International Journal of advancement in electronics and computer engineering (IJAECE)
Volume 14, Issue 12, Dec. 2025, pp.101-109,ISSN 2278 -1412

Comparative Study of AI-Based Deep Learning Models for Image Classification and Recognition: Review

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Abstract- *Image classification and recognition are important areas of computer vision that help machines identify objects, patterns, and features in images. These technologies are widely used in many fields such as healthcare, agriculture, environmental monitoring, and security. Over time, methods have moved from traditional approaches, which depended on manual feature selection, to advanced deep learning approaches that can automatically learn patterns from large amounts of data. This review paper discusses the latest trends in deep learning for image classification, including the use of hybrid models, lightweight designs for real-world use, and techniques that improve both efficiency and accuracy. It also highlights how these methods are applied in real scenarios like disease detection in plants, medical diagnosis, and intelligent surveillance. At the same time, challenges remain, such as the need for large datasets, high computational power, and the difficulty in explaining how models make decisions.*

Keywords:*Image Classification, Image Recognition, Deep Learning, Computer Vision, Artificial Intelligence, Transfer Learning, Lightweight Models, Applications*

I. Introduction

In the field of computer vision, image categorisation and identification have evolved into essential tasks that enable a variety of applications, including autonomous navigation, medical diagnosis, and agricultural monitoring. Automated methods for visual information analysis have attracted a lot of attention because to the quick development of digital photography and the growing accessibility of large-scale datasets [1]. High computational complexity and restricted feature extraction capabilities were common limitations of traditional machine learning techniques, which made them difficult to scale and adapt to a variety of situations [2].By enabling models to automatically acquire hierarchical features from raw data, artificial intelligence and deep learning have solved many of these issues and reduced the need for human feature engineering [3]. More effective and precise pattern, texture, and object detection in complex pictures has been made possible by this paradigm shift [4]. However, problems like data noise, class imbalance, and the need for a lot of processing power still make real-world implementation challenging [5].Plant disease identification in agricultural research is crucial for increasing crop output and guaranteeing food security, and image recognition is a key component of this process. The ability of AI-based techniques to recognise minor visual signs in crops has been shown in recent research, supporting early identification and disease control measures [6]. Because the potato leaf dataset is relevant to precision agriculture and comprises a variety of picture samples that depict various disease situations, it has been used as a case study in this work [7]. This study attempts to provide a comparative overview of AI-driven methods in picture classification and recognition by combining current developments and emphasising future research objectives, applications, and problems.

II. Background and Motivation

Due to its practicality in a variety of fields, including security systems, healthcare, agriculture, and environmental monitoring, image categorisation and identification are among the most researched issues in computer vision. Classifying or recognising objects and characteristics in photos is the basic job, which may often be challenging because of size, illumination, noise, and overlapping items [8]. In order to successfully generalise in dynamic and large-scale datasets, traditional machine learning techniques mostly depended on statistical models and handcrafted features [9].By providing models that can directly build rich & hierarchical representations from picture data, artificial intelligence along with deep learning have completely changed this discipline. In practical applications, this change has greatly increased accuracy, resilience, and flexibility

DOI Member 14.63.476

[10]. Notwithstanding these developments, issues including the necessity for high-quality annotated datasets, interpretability of models, and processing needs still pose serious problems [11].Computer vision systems have shown encouraging outcomes in automating crop monitoring and disease identification in agriculture. For example, image-based identification for early plant disease diagnosis may help with timely treatments, lower losses, and increase production [12]. A notable example for researching the possibilities of AI-based methods in agricultural disease diagnostics is the potato leaf dataset, which includes a variety of disease states [13].This analysis is driven by the increasing need to compile current advancements in AI-based picture categorisation and identification, assess their advantages and disadvantages, and identify potential avenues for scalable and interpretable systems in the future. This study aims to direct both scholarly investigation and applied breakthroughs in the area by connecting research discoveries with real-world applications.

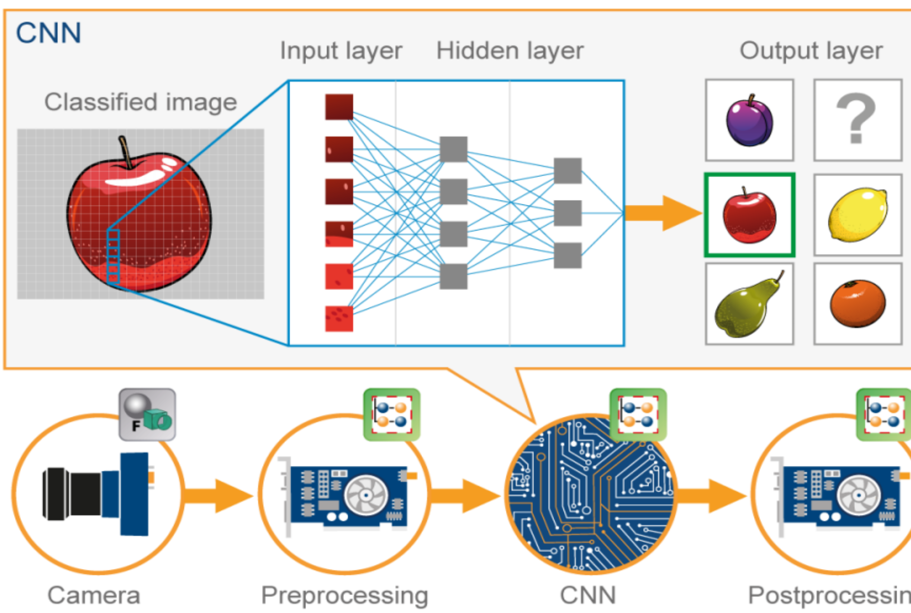

Figure 1:Workflow of Deep Learning

III. Literature Review

Image classification & recognition research has gone through many phases, starting with conventional approaches and progressively moving towards more advanced strategies. Researchers have investigated a variety of methods throughout time, each tackling issues including computing efficiency, scalability, and feature extraction. Examining the body of existing literature offers important insights into the development of methodologies, the major trends that have influenced modern practices, or the applications in which these strategies have proven most successful. It summarises the key advancements in the subject and presents comparative viewpoints that serve as the foundation for comprehending potential future paths in image identification and classification.

The authors of [14] outline, examine, and acknowledge the need of creating a quick, affordable, and trustworthy health monitoring sensor to support agricultural innovations. With the aim of creating ground-based sensor systems to help with plant health and disease monitoring in field settings, they discussed the currently employed technologies, which include spectroscopic and imaging-based plant disease detection methods as well as volatile profiling-based plant disease detection methods. After reviewing their work and the analysis provided by the authors of [15–18], it was determined to employ the image processing disease recognition approach in addition to other methods frequently used for plant disease diagnostics, such as double-stranded ribonucleic acid (RNA) analysis, nucleic acid probes, and microscopy. [19] suggests a Multiple Classifier System (MCS) based on Support Vector Machines (SVM) for identifying patterns in wheat leaf diseases. [20] outlines a software prototype method that uses diseased photos of different rice plants to identify rice diseases. An technique [21] that develops and decomposes scatter matrix and regularises and extracts eigen characteristics from pictures was also used to identify cotton leaf diseases. explains how to create and put

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into use an artificial vision system that can recognise certain morphological and geometric characteristics in plant leaves [22]. A feed forward neural network-based classifier, image processing techniques, and an artificial vision system comprise the suggested system. A fuzzy surface selection method was used for feature selection. A support vector machine-based prediction method is put out in [23] for creating weather-based plant disease prediction models. Multiple regression, support vector machines (SVM), and artificial neural networks (back propagation neural network, generalised regression neural network) were evaluated for performance. The association between environmental factors and illness severity was better described by the SVM-based regression strategy, which may help with disease management. [24] suggested detecting damaged leaves using a backpropagation neural network. It was shown that the geometry of a leaf picture and a back propagation network are enough for identifying the species of a leaf. The Prewitt edge identification and thinning technique is used to locate leaf tokens to feed into the back propagation mechanism. According to the paper, this approach might be improved by conducting further tests using sizable training sets to identify distinct types of damaged leaves brought on by various illnesses. In [23], two prevalent illnesses were identified using banana photos from the PlantVillage dataset [25]. The experiment was conducted on both coloured and greyscale photos, totalling 3700 images that were shrunk to 60x60 pixels. The LeNet architecture [24] was used to build the model, and after many trainings on various train and test split proportions, it attained an accuracy of 92-99%. However, the switch to greyscale greatly diminished those findings, since colour variation is often used to identify disorders. The authors stressed that illness localisation was a crucial stage in the process and acknowledged the value of capturing pictures in actual environments. The same problem was studied in another research [26], however this time, five alternative CNN architectures were tested: AlexNet, AlexNetOWTBn, GoogLeNet, OverFeat, and VGG. The latter achieved the maximum accuracy of 99.53% for 58 different classes.

Table 1 Literature Reviews

Study	**Focus Area**	**Methodology**	**Key Findings**	**Limitations**
Trigka, et.al. [27]	Survey of recent deep learning methods in image processing	Systematic literature survey of recent architectures and applications	Consolidates state-of-the-art trends, highlights strengths of modern approaches and common application domains	Broad scope—limited depth on individual experimental comparisons
Sinamenye et.al [28]	Potato disease detection	Hybrid DL model combining compact conv + attention components trained on potato leaf images	Shows benefit of hybrid architectures for agricultural images and real-world datasets	Focused on a specific hybrid design; limited discussion of generalization across datasets
Sangar et. al [29]	Optimized potato leaf classification	Model optimization and transfer learning strategies on potato leaf data	Demonstrates effectiveness of optimized pretraining & fine-tuning for crop disease classes	Emphasis on a particular model family; limited discussion of multi-label scenarios
Kaur et. al [30]	Multi-species leaf disease detection	End-to-end detection framework evaluated across species (multi-dataset)	Robust detection across species; emphasizes multispecies data collection	Heavy compute; dataset bias toward controlled images
Sujatha	Integra	Compara	Hybrid	Variatio

et.al [31]	ting ML and DL for plant disease	tive evaluation of combined ML+DL pipelines on potato datasets	ML+DL can be complementary for constrained datasets	n in dataset quality; limited cross-site validation
Sa, Jaewon et. al [32]	Efficient hybrid conv–transformer designs	Architectural design study combining convolutional blocks and transformer modules	Hybrid design trades off locality and global context with a favorable efficiency/perf balance	Architectural complexity; needs careful hyperparameter tuning
Tarekegn et.al [33]	Deep learning for multi-label learning (survey)	Comprehensive survey and taxonomy of multi-label methods	Summarizes modern loss functions, label-correlation strategies, and evaluation protocols	Preprint status for some material; may require final journal versions for citation
Bogatinovski et.al [34]	Comparative empirical study of multi-label methods	Empirical benchmarks across many MLC methods/datasets	Provides broad empirical evidence on method strengths across dataset types	Benchmarks subject to dataset selection and implementation choices
Alzubaidi et. al [35]	Broad DL concepts and	Narrative review covering DL	Useful synthesis of DL progress	Rapid field changes mean
	challenges	concepts, advances and challenges	and practical constraints (compute, data)	parts are quickly superseded
Chen et.al [36]	Review of CNN-based image classification	Survey of CNN developments and applications in remote sensing	Traces evolution and practical applications of CNNs for imagery	Focus on remote sensing domain—less emphasis on multi-label / medical / agri specifics
Takahashi et.al [37]	Medical image analysis comparison	Systematic review comparing transformer and CNN performance in medical tasks	Identifies contexts where global attention helps and where CNN locality remains valuable	Domain-specific; results depend on imaging modality and dataset size
Krishna et.al [38]	Plant disease detection across datasets	Multi-dataset evaluation using transfer learning and ensemble methods	Emphasizes dataset diversity and transfer approaches to improve robustness	Cross-dataset heterogeneity and labeling inconsistency impact results
Kumar et. al [39]	Deep learning for hyperspectral image classification	Survey of DL approaches, handling small-sample and high-dimensio	Shows effectiveness of specialized architectures and data-efficient	Hyperspectral specifics; findings not directly transferable to

		nal HSI data	strategie s	RGB leaf datasets

IV. Integrative Analysis of Classification Strategies

Traditional manual methods of picture categorisation and identification have gradually given way to sophisticated deep learning-driven models. Early attempts mostly depended on manual feature engineering, in which edges, textures, or colour patterns were extracted under the direction of subject experts. Although these techniques worked well in certain situations, they were not scalable and had trouble handling complicated, high-dimensional data.

On the other hand, automated feature learning is emphasised in contemporary methods. Models develop hierarchical representations directly from raw data, without relying on pre-made descriptions. This change has made it possible for researchers to identify both global and local dependencies in pictures, leading to more flexible and reliable classification models. There is a definite trend in the literature towards hybrid designs that integrate complementary processes like long-range contextual reasoning and local detail extraction. These pairings seek to strike a compromise between interpretability, accuracy, and efficiency [40].Algorithms for deep learning are essential to this change. Because convolution-based designs include filters that can learn edges, textures, and other visual structures, they are especially good at capturing spatial hierarchies within pictures. Although they were first created for sequential data, recurrent-style models have been modified to capture contextual connections between picture patches. Graph-based methods provide insights into structured dependencies by modelling the interactions between pixels or areas. By allowing models to concurrently concentrate on local and global aspects, transformer-inspired designs with their self-attention mechanisms have advanced the field.Computational demand is another crucial factor in comparative investigations. While some models prioritise accuracy at the expense of more training resources, others are tailored for lightweight deployment on edge devices. Data requirements also differ greatly; some methods work well with transfer learning in low-data regimes, while others only work well with large datasets.All things considered, the comparison study indicates that no one method is inherently better. There are trade-offs between efficiency, interpretability, and performance for each. This variety emphasises how crucial it is to modify strategies to meet domain-specific needs, whether in security-driven applications, healthcare, or agriculture.

V. Evaluation Metrics

Typically, standard evaluation criteria are used to evaluate how well machine learning (ML) and deep learning (DL) models perform in image classification. The most often used metric is still accuracy, which shows the percentage of properly identified samples overall.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

Recall and precision are often used to resolve this. While recall gauges the model's capacity to detect every real positive occurrence, precision assesses the percentage of accurately predicted positive samples among all anticipated positives. In fields like healthcare and agriculture, where false positives or false negatives may have serious repercussions, these two measures are essential.

Precision and **recall** are more informative metrics in such cases. Precision, calculated as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

When working with unbalanced datasets, the F1-score which is the harmonic mean of accuracy and recall offers a fair-minded viewpoint. Additionally, to assess the model's capacity to differentiate between classes across various thresholds, Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) curves are used.

Recall, calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Evaluation measures are crucial, but they may also draw attention to a model's shortcomings. For example, if Recall is poor, a high accuracy model can nevertheless incorrectly identify instances of serious diseases, rendering it inappropriate for medical diagnosis. Similar to this, misclassifications resulting from visual symptoms that are similar across classes may lower precision and F1-score in agricultural disease diagnosis.The F1 score, calculated as:

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$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Thus, for a thorough assessment, a mix of metrics—Accuracy, Precision, Recall, F1-score, and AUC—is necessary. These metrics guide future advancements in model design and dataset balance by highlighting a model's weak points as well as its strengths.

VI. Applications

Classification and identification of images have developed into flexible tools with a wide range of uses. Their versatility enables them to meet various industrial and social demands while bridging disciplinary barriers.

Medical Imaging

Diagnostic processes have changed as a result of automated tumour, lesion, or abnormality recognition in radiological images.

Early illness diagnosis reduces the need for manual interpretation and helps early therapy, particularly in neurology and cancer.

Agriculture

Increased yields and reduced losses are guaranteed by crop monitoring and disease detection using leaf photos.

In order to meet the objectives of food security, precision agriculture uses classification models to optimise irrigation, pesticide usage, and resource allocation.

Security and Surveillance

Large-scale surveillance, anomaly detection, and face verification all use recognition systems.

In metropolitan areas, intelligent surveillance improves public safety and helps avoid crime.

Environmental Monitoring

Satellite-based categorisation identifies patterns of pollution, deforestation, and changes in land cover.

This helps policymakers plan for disasters and manage resources.

Reducing human dependence, minimising mistakes, and speeding up decision-making are the common benefits across various fields. However, rigorous alignment of technological abilities with ethical, social, & environmental factors is often necessary for real-world implementation. Applications therefore serve not just as testbeds for technical progress but also as crucial bridges among research and social benefit.

VII. Challenges andResearch Gaps

Despite significant progress, several persistent challenges shape the current landscape of image classification and recognition:

Key Challenges

Data Dependency: Large, well-annotated datasets are often required for high-performing models, but obtaining them may be expensive and challenging.

Generalisation: When subjected to real-world differences like illumination, noise, or background clutter, models trained on controlled datasets may not perform as well.

Computational Burden: Deep architectures are difficult to train in low-resource environments because to their high resource requirements.

Interpretability: A lot of methods are still opaque, which raises questions about openness in delicate fields like law enforcement or health.

Research Gaps

Limited investigation of low-resource learning techniques capable of preserving accuracy in the absence of large amounts of data.

A lack of uniform standards for assessment in many fields.Integration of ethical frameworks addressing fairness, prejudice, and privacy is understudied.

When taken as a whole, these problems demonstrate the disconnect between successful laboratory work and real-world implementation. In order to bridge gaps, multidisciplinary cooperation that takes into consideration social, economic, and ethical factors is just as important as technological innovation...

VIII. Recent Trends and Future Directions

Efficiency, interpretability, & domain-specific flexibility are becoming more important in image classification and identification. The increasing need for lightweight models made for deployment on mobile & edge devices is one noteworthy development. These methods allow real-time applications in security, healthcare, and agriculture while lowering reliance on pricey hardware. Using hybrid models that combine convolutional, sequential, and attention-based methods to strike a balance between local feature extraction and global context comprehension is another new approach. Complex datasets may now be handled by such architectures with greater precision and resilience.

Pre-trained models and transfer learning have become more popular, providing useful answers for fields with little labelled data. Models may more effectively adjust to specialised applications like plant disease detection or medical diagnostics by using information from large-scale datasets. To improve decision-making, multimodal learning which combines visual data with textual, spectral, or sensor-based inputs has become a potential avenue.

Three main areas are anticipated to be the focus of image classification and identification in the future. First, in order to guarantee that models provide insights into their decision-making processes, explainability and transparency will take front stage. Second, research will be guided by responsible and ethical AI frameworks that address privacy, fairness, and bias in sensitive applications. Lastly, new avenues for multidisciplinary innovation will be made possible by the merging of deep learning with other technologies like robots, remote sensing, and the Internet of Things (IoT). When taken as a whole, these patterns and trends show a path towards systems that are not just more reliable and effective but also more socially significant.

IX. Conclusion

Image classification and recognition have become foundational components of modern computer vision, evolving from handcrafted feature-based methods to advanced deep learning-driven solutions. This progression has allowed researchers and practitioners to address increasingly complex challenges across a wide range of fields, from medical imaging and agriculture to environmental monitoring and security. The comparative insights from existing approaches reveal that while deep learning algorithms have significantly improved efficiency and accuracy, no single method provides a universal solution. Instead, the field benefits from the diversity of techniques, each offering unique strengths and trade-offs.Despite remarkable progress, challenges remain, particularly regarding interpretability, scalability, and the high demand for computational resources and annotated data. Addressing these issues requires not only technical innovation but also ethical considerations and interdisciplinary collaboration. The ongoing integration of explainability, lightweight design, and multimodal capabilities signals a promising future for this domain. Ultimately, the continued advancement of image classification and recognition will play a critical role in shaping intelligent systems that are accurate, transparent, and aligned with societal needs.

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