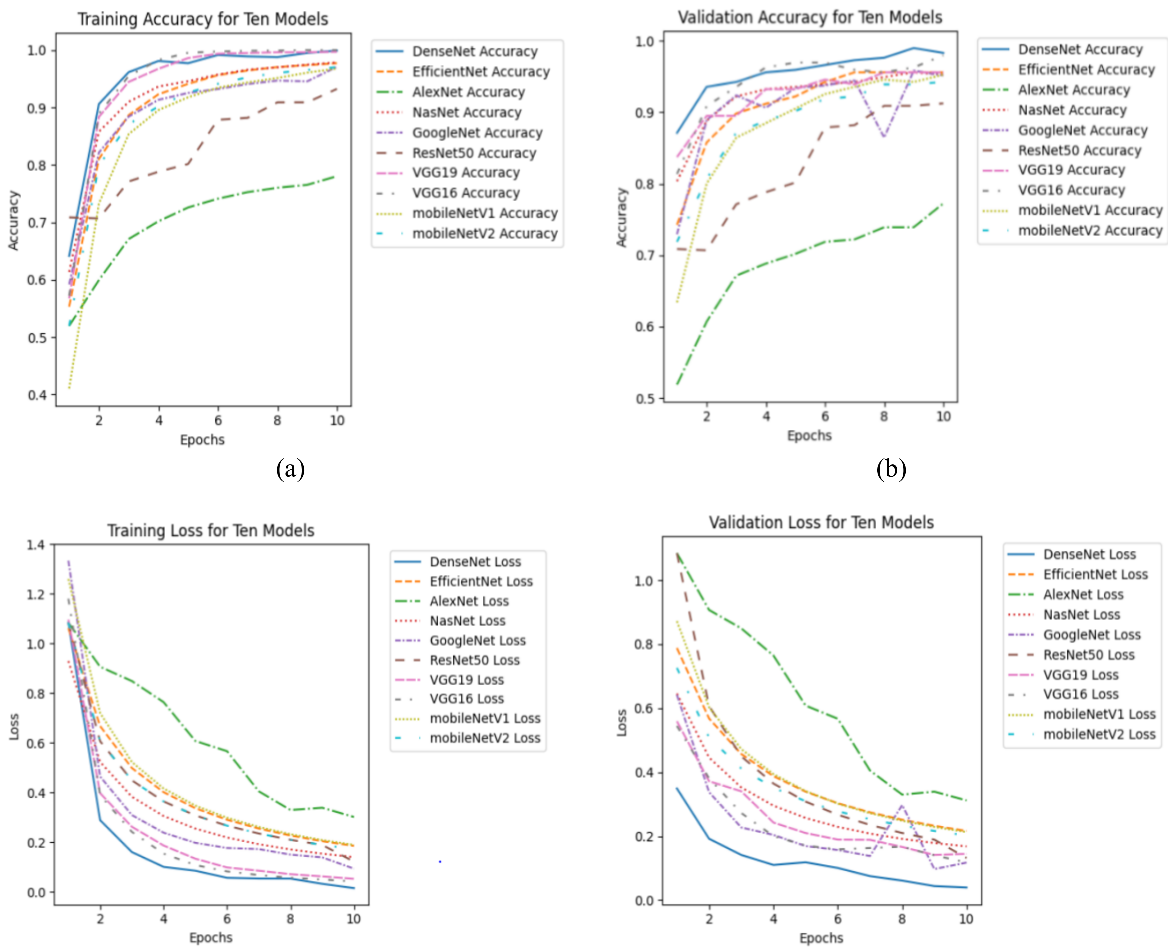
Table 1. The accuracy and loss values of ten models

Model	Accuracy (%)	Loss
VGG19	95	0.14
VGG16	97	0.11
ResNet50	91	0.12
MobileNetV2	94	0.20
MobileNetV1	95	0.21
DenseNet	98	0.03
EfficientNet	95	0.21
AlexNet	77	0.30
NasNet	95	0.16
GoogleNet	95	0.11

Conversely, lightweight architectures like NasNet, GoogleNet, and MobileNetV1 demonstrate commendable computational efficiency. They achieve an accuracy of 95%. These models, characterized by their compact architectures and parameter-efficient designs, offer promising solutions for deployment in resource-constrained environments [29], [30]. Models with shallower architectures, such as AlexNet and MobileNetV2, struggle to achieve comparable accuracies, with AlexNet achieving 77% accuracy and MobileNetV2 achieving 94%. These models, with their simpler architectures, may encounter difficulties in capturing intricate features present in poultry meat images, leading to reduced performance compared to their counterparts [31]. Our comparative analysis sheds light on the strengths and limitations of various CNN models for poultry meat classification. By understanding these nuances, practitioners can make informed decisions when selecting models for real-world applications in the poultry industry, ultimately contributing to more efficient and accurate classification systems.

7.2. Training curves

These curves, as shown in Figure 5, provide insights into the training and validation progress of each model, illustrating how accuracy improves as shown in Figures 5(a) and 5(b) and loss decreases as shown in Figures 5(c) and 5(d) over successive epochs of training. For instance, deeper architectures like DenseNet, VGG16, ResNet50, and EfficientNet exhibit smoother convergence curves, indicating stable learning dynamics and effective feature extraction, while shallower models like AlexNet show more fluctuations, reflecting challenges in capturing complex patterns. Such visualizations offer a deeper understanding of the learning dynamics and convergence behavior of the CNN models, complementing the quantitative evaluation of their performance metrics. By analysing these curves, we can identify models that not only achieve high accuracy but also demonstrate consistent and reliable training behavior, which is crucial for real-world deployment in poultry meat classification tasks.



(a) (b) (c) (d)

Figure 5. Insights into the training and validation progress of each model: (a) training accuracy curves for each model, (b) validation accuracy curves for each model, (c) training loss curves for each model, and (d) validation loss curves for each model

8. FUTURE DIRECTIONS

Looking ahead, future research in poultry meat classification could explore expanding the scope to include minced meat analysis. Incorporating minced meat classification poses unique challenges, such as distinguishing between meat particles and grease content. Future research could utilize advanced image processing and machine learning techniques to achieve precise classification of minced poultry meat, while also estimating the proportion of meat and fat in the samples. This extension would not only enhance the applicability of CNNs in poultry meat analysis but also provide valuable insights for the food processing industry, particularly in quality control and product formulation.

9. CONCLUSION

The study provides valuable insights into the application of CNNs for poultry meat classification, demonstrating the feasibility of automating this task through a comparative analysis of ten CNN architectures evaluated on a standardized dataset. We show that while deeper architectures like DenseNet and VGG16 offer higher accuracy and robustness, lightweight models such as MobileNetV2 provide a more computationally efficient solution, making them suitable for resource-constrained environments. Moreover, data augmentation techniques are essential for improving the generalization ability of CNN models, thereby enhancing their effectiveness in real-world applications. The results of this study support the advancement of intelligent food processing systems that can accurately classify poultry meat, contributing to improved food safety and quality assurance within the industry. Moving forward, further research is warranted to explore advanced techniques such as transfer learning, domain adaptation, and ensemble methods to enhance the performance and scalability of CNN models for food classification tasks.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this article.

DATA AVAILABILITY

The data that support the findings of this study are openly available at Google Drive: https://drive.google.com/drive/folders/1js8Xq0K20y3vGiqW1yP5oTyYXcKF21gk?usp=drive_link.

REFERENCES

[1] S. Salma, M. Habib, A. Tannouche, and Y. Ounejjar, "Poultry meat classification using MobileNetV2 pretrained model," *Revue d'Intelligence Artificielle*, vol. 37, no. 2, pp. 275–280, Apr. 2023, doi: 10.18280/ria.370204.

[2] Calvin, G. B. Putra, and E. Prakasa, "Classification of chicken meat freshness using convolutional neural network algorithms," in

2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies, 3ICT 2020, Dec. 2020, pp. 1–6, doi: 10.1109/3ICT51146.2020.9312018.

[3] N. S. N. Abd Aziz, S. Mohd Daud, R. A. Dziyauddin, M. Z. Adam, and A. Azizan, "A review on computer vision technology for monitoring poultry farm-application, hardware, and software," *IEEE Access*, vol. 9, pp. 12431–12445, 2021, doi: 10.1109/ACCESS.2020.3047818.

[4] H. Mohammed, A. Tannouche, and Y. Ounejjar, "Weed detection in pea cultivation with the faster RCNN ResNet 50 convolutional neural network," *Revue d'Intelligence Artificielle*, vol. 36, no. 1, pp. 13–18, Feb. 2022, doi: 10.18280/ria.360102.

[5] A. Tannouche, K. Sbai, M. Rahmoune, R. Agounoune, and A. Rahmani, "Real time weed detection using a boosted cascade of simple features," *International Journal of Electrical and Computer Engineering*, vol. 6, no. 6, pp. 2755–2765, Dec. 2016, doi: 10.11591/ijece.v6i6.11878.

[6] M. Habib, S. Sekhra, A. Tannouche, and Y. Ounejjar, "The identification of weeds and crops using the popular convolutional neural networks," in *Digital Technologies and Applications*. Cham, Switzerland: Springer, 2023, pp. 484–493, doi: 10.1007/978-3-031-29857-8_49.

[7] A. Tannouche, A. Gaga, M. Boutalline, and S. Belhouideg, "Weeds detection efficiency through different convolutional neural networks technology," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 1, pp. 1048–1055, Feb. 2022, doi: 10.11591/ijece.v12i1.pp1048-1055.

[8] D. Seo *et al.*, "Identification of target chicken populations by machine learning models using the minimum number of SNPs," *Animals*, vol. 11, no. 1, pp. 1–18, Jan. 2021, doi: 10.3390/ani11010241.

[9] I. Tomasevic *et al.*, "Evaluation of poultry meat colour using computer vision system and colourimeter: is there a difference?," *British Food Journal*, vol. 121, no. 5, pp. 1078–1087, Jun. 2019, doi: 10.1108/BFJ-06-2018-0376.

[10] C. Ye *et al.*, "An experimental study of stunned state detection for broiler chickens using an improved convolution neural network algorithm," *Computers and Electronics in Agriculture*, vol. 170, Mar. 2020, doi: 10.1016/j.compag.2020.105284.

[11] N. Darapaneni, B. Krishnamurthy, and A. R. Paduri, "Convolution neural networks: a comparative study for image classification," in *2020 IEEE 15th International Conference on Industrial and Information Systems, ICIIS 2020 - Proceedings*, Nov. 2020, pp. 327–332, doi: 10.1109/ICIIS51140.2020.9342667.

[12] M. S. Deoula *et al.*, "Consumption of meat, traditional and modern processed meat and colorectal cancer risk among the Moroccan population: a large-scale case–control study," *International Journal of Cancer*, vol. 146, no. 5, pp. 1333–1345, Mar. 2020, doi: 10.1002/ijc.32689.

[13] N. Cohen, H. Ennaji, B. Bouchrif, M. Hassar, and H. Karib, "Comparative study of microbiological quality of raw poultry meat at various seasons and for different slaughtering processes in Casablanca (Morocco)," *Journal of Applied Poultry Research*, vol. 16, no. 4, pp. 502–508, Dec. 2007, doi: 10.3382/japr.2006-00061.

[14] X. Fu and J. Chen, "A review of hyperspectral imaging for chicken meat safety and quality evaluation: application, hardware, and software," *Comprehensive Reviews in Food Science and Food Safety*, vol. 18, no. 2, pp. 535–547, Mar. 2019, doi: 10.1111/1541-4337.12428.

[15] I. Tomasevic *et al.*, "Comparison of a computer vision system vs. traditional colorimeter for color evaluation of meat products with various physical properties," *Meat Science*, vol. 148, pp. 5–12, Feb. 2019, doi: 10.1016/j.meatsci.2018.09.015.

[16] R. Malhotra and P. Singh, "Recent advances in deep learning models: a systematic literature review," *Multimedia Tools and Applications*, vol. 82, no. 29, pp. 44977–45060, Dec. 2023, doi: 10.1007/s11042-023-15295-z.

[17] M. Shafiq and Z. Gu, "Deep residual learning for image recognition: a survey," *Applied Sciences*, vol. 12, no. 18, Sep. 2022, doi: 10.3390/app12188972.

[18] D. Theckedath and R. R. Sedamkar, "Detecting affect states using VGG16, ResNet50 and SE-ResNet50 networks," *SN Computer Science*, vol. 1, no. 2, 2020, doi: 10.1007/s42979-020-0114-9.

[19] H. A. Saber, A. Younes, M. Osman, and I. Elkabani, "Quran reciter identification using NASNetLarge," *Neural Computing and Applications*, vol. 36, no. 12, pp. 6559–6573, 2024, doi: 10.1007/s00521-023-09392-1.

[20] L. Zhang, J. Wang, B. Li, Y. Liu, H. Zhang, and Q. Duan, "A MobileNetV2-SENet-based method for identifying fish school feeding behavior," *Aquacultural Engineering*, vol. 99, Nov. 2022, doi: 10.1016/j.aquaeng.2022.102288.

[21] S. El-Khamy, A. Al-Kabbany, and S. El-Bana, "Going shallower with MobileNets: on the impact of wavelet pooling," in *National Radio Science Conference, NRSC, Proceedings*, Jul. 2021, pp. 126–138, doi: 10.1109/NRSC52299.2021.9509825.

[22] D. Sinha and M. El-Sharkawy, "Thin MobileNet: an enhanced MobileNet architecture," in *2019 IEEE 10th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference, UEMCON 2019*, Oct. 2019, pp. 0280–0285, doi: 10.1109/UEMCON47517.2019.8993089.

[23] T. Chauhan, H. Palivela, and S. Tiwari, "Optimization and fine-tuning of DenseNet model for classification of COVID-19 cases in medical imaging," *International Journal of Information Management Data Insights*, vol. 1, no. 2, Nov. 2021, doi: 10.1016/j.jjimei.2021.100020.

[24] M. Tan and Q. V. Le, "EfficientNetV2: smaller models and faster training," *Proceedings of Machine Learning Research*, vol. 139, pp. 10096–10106, 2021.

[25] S. B. Akbar, K. Thanupillai, and S. Sundararaj, "Combining the advantages of AlexNet convolutional deep neural network optimized with anopheles search algorithm based feature extraction and random forest classifier for COVID-19 classification," *Concurrency and Computation: Practice and Experience*, vol. 34, no. 15, Jul. 2022, doi: 10.1002/cpe.6958.

[26] X. Zhang, N. Han, and J. Zhang, "Comparative analysis of VGG, ResNet, and GoogLeNet architectures evaluating performance, computational efficiency, and convergence rates," *Applied and Computational Engineering*, vol. 44, no. 1, pp. 172–181, Mar. 2024, doi: 10.54254/2755-2721/44/20230676.

[27] D. Kim, B. Heo, and D. Han, "DenseNets reloaded: paradigm shift beyond ResNets and ViTs," in *Computer Science*. Cham, Switzerland: Springer, pp. 395–415, 2025, doi: 10.1007/978-3-031-72646-0_23.

[28] R. Ranftl, A. Bochkovskiy, and V. Koltun, "Vision transformers for dense prediction," in *Proceedings of the IEEE International Conference on Computer Vision*, Oct. 2021, pp. 12159–12168, doi: 10.1109/ICCV48922.2021.01196.

[29] N. Zakaria, F. Mohamed, R. Abdelghani, and K. Sundaraj, "VGG16, ResNet-50, and GoogLeNet deep learning architecture for breathing sound classification: a comparative study," in *2021 International Conference on Artificial Intelligence for Cyber Security Systems and Privacy (AI-CSP)*, Nov. 2021, pp. 1–6, doi: 10.1109/AI-CSP52968.2021.9671124.

[30] F. Saxen, P. Werner, S. Handrich, E. Othman, L. Dinges, and A. Al-Hamadi, "Face attribute detection with mobilenetv2 and nasnet-mobile," in *International Symposium on Image and Signal Processing and Analysis, ISPA*, Sep. 2019, pp. 176–18, doi: 10.1109/ISPA.2019.8868585.

[31] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

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