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Review paper

Applications of deep learning in automated image classification: a review

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Abstract

Deep learning's developments have greatly changed automatic picture categorization, proving great accuracy and efficiency in many fields. Medical imaging, agriculture, and environmental monitoring are just a few innovative uses for techniques including hybrid models, transfer learning, and convolutional neural networks (CNNs). Improved precision using ensemble and attention-based models has helped medical diagnosis including diabetic retinopathy and breast cancer detection benefit. Likewise, CNNs are used in environmental monitoring systems for species identification and wind turbine inspection. Although these developments highlight the transforming power of deep learning, problems still exist including limited datasets, computing requirements, and lack of generalizability across many settings. Researchers support lightweight model designs, innovative augmentation techniques, and dataset extension to help solve these challenges. Future developments in architectures and cross-domain applications have great potential to widen the range of efficiency of deep learning in automated picture categorization. This analysis underlines the need for ongoing research to fully utilize deep learning in the solution of challenging categorization tasks.

Keywords: *Automated Image Classification; Deep Learning; Convolutional Neural Networks; Transfer Learning; Medical Image Analysis; Advanced Preprocessing Techniques.*

1. Introduction

The advent of deep learning has revolutionized the field of automated image classification, providing unprecedented accuracy and efficiency in various applications. Deep learning, particularly through the use of Convolutional Neural Networks (CNNs), has emerged as a powerful tool for extracting complex features from images, enabling machines to classify pictures with remarkable precision [1]. This capability is particularly significant in domains such as medical imaging, where accurate classification can lead to timely and effective diagnoses. The integration of transfer learning further enhances the performance of deep learning models, allowing them to leverage knowledge gained from large datasets to improve classification tasks on smaller, domain-specific datasets [2].

Deep learning technologies have shown notable medical field improvements in the imaging-based diagnosis of certain disorders [3]. For example, transfer learning from pre-trained and deep learning models has been used to identify chest X-rays for pneumonia detection, hence attaining great accuracy rates [4]. Likewise, deep learning techniques have helped to improve the categorization of breast cancer pictures utilizing ultrasonic and mammography as they have been demonstrated to be more accurate and efficient than conventional techniques [5] [6]. In healthcare, where the stakes are sometimes life and death, these uses highlight the vital part deep learning performs in improving diagnostic capacity [7].

Deep learning has found use outside of medical applications in legal document analysis, environmental monitoring, and agriculture among other disciplines[8]. For agricultural uses, for instance, deep learning methods have been used to identify soil pictures thereby improving crop management and soil health monitoring [9]. Deep learning has helped to classify photos and documents in the framework of legal document evaluation, therefore simplifying the review process and raising the efficiency [10]. These cases show how flexible deep learning is in tackling challenging categorization problems in many different fields and emphasize its ability to revolutionize sectors by automating labor-intensive and time-consuming activities.

Deep learning's success in automated picture categorization may be ascribed to several elements, including the availability of big datasets, improvements in computer capacity, and the creation of complex neural network topologies. Particularly the application of transfer learning has been revolutionary since it lets models be optimized for certain tasks without requiring significant retraining from scratch [2] [11]. This strategy is preferable in situations when annotated data is limited as it not only saves time and money but also improves the generalizing capacity of the model over several datasets [2] [12].

Moreover, the performance of picture classification tasks has been much enhanced by the ongoing development of deep learning architectures including attention mechanisms and residual networks (ResNets). These developments capture complex patterns and characteristics necessary for good categorization, therefore enabling algorithms to learn from data more efficiently [13]. Deep learning's possible uses in automatic picture categorization are projected to grow as research develops, opening the path for ever more advanced systems able to address challenging problems in several domains [14].

Finally, deep learning finds extensive and diverse applications in automated picture categorization across several sectors and disciplines. Particularly in important domains like medical imaging, deep learning methods especially CNNs and transfer learning have produced notable improvements in accuracy and efficiency when combined. Deep learning has great potential to improve automatic picture categorization as technology develops; with continuous study, new capabilities, and uses are likely to be unlocked that would help society as a whole.

The purpose of this review is to explore the transformative impact of deep learning in automated image classification across various fields. It highlights advancements such as convolutional neural networks, hybrid models, and transfer learning while discussing challenges like limited datasets and computational requirements. The review emphasizes the potential for future innovations in architectures and cross-domain applications to address these issues and expand the utility of deep learning in tackling complex classification tasks.

The rest of this work is arranged as follows: in Section 2, a succinct overview of applications of deep learning in automated image classification. Section 3 presents the findings of the review analysis together with the most significant conclusions. Section 4 offers a discussion of the review analysis. Section 5 concludes with a summary of the study results and future directions.

2. Background theory

The theory underlying deep learning (DL) in automated image classification is rooted in the computational modeling of neural networks designed to mimic the human brain's ability to process and classify visual data. Automated image classification, which aims to assign categorical labels to input images, has historically relied on handcrafted feature extraction methods combined with traditional machine learning algorithms. However, these methods were often limited by their reliance on domain-specific expertise and inability to generalize across datasets and tasks [15].

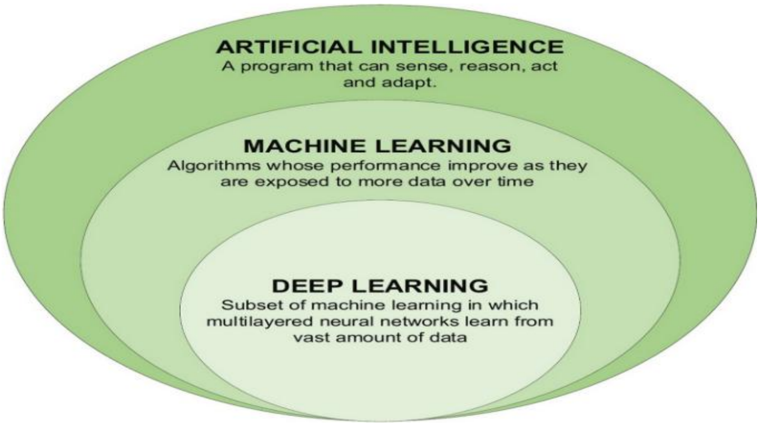

Fig. 1: ML Is A Subset of AI Focused on Algorithms That Improve with Data Exposure, and DL Is A Specialized Subset of ML Leveraging Multilayered Neural Networks for Complex Data Analysis. [16].

2.1. Deep learning: an evolutionary in image classification

Deep learning revolutionized image classification through architectures such as convolutional neural networks (CNNs). Unlike traditional methods, CNNs automatically learn hierarchical feature representations from raw image data. This ability to extract low-level features (e.g., edges, textures) and combine them into higher-level representations (e.g., object shapes) makes CNNs particularly effective for image classification tasks. The advent of deep learning enabled significant breakthroughs in benchmark datasets like ImageNet, demonstrating its superiority over traditional methods [17].

CNNs utilize convolutional layers, pooling layers, and fully connected layers to progressively refine feature extraction. The incorporation of backpropagation for gradient-based learning allows networks to minimize classification errors effectively [15]. This paradigm shift set the stage for the rapid adoption of DL across diverse image classification domains, from medical imaging to autonomous vehicles.

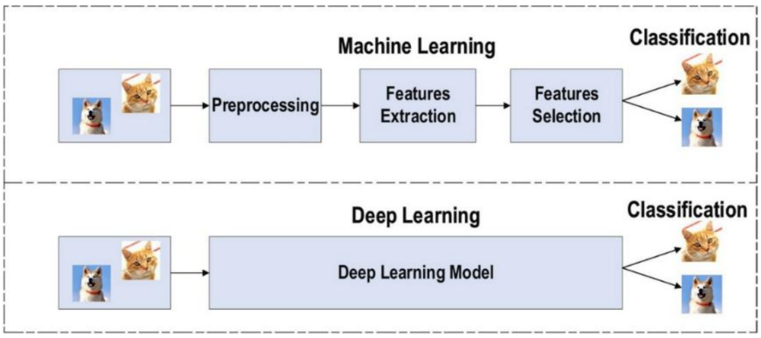

Fig. 2: Machine Learning vs Deep Learning.

Figure 2 The difference between deep learning and traditional machine learning is that in machine learning, preprocessing, feature extraction, and feature selection are performed separately before classification, whereas deep learning integrates these steps within a single deep learning model, streamlining the process [16].

2.2. Architectures and techniques enhancing image classification

Advancements in image classification have been driven by novel architectures and techniques that improve accuracy and efficiency. Convolutional Neural Networks (CNNs), like AlexNet, VGG, and ResNet, have significantly enhanced feature extraction and learning capabilities through layered convolutional filters and residual connections [17]. The introduction of transformers, such as Vision Transformers (ViTs), utilizes self-attention mechanisms to capture global dependencies across images, further improving performance on complex datasets [18]. Techniques like transfer learning allow pre-trained models to be fine-tuned for specific tasks, reducing computational requirements [19]. Regularization strategies such as dropout and data augmentation mitigate overfitting, while ensemble methods enhance robustness by combining predictions from multiple models [20]. Integrating hybrid models combining CNNs with transformers is an emerging trend, showcasing improved adaptability for diverse applications. These advancements collectively enable more accurate and versatile image classification systems.

2.3. Applications in diverse fields

Deep learning has been instrumental in transforming image classification applications across various fields:

- Medical Imaging: CNNs and attention-based models facilitate automated disease diagnosis from X-rays, MRIs, and histopathological images, significantly improving diagnostic precision [21].
- Agriculture: DL models detect crop diseases, classify plant species, and monitor nutrient deficiencies, enhancing agricultural productivity [22].
- Autonomous Vehicles: Real-time image classification systems aid object detection and road scene segmentation, contributing to vehicle safety and efficiency [23].
- Remote Sensing: DL-powered methods analyze satellite images for land use, deforestation, and urban planning, offering unparalleled scalability and accuracy [24].

2.4. Challenges and emerging trends

Despite its success, DL in image classification faces challenges, such as the need for large labeled datasets, high computational costs, and interpretability concerns. To address these issues, researchers are exploring unsupervised and semi-supervised learning, lightweight models, and explainable AI frameworks [25].

3. Literature review

This section provides a comprehensive overview of the existing body of knowledge, highlighting key findings, methodologies, and gaps relevant to the study. It establishes the theoretical framework and situates the current research within the broader academic discourse. Additionally, it identifies areas for further investigation to advance understanding of the subject:

Sadak et al., in 2020 Provided a real-time deep-learning system for microinjection tasks' automated zebrafish embryo recognition and placement. It accomplished 89% mean IoU accuracy, 100% detection accuracy, and 33 FPS using YOLOv2 with a ResNet-50 backbone. To consistently place embryos inside the microscope's field of view, the system used bounding box localization, data augmentation, and transfer learning, thereby improving automation and reducing manual participation in biological microinjection applications. However, the system was constrained to zebrafish embryo records, which limited its application to other biological cells or settings. The authors proposed using domain adaptation methods to increase adaptability and applicability and extending the dataset to incorporate different biological cells to address this limitation [26].

R. J. S. Raj et al., in 2020 Provided a deep learning-based medical image classification model utilizing Optimal Feature Selection via the Opposition-based Crow Search (OCS) technique. The framework comprises preprocessing (histogram equalizing), feature extraction (GLCM and GLRLM), and deep neural network classification. On datasets for brain, lung, and Alzheimer's disease it achieved 95.22% accuracy, 86.45% sensitivity, and 100% specificity by methods of feature selection and computational time reduction. These results demonstrate great potential for automated medical diagnosis. Still, the method incurred significant computing costs, which would hinder scalability for large-scale projects. The authors advocated employing lightweight designs and parallel processing techniques to overcome this issue [27].

Alyoubi et al., in 2021 A deep learning-based system for lesion localization and diabetic retinopathy (DR) diagnosis was presented in this work On the DDR dataset it obtained 89% accuracy, 89% sensitivity, and 97.3% specificity by using CNN512 for classifying pictures into five DR phases and a modified YOLOv3 for lesion location. Transfer learning, data augmentation, and model fusion methods helped to produce these outcomes. The technique was intended to help ophthalmologists by allowing exact lesion location and accurate DR stage categorization. Nevertheless, unbalanced datasets hindered the effectiveness of the model, especially in the Mild and Severe DR categories, hence lowering sensitivity for these phases. The authors proposed balancing the dataset via data augmentation or further data collecting to overcome this restriction and raise sensitivity and resilience [28].

Hameed et al., in 2020 Presented an ensemble deep-learning system for categorizing breast cancer histomorphology photos into carcinoma and non-carcinoma classes. With data augmentation and 5-fold cross-valuation, the method combines fine-tuned VGG16 and VGG19 models to provide an F1 score of 95.29%, 95.29% accuracy, and 97.73% sensitivity. Designed to provide pathologists with accurate, automated breast cancer detection, the method improved classification accuracy by the use of average probability fusion. The study limited its extension to more complicated, multi-class classification scenarios by depending on a tiny, binary-class dataset, though. The authors proposed increasing the amount of the dataset and using multi-class classification for other histological categories to solve this restriction thereby enhancing model robustness and usefulness [29].

In 2019 Yan et al., To evaluate breast cancer histopathology pictures, the work presented a hybrid deep learning model combining Inception-V3 for patch-wise feature extraction and Bidirectional LSTM for image-wise classification. With fine-tuning, data augmentation, and multilayer feature representation, the model attained 91.3% accuracy for 4-class classification (normal, benign, in situ cancer, aggressive carcinoma). Using a sizable, varied collection consisting of 3771 photos improved performance and showed promise for automated cancer diagnosis. Limited and varied feature representation in the model, however, caused it to show reduced classification accuracy for benign and normal categories. To raise classification accuracy and resilience, the authors advised increasing feature diversity for benign and normal categories and extending the dataset [30].

Welikala et al. in 2020 presented a deep learning-based system to support oral cancer screening using early identification and categorization of oral lesions. ResNet-101 was used for image classification; with an F1 score of 87.07% for lesion detection and 78.30% for referral case identification; Faster R-CNN was used for object detection and produced an F1 score of 41.18% for lesion detection. Transfer learning, data enrichment, and composite annotations from several doctors helped to produce these outcomes. Still, the tiny dataset, fluctuating image quality, and uneven annotations limited the system's performance. The writers proposed using enhanced attention techniques to boost consistency and performance as well as expanding the dataset size with standardized, high-quality photos [31].

Hadeer A. Helaly et al. in 2021 suggested utilizing CNN architectures and transfer learning with VGG19 the E2AD2C framework for early detection and categorization of Alzheimer's disease phases. For 2D and 3D multi-class classification, the model attained 93.61% and 95.17% respectively; with the fine-tuned VGG19, it attained 97% accuracy. Preprocessing, data augmentation, resampling, and weight leveraging pre-trained helped to produce these outcomes. Along with stage detection, web apps for remote Alzheimer's screening and tailored advice comprised the system. Its generalizability was constrained, therefore, by the short dataset size and dependence on simple augmentation methods, which also limited its efficacy. The authors proposed using more varied datasets to improve the generalizability and resilience of the framework and include cutting-edge augmentation techniques such as GANs to handle this [32].

Banan et al., in 2020 proposed a VGG16-based CNN model-based deep learning-based system for automatic identification of four carp species. By using hierarchical feature extraction, global average pooling, and data augmentation methods, the system attained 100% classification accuracy by 5-fold cross-valuation. By addressing pragmatic demands including species monitoring and economic evaluation, this non-destructive approach offered a quick tool for fish species identification, thereby supporting aquaculture and fisheries management. The model's real-world relevance was limited, though, to controlled settings with unchanging backdrops and one fish in each photograph. The authors proposed using photos with natural backdrops, many fish, and improved model adaptability using sophisticated fine-tuning approaches to increase its resilience and generalizability and thus solve the issue [33].

Tulin Ozturk et al., in 2020 created the DarkCovidNet model from chest X-ray images for automatic COVID-19 detection. For binary classification (COVID-19 against No-Findings) the model attained 98.08% accuracy; for multi-class classification, it obtained 87.02%. Customized CNN architecture based on DarkNet-19 with 17 convolutional layers, data augmentation, and 5-fold cross-valuation produced these findings. Particularly in resource-limited regions, the model gave radiologists a quick and reasonably priced diagnostic tool to help. A tiny and unbalanced dataset, however, hampered the model's efficacy and hence limited its generalizability to many clinical settings. The authors proposed expanding the dataset with varied, high-quality photos and fine-tuning the model to increase resilience and usability in practical environments to solve this restriction [34].

Soumya Ranjan Nayak et al., in 2021 Evaluated eight pre-trained CNN models and developed a deep learning-based technique for automatic COVID-19 identification using chest X-ray images. With an accuracy of 98.33% and a sensitivity of 100% for binary classification (COVID-19 against normal ResNet-34 showed the best result. These outcomes were obtained using hyperparameter tuning, data augmentation, and transfer learning. Particularly in resource-constrained environments, the technique gave radiologists a quick and dependable diagnostic tool. The study's narrow dataset and emphasis on binary categorization, which limited its generalizability to more general situations, however, hindered its The writers advised broadening the dataset with varied samples and adding multi-class classification features to increase the model's resilience and applicability to handle this [35].

Muralikrishna Puttagunta and S. Ravi, in 2021 examined deep learning applications in medical image processing, with an eye toward X-ray, CT scan, mammography, and histopathology tasks including classification, detection, and segmentation. By using feature extraction, transfer learning, and sophisticated architectures, they discovered that methods like CNNs, U-Net, GANs, and DenseNet attained great accuracy in illness identification and localization. These techniques greatly improved diagnosis efficiency and healthcare results as well as automating difficult activities. However, the assessment found that two main obstacles restricting the generalizability of deep learning models in medical image analysis are the absence of big, varied datasets and standardizing. The authors proposed creating several, high-quality datasets and implementing consistent assessment techniques to increase the generalizability and repeatability of deep learning models to handle these problems [36].

In 2020 Argyris et al., looked examined how visual congruence, via influencer marketing on Instagram, may improve brand engagement. Examining over 45,000 photos using deep learning models—including VGG19, ResNet-50, and Inception-V3—they obtained an accuracy range of 85–95% in categorizing visual themes. The study showed that visual congruence enhanced influencer-follower interaction by 73.5%, which then mediated rises in brand engagement. This research offered a scalable means of examining visual marketing tactics and revealed how common visual interests enhanced social ties and motivated customer engagement. However, the study's dependence on Instagram data reduced its generalizability to other social media platforms and other cultural settings. The authors proposed extending the research to include more platforms and using cross-cultural datasets to improve the applicability and resilience of the model to solve this restriction [37].

Abubakr et al. in 2024 investigated the application of deep learning in damage classification for reinforced concrete bridges, focusing on five common defects: cracks, corrosion, efflorescence, spalling, and exposed steel reinforcement. They used Convolutional Neural Networks (CNNs), particularly the Xception model and a Vanilla CNN. The Xception model achieved a higher accuracy of 94.95% compared to the Vanilla model's 85.71%, utilizing transfer learning and depth-wise separable convolutions. Both models were trained and tested on the CODEBRIM dataset, with their performance validated using metrics like precision-recall and ROC curves. However, the study heavily depended on the CODEBRIM dataset, limiting generalizability to datasets with different defect distributions. Incorporating additional datasets with diverse defect types and augmenting the training data was suggested to improve the model's adaptability [38].

Armstrong and Fletcher in 2019 Using Hinode/SOT data, created a convolutional neural network (CNN) for solar picture categorization. With 99.92% accuracy on unseen photos, the model categorized five solar features: filaments, prominences, flare ribbons, sunspots, and calm Sun—processing findings within 4.66 seconds. Data preparation, transfer learning, and hyperparameter optimization helped to get this great precision. Managing the increasing data volume in solar physics depends on quick and dependable automation of solar image processing, which the system supplied. The model did, however, have limited generalizability across several wavelengths and data from other solar observatories. The authors proposed expanding the dataset to include multi-wavelength pictures and adding other training techniques to improve the resilience and applicability of the algorithm to handle this [39].

Xiyun Yang et al. in 2021 suggested a deep learning model for UAV image-based wind turbine blade flaw detection combining AlexNet with transfer learning and a random forest ensemble classifier. Through random forest for robust classification and transfer learning for feature extraction, the approach attained an accuracy of 97.11% with a sensitivity of 87% and specificity of 100%. This technology helped with maintenance by offering a non-destructive and effective means of blade inspection for wind turbines, therefore lowering running costs. The study's general diagnostic efficacy was restricted, nonetheless, by its detection of flaws devoid of classification or evaluation of their degree. The authors proposed using multi-class classification for fault kinds and severity and investigating sophisticated deep learning architectures to improve their diagnostic capacities and applicability to handle this [40].

Tang et al., in 2020 suggested a deep learning-based system employing electroluminescence (EL) pictures for automated flaw identification in photovoltaic (PV) modules. Generative Adversarial Networks (GANs) for data augmentation and a bespoke CNN for fault classification were combined in the method. Using GANs to create varied high-quality datasets and improving the CNN architecture, the technique attained a validation accuracy of 83% in identifying micro-cracks, breaks, and finger interruptions. Among the uses were scaled solar farms and better PV quality management. The model showed significant computing needs and could not identify several coexisting fault kinds, nevertheless. Lightweight CNN architectures tuned for real-time UAV-based operations and multi-label classification were proposed to handle this [41].

K. Shankar et al., in 2020 presented the HPTI-v4 model, which used Inception-v4 with Bayesian optimization for hyperparameter tuning and feature extraction, histogram-based segmentation, and Contrast-limited Adaptive Histogram Equalization (CLAHE) for preprocessing. We used a multilayer perceptron (MLP) for classification. Utilizing preprocessing, segmentation, and parameter adjustment, the model attained 99.49% accuracy, 98.83% sensitivity, and 99.68% specificity on the MESSIDOR dataset. The program aimed at automated diabetic retinopathy detection sought to enable early diagnosis and stop visual loss. However, the model's reliance on the MESSIDOR dataset limited its capacity to generalize to other imaging settings. Larger, more varied datasets and the use of transfer learning approaches were advised to improve generalizability and adaptability [42].

Malhotra et al. in 2022 Emphasized applications including tumor identification and organ segmentation, the research investigated the usage of deep neural networks (DNNs), including CNNs, U-Net, and Mask R-CNN, for medical picture segmentation. With possible uses in automated illness diagnosis and treatment planning, it asserted to reach great accuracy using optimal designs and strong dataset usage. However, problems including data inconsistencies, improper citations, and peer-review manipulation compromised the validity of the paper's conclusions, therefore it was withdrawn. It was advised to guarantee thorough peer review, open data reporting, and strong adherence to ethical publishing standards to handle similar problems in the next studies [43].

Salama and Aly, in 2021 proposed a mammography image-based deep learning-based breast cancer screening system. It applied modified U-Net and CNN models including ResNet50, DenseNet121, and InceptionV3 for segmentation under classification. Employing data augmentation and transfer learning, the system obtained 99.43% accuracy, 99.22% AUC, and 99.12% sensitivity on the DDSM dataset. These results revealed lessened radiologist effort, improved detection accuracy, and automated breast cancer diagnosis performance. Therefore, depending on specific datasets like DDSM, MIAS, and CBIS-DDSM limited the application of the study to different demographics and imaging conditions. The authors suggested tackling this by means of additional imaging sources to increase dataset variation and to improve generalizability and robustness utilizing domain adaptation techniques [44].

In 2021 Yadav et al., introduced SqueezeNet and VGG-16 CNN models to provide a deep-learning approach for automated food photo recognition. SqueezeNet obtained an accuracy of 77.20%; VGG-16, with its deeper architecture, obtained an accuracy of 85.07%, on the Food-101 dataset. One arrived at these results by use of hyperparameter fine-tuning and data augmentation. The curriculum focused on dietary management, calorie approximations, and techniques of health-related monitoring. The study limited itself to a subset of ten food categories, so its generalizability to bigger datasets with more diverse food items was reduced. More food categories should be included in the dataset, and ensemble learning techniques should be used to increase generalizability and classification performance [45].

Sommer and Schumann, in 2021 investigated deep learning-based UAV type categorization using electro-optical (EO) images to handle UAV-induced safety concerns. It assessed two-stage techniques like Faster R-CNN and PA-FPN and single-stage models including YOLO and RetinaNet, with the latter obtaining greater results. ResNetV1D-152 with asymmetric loss, class-balanced sampling, and enough UAV resolution (≥482 pixels) produced the best classification accuracy—89.3%. Among the applications were UAV capability evaluation and early threat detection security systems. The study was hindered, nonetheless, by incorrect classifications brought on by overlapping detections and identical UAV appearances as well as low training data variety. Using multi-frame input and sophisticated augmentation methods to increase training data variety was advised as a means of addressing these problems [46].

Pierdicca et al., in 2023 Leveraging deep learning models like ResNet, DenseNet, InceptionV3, and Vision Transformer, the UAV4Tree system recognized tree species using RGB optical pictures acquired by UAVs. By up to 10%, dataset augmentation and super-resolution (SR-GAN) enhanced classification accuracy; on supplemented datasets, the Vision Transformer B16 model attained the best overall accuracy of 81%. Important strategies included learning rate changes and fine-tuning via dropout as well as using high-resolution pictures for optimal performance. The research used these techniques to assist in conservation, monitoring of biodiversity, and forest management. Variations in image perspectives, resolutions, and phenological states between training and test datasets limited the accuracy of the research, nevertheless. The authors proposed using sophisticated data augmentation methods to increase model resilience and generalization and including several datasets with thorough ground truth annotations to help solve the issue [47].

In 2019 Seong and Park, demonstrated a two-photon calcium imaging automated brain cell identification method. U-Net was used for segmentation with 93.2% accuracy; ResNet18, ResNet50, and Inception-v3 were used for transfer learning classification. By use of elastic deformation for data augmentation and re-training certain layers, Inception-v3 attained the highest classification accuracy of 96.17%). Highly relevant in high-throughput neuroscience research, these methods assisted in finding excitatory, inhibitory, and glial cells. Restrictions also resulted from the small and less diverse dataset of the study, which limited its generalizability to other imaging conditions, therefore affecting varied imaging conditions. The authors suggested utilizing more complex augmentation methods to improve model generalizability and resilience as well as boosting the volume and diversity of the dataset [48].

Nigjeh et al., in 2023 developed an automatic method for white matter lesion (WML) categorization in MRI imaging multiple sclerosis (MS). Its preprocessing was gray-level augmented using ResNet18 with transfer learning for classification to get a 93% accuracy. Gray-level linear correction and data augmentation among other techniques improved lesion visibility and model performance. The system aimed to assist radiologists by automating WML classification, raising MS diagnosis accuracy, and thereby reducing manual work. Still, a small dataset reduced the generalizability of the model to various imaging settings. To address this, the authors suggested looking at customized CNN architectures to improve robustness and accuracy for more broad clinical usage and increasing the dataset size [49].

In 2024 Surya et al. created a Hierarchical feature extraction and transfer learning-based automated medical picture classification system utilizing PyramidNet. Among the various imaging modalities tested, X-rays, MRIs, CT scans, and histopathology slides brought the model an AUC score of 0.96, 92.5% accuracy, 91.2% precision, and 93.1% recall. Support for these results came from data augmentation, adaptive learning rates, and regularizing techniques. The technology demonstrated ability across several medical disciplines to improve diagnosis accuracy, efficiency, and clinical workflow quality. Still, the generalizability of the method was limited by imaging modality-specific challenges and dataset heterogeneity. The authors suggested enhancing PyramidNet's architecture for some medical contexts and increasing dataset diversity to increase robustness and applicability to overcome this [50].

Table 1 provides a comparative summary of recent advances in deep learning for automated image classification, showcasing various algorithms (e.g., CNNs, YOLO, VGG16), datasets, and applications across domains such as medical imaging, agriculture, and environmental monitoring. It highlights techniques like transfer learning, data augmentation, and ensemble methods, which have improved accuracy and efficiency, with results often exceeding 90%. Despite these advancements, limitations such as small, imbalanced datasets, high computational demands, and challenges in generalizability persist. Key recommendations for future research include expanding datasets, adopting lightweight models, improving augmentation techniques, and integrating advanced architectures like transformers and GANs to enhance model robustness and cross-domain applicability.

Table 1: Comparison Summary Table of Literature Review Recent Advances in Deep Learning Techniques for Automated Image Classification

Reference No., Author(s), and Year	Algorithm Name	Dataset(s) Used	Accuracy	Research Focus	Methods/Techniques	Key Findings	Limitations	Future Work Recommendations
[26] Sadak et al., 2020	YOLOv2 with ResNet-50	Zebrafish embryo records	89% mean IoU, 100% detection	Zebrafish embryo automation	Bounding box localization, transfer learning	Enhanced automation in biological applications	Limited to zebrafish embryos	Expand datasets, domain adaptation
[27] R. J. S. Raj et al., 2020	Deep neural network with OCS	Brain, lung, and Alzheimer's datasets	95.22%	Medical image classification	Histogram equalization, GLCM, GLRLM	Improved diagnosis with optimal features	High computational cost	Lightweight designs, parallel processing
[28] Alyoubi et al., 2021	CNN512 and YOLOv3	DDR dataset	89%	Diabetic retinopathy	Transfer learning, data augmentation	High accuracy for lesion localization	Unbalanced dataset	Balance dataset, improve sensitivity
[29] Hameed et al., 2020	VGG16 and VGG19 ensemble	Binary-class dataset	95.29%	Breast cancer detection	Probability fusion, cross-validation	F1 score improvement through ensemble methods	Binary classification only	Increase dataset size, multi-class
[30] Yan et al., 2019	Inception-V3 and BiLSTM	3771 breast cancer images	91.30%	Breast cancer classification	Patch-wise and image-wise classification	Better classification of breast cancer histopathology	Reduced accuracy for benign/normal	Enhance feature diversity
[31] Welikala et al., 2020	ResNet-101 and Faster R-CNN	Oral lesion images	87.07%	Oral cancer detection	Transfer learning, data enrichment	Support for oral cancer early detection	Small dataset, uneven annotations	Expand dataset, improve annotations
[32] Helaly et al., 2021	VGG19	2D and 3D Alzheimer’s datasets	97%	Alzheimer’s detection	Transfer learning, augmentation	Efficient Alzheimer’s classification	Small dataset, simple augmentation	Diverse datasets, GANs for augmentation
[33] Banan et al., 2020	VGG16-based CNN	Carp species images	100%	Fish species classification	Hierarchical feature extraction	Non-destructive fish species identification	Controlled settings only	Photos with natural backdrops
[34] Ozturk et al., 2020	DarkCovidNet	Chest X-ray images	98.08%	COVID-19 detection	DarkNet-19, 5-fold cross-validation	Quick COVID-19 diagnosis for binary/multi-class	Small dataset	Expand dataset, fine-tune model
[35] Nayak et al., 2021	ResNet-34	Chest X-ray images	98.33%	COVID-19 detection	Hyperparameter tuning	ResNet-34 excels in binary COVID detection	Binary classification focus	Broaden dataset, multi-class support
[36] Puttagunta and Ravi, 2021	CNNs, U-Net, GANs	Medical imaging datasets	High accuracy	Medical image analysis	Transfer learning, advanced architectures	Diverse uses in medical image segmentation	Small, non-standardized datasets	Create large, diverse datasets
[37] Argyris et al., 2020	VGG19, ResNet-50, Inception-V3	Instagram data	85 - 95%	Brand engagement	Visual congruence analysis	Visual marketing strategies improved	Instagram-specific data	Apply to other platforms
[38] Abubakr et al., 2024	Xception and Vanilla CNN	CODEBRIM dataset	94.95%	Bridge defect classification	Depth wise separable convolutions	Xception outperforms in defect detection	Dataset dependence	Add diverse datasets
[39] Armstrong and Fletcher, 2019	CNN	Hinode/SOT data	99.92%	Solar image classification	Transfer learning, optimization	High-speed solar image processing	Limited generalizability	Include multi-wavelength data
[40] Yang et al., 2021	AlexNet and Random Forest	Wind turbine blade images	97.11%	Wind turbine inspection	Random Forest ensemble	Robust wind turbine inspection tool	No fault severity classification	Multi-class fault classification
[41] Tang et al., 2020	Custom CNN and GANs	Electroluminescence images	83%	PV defect detection	GANs for augmentation	PV module defect detection augmented by GANs	High computational requirements	Lightweight models for UAVs
[42] Shankar et al., 2020	Inception-v4	MESSIDOR dataset	99.49%	Diabetic retinopathy detection	Bayesian optimization	Accurate DR detection via advanced preprocessing	Dataset dependence	Add transfer learning

[43] Malhotra et al., 2022	DNNs, including U-Net and Mask R-CNN	Various medical datasets	Various (no specific value)	Medical image segmentation	DNN optimization	Potential in automated segmentation	Ethical and consistency issues	Standardize and validate datasets
[44] Salama and Aly, 2021	ResNet50, DenseNet121, InceptionV3	DDSM dataset	99.43%	Breast cancer screening	Augmentation, transfer learning	Streamlined mammography workflows	Limited demographic variation	Improve dataset diversity
[45] Yadav et al., 2021	SqueezeNet and VGG-16	Food-101 dataset	85.07%	Food recognition	Hyperparameter tuning, augmentation	Accurate food image classification	Small food categories	Expand dataset, ensemble learning
[46] Sommer and Schumann, 2021	YOLO and RetinaNet	Electro-optical images	89.30%	UAV classification	Asymmetric loss, sampling	Improved UAV classification for security	Low data variety	Increase training data variety
[47] Pierdicca et al., 2023	ResNet, DenseNet, InceptionV3, Vision Transformer	UAV RGB images	81%	Tree species identification	Super-resolution, augmentation	Tree species recognition for conservation	Dataset limitations	Sophisticated augmentation
[48] Seong and Park, 2019	U-Net and Inception-v3	Multi-photon images	96.17%	Brain cell identification	Elastic deformation	Efficient brain cell identification	Limited dataset diversity	Complex augmentation methods
[49] Nigjeh et al., 2023	ResNet18	MRI images of MS patients	93%	MS lesion classification	Gray-level enhancement	MS lesion identification improvements	Small dataset	Increase dataset size
[50] Surya et al., 2024	PyramidNet	Various medical imaging modalities	92.50%	Medical image classification	Adaptive learning rates	Hierarchical feature extraction benefits medical imaging	Modality-specific challenges	Enhance architecture robustness

4. Discussion

Emphasizing its transforming power, the examined literature shows the major developments in deep learning applications for automatic image categorization in several fields. With excellent identification accuracy but restricted by dataset specificity, Sadak et al. (2020) showed the efficiency of a YOLOv2-ResNet50 system in automating zebrafish embryo recognition. Likewise, R. J. S. Raj et al. (2020) demonstrated great accuracy but at the expense of computing economy by optimizing medical picture categorization using feature selection approaches. While Hameed et al. (2020) used VGG16 and VGG19 ensembles for breast cancer identification, highlighting ensemble learning's efficacy despite dataset restrictions, Alyoubi et al. (2021) enhanced diabetic retinopathy diagnosis using CNNs and YOLOv3, addressing lesion localization issues. For breast cancer histology, Yan et al. (2019) presented a hybrid model integrating Inception-V3 with BiLSTM, hence improving classification accuracy but needing more feature variety. Though both types of research suffered with dataset variety, Welikala et al. (2020) and Helaly et al. (2021) broad deep learning's reach to oral cancer and Alzheimer's detection respectively. While struggling with generalization to natural settings, Banan et al. (2020) obtained 100% accuracy in fish species recognition using VGG16-based CNN. Emphasizing fast diagnostic methods despite dataset constraints, COVID-19 diagnosis was notably expedited by Ozturk et al. (2020) and Nayak et al. (2021) utilizing DarkCovidNet and ResNet-34. Advanced models such as PyramidNet investigated by Surya et al. (2024) showed strong performance in medical picture classification, therefore highlighting the function of adaptive learning in tackling modality-specific difficulties. Acknowledging the ongoing problem of tiny, non-standardized datasets, Puttagunta and Ravi (2021) further confirmed the value of CNNs and U-Net in different medical imaging applications, including segmentation and classification, thus improving the diagnosis efficiency. Armstrong and Fletcher (2019) also showed the extraordinary potential of CNN-based models in solar image classification, attaining great accuracy and processing speed while emphasizing the difficulty of generalizing across several data sources and wavelengths.

Yang et al. (2021) used AlexNet mixed with random forest classifiers in agricultural settings for wind turbine blade inspection, obtaining strong results albeit with limits in defect severity classification. Emphasizing the application of GANs and CNNs for solar module defect diagnosis, Tang et al. (2020) noted increased fault detection boosted by GAN-generated data but also significant processing demands. Though its reliance on a single dataset is limited to more general use, Shankar et al. (2020) used Inception-v4 for diabetic retinopathy identification, attaining considerable accuracy with enhanced preprocessing approaches.

Figure 3 highlights the diverse algorithms applied in automated image classification and their corresponding accuracy. Notably, VGG16-based CNN achieved 100% accuracy for fish species classification, demonstrating the potential of specialized hierarchical feature extraction in controlled settings. Inception-v4 and ensemble methods like VGG16 and VGG19 also showed high accuracy (>99%), emphasizing the effectiveness of advanced architectures and ensemble learning in improving diagnostic performance. Algorithms like YOLOv2 with ResNet-50 and ResNet-34 effectively achieved high accuracy (above 89%) in applications requiring fast and reliable classifications. However, lower accuracy for some models, such as custom CNNs with GANs (83%), indicates challenges like computational overhead or dataset limitations. The discussion underscores the importance of dataset diversity, advanced architectures, and model optimization for enhanced generalizability and accuracy in image classification tasks.

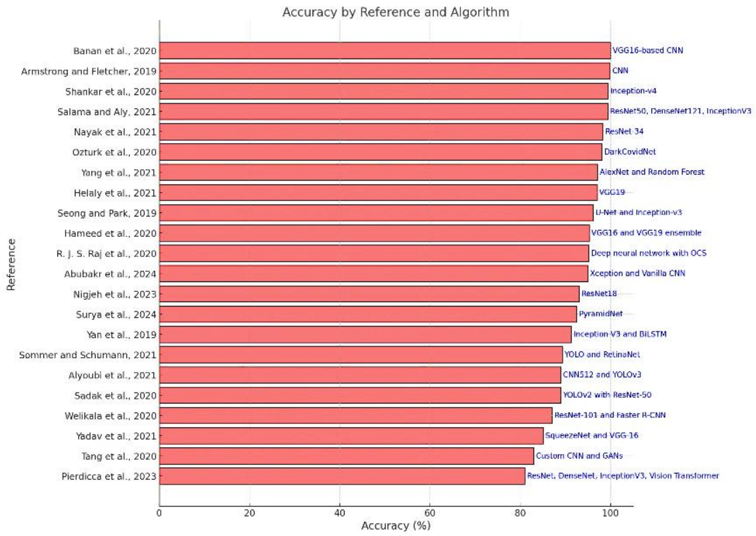

Fig. 3: Accuracy by Reference and Algorithm Name.

Figure 4 illustrates the frequency of different categorized methodologies and techniques employed in damage similarity analysis across various research. Transfer learning is the most commonly utilized method, demonstrating its adaptability in applying pre-trained models to other applications. Augmentation approaches, such as GANs and data augmentation techniques, are extensively employed to mitigate dataset restrictions and boost model resilience. Feature extraction and optimization methods are crucial for enhancing model accuracy, whereas sophisticated architectures such as DarkNet-19 and adjustable learning rates reflect a movement toward utilizing modern technology for superior performance. These developments highlight the necessity of integrating several techniques to attain dependable and effective solutions.

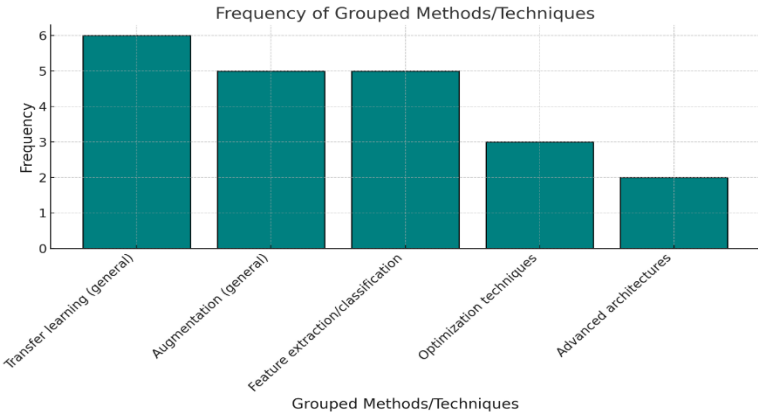

Fig. 4: Frequency of Grouped Methods/Techniques.

The examined research taken together highlights how important deep learning is in improving accuracy and efficiency in many different applications. These developments highlight how clever designs such as transformers, hybrid models, and ensemble approaches combine to address problems including limited datasets, computational restrictions, and domain-specific adaptation. Maximizing the generalizability and effectiveness of deep learning applications in automated image classification will depend on addressing these constraints via dataset extension, multi-class classification, improved augmentation methodologies, and cross-domain adaptations.

5. Conclusion

Deep learning is transforming automatic picture categorization, therefore advancing fields including environmental monitoring, medical imaging, and agriculture. Accuracy and efficiency have been improved significantly thanks to methods including hybrid models, convolutional neural networks, and transfer learning. From agriculture monitoring to disease diagnostics to renewable energy and biodiversity preservation, these developments have supported uses. Still, there are difficulties like limited datasets, computing requirements, and a lack of generalizability throughout several environments. Future work on these problems should concentrate on building big, varied datasets, designing lightweight models, and using innovative augmentation methods. Architectural constant change, including transformers and attention methods, promises to improve model performance yet more. Deep learning has great potential to transcend present constraints and offer creative answers to challenging categorization problems, therefore transforming its effect over additional disciplines.

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