FUSION OF DEEP LEARNING WITH TRADITIONAL IMAGE PROCESSING TECHNIQUE

Kanthavel R[1], Dhaya R[2] , Adline Freeda R[3]
[1,2]School of ECE,PNG University of Technology, Lae, Papua New Guinea
Department of IT,KCG College of Technology, Chennai, India

Abstract

The intersection of deep learning with traditional image processing ensures accurate results in computer vision. A traditional approach for preprocessing and feature enhancement, particularly for CNNs to perform feature extraction and classification, relies on traditional image processing techniques such as filtering, edge detection, and morphological operations. We then review recent advancements in these fields focusing on applications in medical imaging and remote sensing. Finally, this review evaluates the effectiveness of the hybrid methods according to different domains through its performance in real-world applications. The paper focuses on the combinations of these techniques and some of the associated challenges such as complexity, data-dependency, computational cost, interpretability, as well as end-to-end optimization. In order to extract the best from both techniques, some innovative solutions are needed to bridge the gap between deep learning and classical image analysis. This review seeks to provide a comprehensive perspective on the harmony of deep learning and conventional image processing and their influence on enhancing the efficacy of image recognition systems. Moreover, it emphasizes the role of hybrid models in improving the interpretability of deep learning networks through feature extraction methods, a significant dimension of research for investigating the applicability of AI systems for macroscopic representation techniques, and evaluates their performance in a wide spectrum of application domains.

Keywords: Deep Learning, Image Processing, Hybrid Models, Computer Vision, Feature Extraction, CNN, Preprocessing

1. Introduction

In computer vision, deep learning blends with the classic image processing paradigm, delivering surprisingly robust results with increased accuracy. The conventional means of preparing the Image with image processing techniques such mentioned filtering edge detection morphological operations has a significant role in preprocessing feature extraction of deep learning with CNN and the classification using multiple complex algorithms. A number of newly developed methods of fusion with applications such as medical imaging and remote sensing are discussed. Additionally, an exploration of an array of hybrid techniques and analyse their success in varying domains need to be introspected. It is a vital thing to take a deep look at how to make fusion work in practice in the face of many obstacles.

1.1 Background on Image Processing and Deep Learning

Typical image processing methods make use of predefined features and algorithms to deal with digital images in a process, analyse, and modify process. These methods are comprised of filtering techniques, edge detection, noise removal, image segmentation, and geometric transformations [1]. Although these methods prove to be effective in various situations, they are often found to be ineffective in complex situations like pattern recognition, which is handled by deep learning models. In image analysis, deep learning, especially CNNs, has risen to be a crucial tool in image analysis because of the ability to learn features automatically from a large amount of data without the need for feature extraction [2]. The application of deep learning in image processing has significantly improved the performance of tasks like image categorization, image segmentation [3] and so much more.

1.2 Motivation for Fusion of Traditional and Deep Learning Approaches

Deep learning seems to become more and more popular, because of its outstanding performance, but it can be useful to combine it with traditional image processing and signal processing techniques. Pre-processing and feature engineering can be done by using traditional methods, but deep learning models can be used to extract high-level features and classify what was not done by traditional methods. The combination will exploit the advantages of deep learning as well as its shortcomings as the need for large numbers of labels (for supervised learning) and the difficulty in understanding and interpreting models that are often black boxes. For example, conventional filtering and edge discovery strategies can be used to attenuate noise and amplify the vital characteristics within the images earlier than contributing into deep studying fashions, thus rising studying effectivity [4]. In addition to this, hybrid models can also enhance the interpretability of deep learning networks by adding in traditional feature extraction stages [5].

Traditional techniques to reduce input complexity can also help alleviate some of the issues related to memory and processing that are common in deep learning, but this is also an interesting side effect of the combination of the two paradigms. Furthermore, the development of hybrid paradigms not only provides flexibility of approach across multiple applications, such as medical image processing [6] and autonomous vehicles [7] but also continuously pushes the boundaries of the fields, driving important answers and progress in the domain. Further, fusing deep learning with traditional image processing is stimulating due to transformations in method, data necessities, and computational rate. Outdated methods are well-organized but not as much of flexible, whereas deep learning models are influential but resource-intensive. Achieving an equilibrium between interpretability, generalization, and optimization across both methods is multifaceted. Effective integration needs overcoming these blocks for improved operations.Traditional image processing techniques, when combined with deep learning architectures, can pave the path towards solving advanced computer vision tasks, as recently shown. For example, Zhang et al. (2021) introduced a hybrid CNN framework in conjunction with Sobel and Laplacian filters to boost edge feature extraction in medical image segmentation, observing improved accuracy compared to end-to-end deep models alone. In a similar manner, Li et al. (2022) combined NDVI-based preprocessing and adaptive histogram equalization using a ResNet backbone, which notably improved land use classification with respect to changing light conditions. Another example by Kumar and Mehta (2023) offered a combination of morphological operations and a U-Net architecture for cell segmentation in histopathological images. Moreover, Wang et al. (2024) proposed an interpretable CNN pipeline that utilized standard filtering to identify informative regions in industrial X-ray scans, contributing to explainability in defect classification. However, integration is still difficult due to it is crossing data. Research is also increasingly interested in the interpretability of deep models, especially hybrid methods that are gaining notoriety for their ability to introduce transparency by adopting explicit feature engineering steps into their models. But most studies focus on one domain and there is still a big gap for the generalized hybrid framework to be developed in multiple disciplines. Thus, this review paper fills the gap in the literature by analyzing recent hybrid models and presenting trends, opportunities, and challenges of combining traditional and deep-learning based image processing techniques.

1.3 Objectives of the Review

This review paper explains the literature on traditional image processing methods, deep learning methods, challenges of hybrid works and their applications. This review aims to:

- Utilize a comprehensive examination on traditional image processing and deep learning models for image analysis.

- Explore different hybrid approaches that integrate deep learning with classical methods for enhanced image processing results.
- Explore how hybrid models can be applied in real-world scenarios including medical imaging, remote sensing, object recognition, and industrial inspection.
- Recognize challenges and limitations in the combined integration of these techniques as well as indicate future studies to eventually optimize the fusion of these approaches.

This review provides theoretical guidance for researchers and practitioners embracing the strengths of traditional image processing and deep learning as they strive to adopt more efficient and robust image analysis systems for their application scenarios.

2. Traditional Image Processing Techniques

Traditional image processing refers to a set of techniques and algorithms used to analyze and manipulate digital images. It is a well-known image processing that processes the image data using several algorithms and techniques to obtain useful information and get an image enhance. The majority of these operations are within the range of spatial domain and considered preprocessing methods and need to smooth the components of our image in order to be ready for advanced processing ex: feature extraction or object recognition. The figure 1 illustrates the traditional image processing techniques.

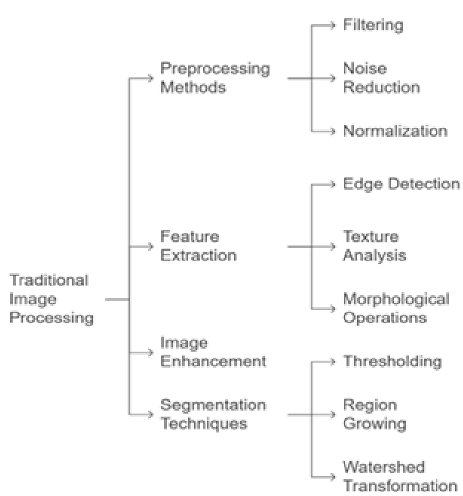

Figure 1: Traditional image processing techniques

2.1 Preprocessing Methods (Filtering, Noise Reduction, Normalization)

Preprocessing is an inalienable stage of image processing, the task of which is aimed at enhancing the quality of the image or making it more suitable for further analysis. Filtering, noise reduction, and normalization are used as methods for preprocessing.

- **Filters:** Filters are used to enhance the salient features or remove irrelevant elements, such as noise, from an image. Among the common filtering techniques are the mean filters, such as Gaussian filters and median filters Mean and Gaussian filters are used for smoothing. On the other hand, median filters are particularly useful for removing salt-and-pepper noise without blurring the edges.

- **Noise Reduction:** Image noise may originate from different sources, e.g. sensor imperfections or transmission errors. The purpose of the noise reduction techniques is to remove noise while keeping the important features of the image. Wiener filtering [8] and adaptive filtering are well-known noise reduction methods, in which the filter changes its behavior depending on the characteristics of the image in the certain neighborhood.
- **Normalization:** Normalization includes the techniques of changing the intensity values of an image to fit within a standard range. This is important in standardizing the image for further processing. Normalization is necessary for handling images obtained under varying lightning conditions. normalization aims to enhance the contrast of the image [9].

2.2 Feature Extraction (Edge Detection, Texture Analysis, Morphological Operations)

Feature extraction is the act of identifying and isolating critical details or patterns from an image. This is crucial for activities such as object detection or classification. Many techniques have been developed for this purpose.

- **Edge Detection**: Edge detection methods emphasize regions that contain significant intensity variations in an image, simplifying the process of recognizing objects or borders. Edge detection algorithms are often used, such as Sobel, Prewitt and Canny edge detections [10]. A common approach is the Canny edge detector, which tends to find the strongest and weakest edges in an image while causing only little noise.
- **Texture Analysis**: Texture analysis is concerned with recognizing patterns or textures in an image, like smooth, rough, or repeating textures. Common methods for texture analysis are the Gabor filters and gray-level co-occurrence matrices (GLCM) [11] These techniques the spatial distribution of pixel intensities which frames the texture attributes of a photo.
- **Morphological Operations**: Morphological operations are a family of image processing operations that extract image components, such as dilation, erosion, opening, and closing. Such operations are typically used for shape analysis and are applied to binary images (or images that have been manipulated by a threshold) or grayscale images [12]. Examples include dilation and erosion which expand or shrink objects, or opening and closing operations that remove small noise or fill in gaps in object boundaries.

2.3 Image Enhancement and Segmentation Techniques

Image Enhancement refers to processing an image for a better visual representation of some features. Segmentation methods can be used to divide an image into local sections for analysis or classification.

- **Image Enhancement**: Image enhancement techniques are used to enhance the quality of received image by highlighting features like edges, textures and boundaries, which help in better analyzing and extracting features from images. A number of common methods are used for improving the contrast of an image, such as histogram equalization [13]. Similar techniques like contrast stretching or gamma correction may be applied to brighten or change the contrast of the image.
- **Segmentation:** The segmentation process partitions an image into semantically meaningful regions or objects — a fundamental step in image analysis. Localization segmentation was done with several techniques like thresholding, region growing, watershed transformation, etc. Thresholding can be used to classify pixels into different regions based on intensity values[14]. Region growing is the process of iteratively adding pixels based on thresholding properties until the maximum step size is reached and creation of image segments based on the topology of the gradient map using the watershed algorithm[15].

Traditional image processing methodologies underpin most of the computer vision and image analysis ecosystem. These image preprocessing techniques are instrumental in tasks such as image filtering, noise reduction, and image normalization, laying the foundation for better quality images for later stages in analysis. Feature extraction techniques such as edge detection, texture analysis, and morphological operations are essential for separating meaningful patterns and structures in images, which are crucial for tasks such as object detection and classification. Not only that, but our functionalities for image enhancement and segmentation serve as critical tools for enhancing the visual quality of images and partitioning them into separate regions for more effective and accurate analysis. Although these older ways have been heavily employed through time, and they continue to obtain the job done in a number of uses, the integration of these older techniques with more recent techniques, most notably deep learning techniques is inspiring. The continued evolution of image processing will likely lead to the integration of traditional methodologies with modern ones, ultimately creating a more robust and effective platform for addressing a wide spectrum of applications including medical imaging, remote sensing, and industrial inspection where the need for accurate and efficient image analysis is paramount.

To sum up, classical image processing methods still play a crucial role in building more effective and precise computer vision systems, and their combination with deep learning methods will keep leading to breakthroughs in image analysis.

3. Sequential Generative Models Based on Deep Learning

In fact, CNNs represent the most groundbreaking change in image processing in the last ten years. That's how CNNs have provided significant advances in taking on tasks such as image classification, segmentation, and feature extraction without extensive feature extraction, allowing you to learn hierarchical features from large datasets. This has resulted in long-lasting breakthroughs in domains ranging from medical imaging to autonomous driving. Image Processing: In addition to CNNs, the introduction of transfer learning, GANs, and autoencoders has greatly extended the domain of deep learning in image processing. In this section, exploring these techniques in greater depth, and how they can be applied in the context of image processing.

3.1 An Introduction to Convolutional Neural Networks

Image Processing based on deep learning and image recognition has grown into the CNNs. Convolutions, which are used as the fundamental building block of CNNs, retain the 2D structure of images, allowing the network to learn spatial hierarchies of features automatically. CNNs employ multiple stages, such as convolutional stages, pooling stages, and fully connected stages, to iteratively derive and aggregate features from the input image [16]. CNNs have demonstrably ruled the roost in processing images, detecting faces, recognizing objects, and analyzing medical images. The AlexNet model won the ImageNet competition by far surpassing the previous methods. Since then, CNN architectures such as VGGNet [17] , ResNet [18] and Inception have dominated image classification and feature extraction. CNNs are very much suitable for this high-dimensional data because they are hierarchical in nature.

3.2 Transfer Learning & Pretrained Models

Transfer learning, a technique which allows deep learning models to use knowledge gained while solving one problem at a new but related problem. Its popularity largely stems from the fact that large labeled datasets are in short supply for tasks such as image processing. Transfer learning, a DL practice, allows a model trained on a data-rich dataset to be further adapted on a smaller (but more specific) dataset to address the particular task [19]. Several pretrained models including VGG16, Resnet & InceptionV3 are commonly used for transfer learning when working with images. These are models trained on a large-scale dataset, which has learned generalized features such as edges, textures, shapes, etc., that can be reused for other image classification tasks. These pretrained models can be fine-tuned by optimizing the weights of the top layers to make the model learn task specific [20]. Given the limited amount of annotated data provided to train machine learning models to solve tasks such as imaging in the medical field (e.g. identifying tumor types in radiology images), transfer learning has been shown to be very effective.

3.3 State-of-the-Art Transformations: Transformers, GANs and Autoencoders

Although the CNNs, and transfer learning have been the backbone for image processing, recent achievements have introduced models and architectures that improve the performance of deliverables at the earth of deep learning-based image analysis. The figure 2 shows the advanced deep learning techniques in image processing.

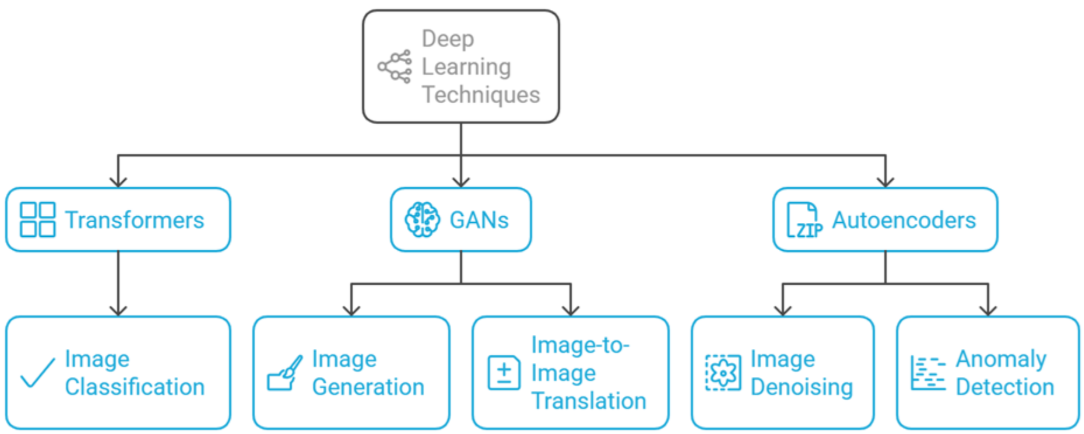

Figure 2: Advanced deep learning techniques in image processing.

- **Transformers**: Transformer networks [21] were initially designed for natural language processing tasks, but have found recent application in image processing tasks. For example, transformer models (including Vision Transformers (ViTs)) view images as sequences of patches similar to how transformers view text as a sequence of words. Indeed, these types of models exhibited state-of-the-art performance on several image classification tasks, outperforming classical convolutional neural networks in some cases [22]. The key to their success is the self-attention mechanism that allows the model to pay attention to important areas of an image and provide exceptionally strong performance in encoding long-distance pixel dependencies.
- **Generative Adversarial Networks (GANs)** : GANs [23] are two neural networks, a generator and a discriminator, that are trained together in an adversarial process. Generator and Discriminator The generator generates fake images, and the discriminator checks whether they are fake or authentic. They have been in various applications for images such as image generation, image-

to-image translation, super-resolution, etc. The most popular image-to-image generation models such as Pix2Pix and CycleGAN [24]can be used with a wide variety of tasks, converting photos to artistic styles or enhancing low-definition images.

- **Autoencoders:** Autoencoders are a type of unsupervised learning model that learn compressed representations (or embeddings) of input data by encoding it into lower-dimensional space and then reconstructing it to the original input. It's often used for image denoising, compression, and anomaly detection tasks [25] Variational autoencoders (VAEs) extended the concept of the standard autoencoder by adding a probabilistic element, which allows VAEs to generate new images by sampling from the learned distribution.

Since then, deep learning approaches, especially convolutional neural networks (CNNs), have revolutionized the field of image processing, offering powerful methods for feature extraction, classification, and segmentation. Transfer learning techniques have made it possible to apply pretrained models to for many of these tasks, tailoring their use to low-data sets, allowing even more flexibility and versatility for deep learning in image analysis. In addition, the emergence of newer architectures like transformers, GANs, and autoencoders have opened the doors for many new applications like high-quality image generation, image-to-image translation, and outlier detection. As deep learning models get better and better, incorporating them with traditional image-processing techniques should lead to increased performance, robustness, and efficiency across a variety of image processing tasks.

4. Integration of Image Processing Concepts in Deep Learning

Additionally, it combines traditional image processing techniques with current deep learning strategies to parallelize their implementation for practical cases, demonstrating more accuracy in reports of image analysis systems. Conventional approaches like filtering, edge detection, and morphological techniques have served as cornerstones of image enhancement and feature extraction. Learning hierarchically from raw data known as deep learning generally through CNN is game-changing. Combining these two strategies allow researchers to make use of the benefits of each to tackle challenges like a lack of labeled data, reductions in computational demand, and increased resilience in a multitude of fields including medical imaging, object retrieval, and self-driving vehicles. It covers hybrid approaches, feature engineering techniques and post-processing methods that utilize traditional image processing and deep learning. One of the ways to keep data up to date is to train with the latest versions of label sets, but this would appear more accurate for traditional deep learning approaches. Figure 3 elucidates the integration of image processing concepts in Deep Learning.

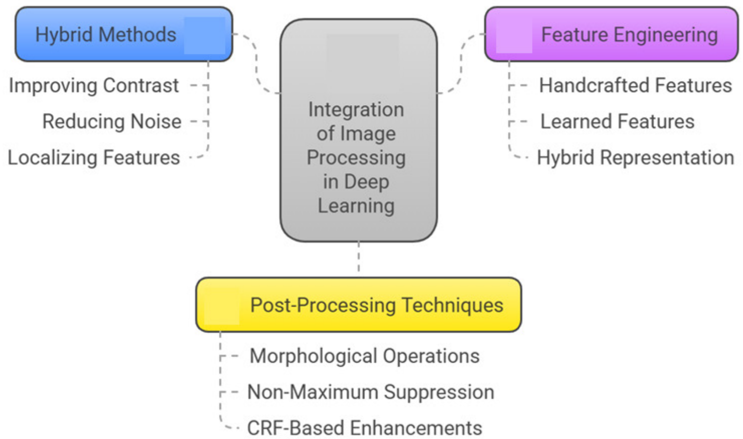

Figure 3 : Integration of Image Processing Concepts in Deep Learning.

4.1 Hybrid methods

Hybrid methods are focused on improving the input data or pre-training it for the deep learning task. Most image processing techniques are classically used as preprocessing steps prior to passing information into the network. These methods have multiple roles, including improving contrast, reducing noise, and localizing features, which can provide the deep learning models the ability to learn better features from the data. For instance, medical images this such as MRI scans are usually noisy and inconsistent than the denoising process with Gaussian filtering or median filtering are used to remove the high-frequency noise [26]. Also, edge detectors, such as the Canny edge detector, can be used to emphasize the boundaries of objects, which can help CNNs localize them . The networks will have accurate and efficient learning if, applying these conventional Preprocessing methods along with the Deep learning models and they will only focus on the significant features in the image.

4.2 Handcrafted and Learned Features Combined: Feature Engineering

Feature engineering is still a critical component of image processing, particularly when domain-specific knowledge is available to enhance model accuracy[28]. Deep learning based methods are recent encouraging techniques that can learn highly complex and high-dimensional features without the need for traditional handcrafted features, which can ensure the extraction of well-suited features for each task L(m, y) and can significantly surpass traditional handcrafted features which cover the SIFT (Scale-Invariant Feature Transform), HOG (Histogram of Oriented Gradients), or LBP (Local Binary Patterns) [27] The features extracted by each of them are then combined with those learned by deep learning models to form a better representation. In face recognition, textured object detection, and medical image analysis, hybrid models have performed well when integrating handcrafted features with learned deep features [29]. This in turn means that combining different kinds of features together will also allow the model to learn both general and detailed representations, such as combining HOG features and a CNN . It allows for improved generalization and robustness, especially on smaller datasets where pure deep learning may not work as effectively. Evidence based on such techniques as multi-feature fusion suggests that handcrafted features can be concatenated or fused with CNN learned ones in order to produce hybrid features. Not only that, such low and high image patterns lead to a hybrid representation that considerably improves classification accuracy.

4.3 Post-Processing Techniques for Deep Learning Outputs

After a deep learning model is trained, it is used to make predictions. These predictions are often post-processed to correct mispredictions by applying various techniques to improve their accuracy and robustness. They are particularly beneficial for applications such as image segmentation, object detection, and scene analysis, where accuracy is predominantly required. For example, morphological operations such as dilation and erosion are frequently applied to output of deep learning models in image segmentation to get rid of very small noise or close gaps in objects that have been detected . For object detection tasks, post-processing such as non-maximum suppression (NMS) is performed to remove overlapping bounding boxes and keep only the most confident detections [30]. Like-wise, CRF-based post-processing (Conditional Random Fields) could enhance pixel-wise outputs in segmentation tasks, according to the spatial dependencies between neighboring pixels . For example, in medical imaging, hybrid approaches integrating traditional image analysis with deep learning predictions can be leveraged to improve the visibility and quality of detected anomalies. As an example, histogram equalization can be applied to MRI data to help with better image contrast making it easier to train deep learning models to detect small lesions .

This combination of traditional image processing methods and deep learning techniques provides a strong solution for a wide range of challenges in image analysis applications. Complementary deep learning methods or hybrid approaches, which apply classical preprocessing methods for further data cleaning and enrichment prior to inputting the data into deep learning methods can also speed up the learning process while maintaining or even improving accuracy. Moreover, incorporating manually-engineered features with learned deep features results in more descriptive image representations that are often essential in the domain-specific tasks. Post processing Techniques finally post processing techniques are applied to increase the performance of deep learning models and they are more usable for real world problems. The fusion of these methodologies opens new possibilities for elevating the performance of image analysis systems in diverse fields including medical imaging, autonomous systems, and industrial applications.

4.4 Traditional Image Processing Combined with Deep Learning Models Examples

The combination of traditional image processing methods and deep learning algorithms has demonstrated tremendous success in diverse real-world applications. In medical imaging, for example, traditional image processing techniques, such as histogram equalization, edge detection (e.g., Sobel or Canny), or morphological operations, are commonly used as preprocessing techniques to improve image contrast and find boundaries of regions, which results in CNN-based models of tumor segmentation or disease classification demonstrating increased performance. In remote sensing applications, measure such as NDVI computation, edge sharpening, or threshold values may be used to decrease noise and capture geographic features before applying deep networks, such as ResNet models, to classify land cover. Furthermore, industrial defect detection involves techniques, such as filters or morphological operations, to make a crack or surface defect more visible, before being detected with CNNs or object detection methods, like YOLO detector models. In OCR applications, methods of preprocessing, such as binarization methods (e.g. Otsu's method) or noise removal, further simplifies the input to LSTM-CNN hybrid networks used for text recognition5. Applications of Hybrid Techniques

New approaches using deep learning in the classical image processing–based workflows have been examined to be beneficial in many domains, increasing the quality and performance of image contents interpretation systems drastically. Hybrid solutions can combine the best of both worlds, namely the structured and brighter image processing methods come from traditional algorithms and at the same time learn the complex internal data patterns from large datasets through deep learning. This approach has shown promising results in various domains such as medical imaging, remote sensing, object recognition and detection, and industrial inspection. Far more details of these applications follow in this section.

5.1 Medical Imaging (Disease Detection, MRI/CT Image Enhancement)

One of the most influential areas utilizing the combination of classic image processing and deep learning is medical imaging. Image preprocessing usually performed using traditional techniques like image filtering, edge detection and segmentation to reduce the noise and enhance features like Tumors or organs in medical scans. By employing these techniques, deep-learning methods are able to concentrate attention on relevant features for improved detection & classification accuracy. MRI and CT scans, for instance, typically involve several pre-processing steps (e.g., denoising, contrast enhancement) to render clearer images. Deep learning methods are also often combined with traditional image processing techniques such as histogram equalization or Gaussian filtering to preprocess the images and enhance their quality while being analyzed [31]. Compared with methods based on deep learning, it has made some progress, (e.g., tumor detection and organ segmentation) but hybrid techniques make segmentation results better and this will enable more accurate diagnosis [32]. The deployment of more exact traditional methods bolstered with a deeper learning can enhance disease detection, which can be effective for diagnosis and improve medical workflow mainly in radiology and oncology domains.

5.2 Remote Sensing and Satellite Image Analysis

Satellite image analysis plays an important role in monitoring environmental changes, agriculture, and urban development among others in remote sensing applications. Such techniques include traditional image processing methods to enhance satellite images by mitigating noise and atmospheric distortion effects, while enhancing features like land cover and vegetation. Such preprocessing methods are very important to optimize the deep learning models for tasks such as image classification, object detection and change detection. Examples of image preprocessing include approaches such as image filtering and edge detection, which improve satellite images before passing them through deep learning models to classify land use or illustrate vegetation mapping [33]. The latest hybrid techniques adopt CNN with conventional morphological procedures for detecting change between images obtained at distinct timestamps. They are especially useful for tracking deforestation, urban sprawl, and other environmental phenomena [34] .Integrating conventional techniques with deep learning can significantly improve the accuracy of remote sensing applications, both in spatial resolution and classification accuracy, which are essential for areas such as environmental monitoring, disaster management, and agriculture.

5.3 Object Detection and Recognition for Surveillance

The domain of surveillance requires high-performance object detection and object recognition due to requirements related to safety and security for urban infrastructures such as airports or industrial factory sites. Common techniques to detect regions of interest in video streams include general methods motion detection, background subtraction or edge detection. This allows the traditional models to reduce the quantity of data which the deep learning model will have to process, thus increasing the efficiency of the whole system. These signals are then subjected to Deep learning models like CNN and RNN (Recurrent Neural Network) for tasks including object detection, face recognition and activity recognition. For example, hybrid methods integrating existing approaches with CNN-based models have shown great results in scenarios such as real-time surveillance [35]. In fact, traditional methods are used to eliminate irrelevant portions from an image or video, allowing deep learning models to concentrate only on points of interest so as to increase both performance and accuracy. Moreover, hybrid feature extraction methods, including both handcrafted feature-based and CNN-learned feature-based methods, have achieved greater motion tracking accuracy and improved activity recognition in surveillance systems, resulting in more robust systems in real-world applications such as video surveillance for security and safety.

5.4 Industrial Inspection and Quality Control

Quality control and visual inspection are essential in the industrial sector to guarantee defect-free products are produced. For example, edge detection, thresholding, and morphological operations have been employed for many years to perform tasks ranging from defect detection to dimensional measurements. These techniques are commonly applied to emphasize on anomalies of product surfaces or structures to enable easier classification of the objects or defect detections by deep learning models. Traditional approaches, when combined with deep learning, improve the performance of the visual inspection system in terms of accuracy and speed. For example, CNNs are widely used for defect detection in items like electronics, automotive components, or fabrics. Using hybrid systems that combine traditional approaches such as image thresholding and CNNs can greatly enhance the ability of systems to detect small defects that would otherwise remain undetected [36]. Moreover, hybrid approaches focused on visual inspection have advanced the development of automated visual inspection systems, resulting in improved production throughput and decreased human error in quality control, which is significant for high-volume sectors including electronics, pharmaceuticals, and automotive production.

The hybrid methods, which include classical image processing followed by deep learning, can effectively solve complex problems in diverse applications. Preprocessing methods have been consulted with the deep learning models in medical imaging, resulting in an optimized approach for disease detection and image segmentation . Hybrid methods are used to improve analysis of satellite images for environmental monitoring within the field of remote sensing. In the field of surveillance, conventional approaches aid in optimizing object detection and recognition processes, which in turn allows for more efficient real-time performance. This becomes significant in industrial inspection where integration of deep learning with traditional image processing improves accuracy and automation in defect detection as well as quality control. While deep learning algorithms are undoubtedly complex and powerful, this information can serve as a guide for future research and application as the two fields continue to converge. **6. Challenges and Limitations**

Although integration between classical image processing techniques and deep-learning methods has resulted in greatly improved solutions to image analysis problems, many challenges and restrictions persist. They are computational complexity, generalization capability of models, deep learning system interpretability, data dependency for model training, etc. New approaches using deep learning in the classical image processing–based workflows have been examined to be beneficial in many domains, increasing the quality and performance of image contents interpretation systems drastically. Hybrid solutions can combine the best of both worlds, namely the structured and brighter image processing methods come from traditional algorithms and at the same time learn the complex internal data patterns from large datasets through deep learning. This approach has shown promising results in various domains such as medical imaging, remote sensing, object recognition and detection, and industrial inspection. Far more details of these applications follow in this section.

6.1 Computational Complexity and Processing Time

The computational cost is one of the biggest downsides to mixing deep learning with traditional image processing methods. Training and inference of deep learning models, specifically Convolutional Neural Networks (CNNs), demand high computational power. Training requires passing multiple aircraft from a source of data through layers of the network one byte at a time in a way that uses high-performance hardware (for example, GPUs, which can be expensive). Moreover, the traditional preprocessing techniques (e.g., filtering, edge detection, segmentation, etc.) in this step seems to be slaughtering more time for processing in the pipeline, resulting in higher complexity [37].These lags in real-time processing use cases, like autonomous driving or medical diagnosis, make deep learning in practice many times useless. These systems have a traditional component and a deep learning component, so optimizing the two components to reduce processing time and computational cost is crucial to the successful application of such systems in time-sensitive tasks [38].

6.2 Generalization and Overfitting Issues

A significant problem in deep learning is generalization. The nature of deep neural networks is too overfit to the training set particularly when the dataset is small or does not represent real-life scenarios. In the context of hybrid systems, the concern may arise that these approaches where traditional and deep learning techniques are merged can result in models that perform well on specific tasks or datasets but do not generalize well to other conditions or domains. Overfitting happens if the model is too complex that it gets our noise data instead of our main data from the train. As a result, it could perform poorly on unseen data. Hybrid models, while being a combination of previously hand-crafted features and deep learning can sometimes enhance overfitting [39] by corrosive features extraction or avowing over-generalization pattern. For this reason, data augmentation, dropout, and regularization are used frequently to prevent overfitting, but they do not always work for hybrid systems, in particular when domain knowledge is required.

6.3 Interpretability Problem of Deep Learning Models

One of the biggest issues with deep learning models is their lack of interpretability. Whereas in typical image processing methods the operations performed on the data are well-understood (e.g., filtering, thresholding), deep learning models, and in particular deep neural networks, operate as a "black box." One limitation of deep learning models is that they are often seen as black boxes because there is no way to interpret how the model came to a final conclusion [40] which can become problematic if deep learning is being used for critical applications like medical imaging, autonomous driving, etc. It is critical in these areas that technology be interpretable to ensure trust and accountability. For example, a deep learning based medical imaging system must provide both a prediction and an explanation regarding how the system reached that prediction. Some hybrid models, which use both traditional techniques as well as deep learning, could provide some insight into the specific features used by the model, but still lack the ability to solve the interpretability problem that plagues deep learning models.

6.4 Data Dependency and Challenges in Labeling

Traditionally, deep learning models depend on sufficing the availability of such labeled data in order to achieve high performance, as a result this ever-more demanding need of labeled data can be a considerable hindrance in specific applications especially those with a narrower focus, such as remote sensing and medical imaging. Dependence on large datasets for training deep learning models can be expensive, time-consuming and often requires skilled annotators. For example, one of the most challenging things in medical diagnostics is the fact that the number of labeled datasets is naturally very limited (and also suffers from the high cost of expert annotation, both the collection and the interpretation of diagnostic data is usually sensitive) Additionally, data imbalance, when some classes or categories are underrepresented throughout the dataset, can deeply affect model performance providing biased predictions [41]. Hybridizing traditional with deep learning still does not address the variability or noise in the data that can lead to models that work well on the datasets in training, but less well in the wild or unseen domains. Consequently, the performance of hybrid methods is frequently constrained by the data's quality and volume. The figure 4 shows the integration of image processing techniques.

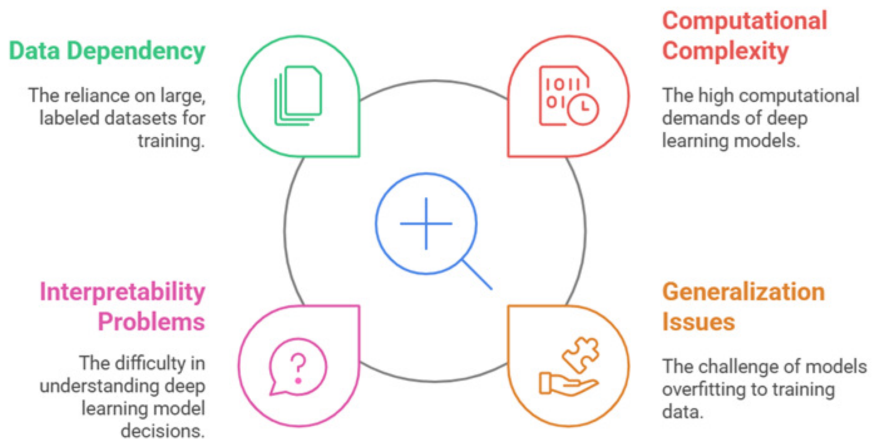

Figure 4: integration of image processing techniques

7. Future Research Directions

The combination of classical image processing methods with deep learning is an active area of research and several future directions can be proposed to tackle the mentioned challenges and augment the efficiency of hybrid architectures. The focus on these research directions will help accelerate the advancement of image processing models that are not only more effective but also more reliable, interpretable, and ethical in nature[45]. The AI is a fundamental tool for the image processing systems, providing various strategies of explanation and combination with layers of convolutional, flatten, fully connected and etc.

7.1 Improving Explainability and Interpretability

In spite of the remarkable performances by deep learning approaches in image modelling, interpretability of these models is one of the issues which is yet to be completely resolved. Since deep neural network are considered 'black boxes' in many circumstances, discussing interpretability of the decision or branching process behind prediction is a pressing issue, particularly in high-risk fields like medical diagnostics and self-driving cars. Methods aimed to increase the transparency of deep learning models and bring explainability (to a degree) to users by not only providing the results of a model but also, through the path that the model took to reach that conclusion. Techniques such as Layer-wise Relevance Propagation (LRP) and Shapley values are potential methods for enhancing the interpretability of deep learning models . These techniques can be combined with conventional image processing methods to improve explainability in hybrid mode by pointing out the features that eventually drive the final decision. With an increase of hybrid approaches, supporting the increasing need for transparency of the model and assuring valid predictions are expected to be the main challenges in further research.

7.2 Model Architectures for Hybrid Methods

The development of efficient model architectures for hybrid approaches to the task also is an important area of research. Although these approaches can enhance the performance based on classical image processing methods whenever combined with the deep learning, they increase the computational complexity generally. Hybrid systems can achieve high processing power, but research is needed to design lightweight deep learning models for efficient use on embedded systems or mobile devices while maintaining performance. Future studies may explore the development of model compression methods, i.e., quantization and pruning to decrease deep learning model size without compromising performance [47]. Moreover, neural architecture search (NAS) may be used for automatically designing efficient hybrid models for specific tasks. Such models would be small, powerful and suitable for real-time image processing in low-resource environments[54].

7.3 Real Time Execution and Edge Computing

Many applications, such as real-time image processing in autonomous vehicles, surveillance, and robotics, demand this constraint. Fusion of conventional image processing with deep learning would produce better results in real-time. But the state-of-the-art models can still demand high-performance computing resources, and thus they cannot be deployed in localization or embedded systems that require low response time and swift computation speed. More studies must be done on optimizing hybrid models for edge computing, where the models could be deployed on device with limited computing power. Model distillation and edge AI, for example, can be employed to ensure that deep learning models combined with the conventional image processing can be processed effectively at the mobile and IoT, keeping the efficiency and accuracy of the image classification [46]. Research opportunities: A promising research opportunity is to integrate the deep learning models with edge computing infrastructure to perform on-device processing in real-time.

7.4 Ethical Concerns Related to AI-Powered Image Processing

With the proliferation of AI-driven matchmaking image processing technologies, these ethical considerations are more important than ever. The use of hybrid models in sensitive domains like healthcare, security, and surveillance poses potential risks related to privacy, bias, and accountability. Moreover, research is necessary to resolve problems like data privacy to guarantee that the image data used to train models do not infringe upon the right to privacy of individuals[44]. .In addition, hybrid models should be constructed in such a way that they are not biased. Deep learning models are typically trained by exposing them to large datasets and this data may capture existing biases or imbalances. A major challenge for research is ensuring fairness and mitigating bias in AI systems so that trustworthy and inclusive AI solutions can be developed [48]. These ethical AI dynamics, with both old school image processing methods integrated with deep learning, should be part of the AI technologies that have in the domain . By obtaining better stability and interpretability properties of machine learning models, these advancements will prevent trying to use hybrid image processing models in a lot of domains (healthcare, autonomous systems, etc.), such that they are not applicable, and will ultimately make sure that they will be rather safe in application.

8. Summary of Key Findings:

This summary talks about the possible benefits and challenges, then emphasis on crucial characteristics such as integration intricacy, computational difficulties, and generalization subjects**.** CNN and other deep learning techniques have transformed how should handle many image processing tasks by removing the need for manual feature engineering, resulting in more precise image classification and identification[53]. Deep learning has also demonstrated good results in hybrid approaches that combine traditional high and low-level techniques with these end-to-end approaches for a range of applications, including medical imaging, remote sensing, object recognition, and industrial inspection. These techniques alleviate problems such as generalization problems, overfitting, and computational complexity. However, hybrid methods pose several challenges such as high computational cost, the requirement for larger labeled datasets, and the interpretability of deep learning models. The review also highlighted the need for future research on model efficiency, explainability, real-time processing and ethical considerations in building AI-powered image processing systems. This will not only ensure that hybrid image processing models will work provisionally in practical use but also that they will be deployed ethically and responsibly[52].

8.1 Final Thoughts and Recommendations

It has with the ability to transform the budding into deep learning imaging perspective likewise bringing together conventional image processing. Nonetheless, the difficulties of computational complexity, overfitting, and lack of interpretability need to be overcome to help make these hybrid systems more feasible for implementation in real-time settings. Further, the explainability of deep learning models is also finding practical way with the development of techniques which is crucial in trust in AI-based systems especially in mission-critical domains such as healthcare and autonomous driving. Furthermore, ethical aspects must be the focus of developments behind AI-based image processing systems. The successful adoption of models in sensitive domains will depend on ensuring that models are fair, transparent and respect data privacy. The integration of conventional image processing techniques with deep learning is an exciting frontier in image analysis. Through overcoming current limitations and embracing progress, hybrid models have the capacity to provide more robust, accurate, and interpretable image processing systems across a variety of domains.

8.2 Interpretation and Implications of Findings

This review highlights that the fusion of traditional image processing techniques with deep learning models leads to improved performance, especially in tasks that require fine-grained feature localization, enhanced interpretability, and adaptability to limited or noisy datasets. Recent literature review indicates that traditional methods are crucial for preprocessing, feature enhancement, and attention guidance of the deep model. Examples include processes like edge detection and histogram equalization, which have been demonstrated in the past to enhance the clarity of feature maps from convolutional neural networks (CNNs) providing pixel density resolution in cases, such as segmentation in medical images, where accuracy boundary measures are needful. In analogous manner, cell segmentation and defect detection approaches using U-Net and ResNet architectures have benefitted significantly from applying morphological operations for suppressing unwanted background noise. The value of these results is not only accuracy enhancement, but also more explainable deep models, which is vital for applications, e.g., in the media of healthcare and industrial safety, that place premium on interpretability. In addition, hybrid models lower data usage and achieve great generalizability to low-data or cross-domain applications. This said, however, challenges still prevail with model integration complexity, optimizing a hybrid pipeline, and an increased computational load. Plugging these through modular designs, adaptive pre-processing, and explainable AI frameworks could set the foundation for next-gen, high-power yet trustworthy vision systems.

8.3 **Contribution & Implications**

This review contributes to the field of computer vision by synthesizing current knowledge on the synergistic integration of traditional image processing techniques with deep learning models. While previous studies have either focused on conventional methods or pure deep learning approaches, at a time when most studies are always combining with each other. Through a diverse body of applications of hybrid models in medical diagnostics, remote sensing, industrial inspection and OCR, this review showed that hybrid models improve accuracies but also can make models more robust and less reliant on data while also improving the interpretability. These benefits are essential for deploying in real-world, resource-constrained, or high-stakes settings where black-box AI models alone are likely inadequate. Moreover, we note emerging methods for hybrid pipeline optimization to pave the way for future work on the design of scalable, explainable, energy-efficient vision systems. This research has the potential to significantly influence the design of future intelligent systems, balancing high performance with transparency and ensuring trust and adoption, particularly in sensitive sectors such as healthcare, defense, and environmental monitoring.

8.4 Impact of Future Research

There is significant opportunity for future research at the intersection of deep learning and traditional image processing methods that can help to push computer vision and its applications forward. Exploring a combination of deep learning and the traditional techniques of edge detection, filtering, morphological operations and others, will allow researchers to work toward addressing model interpretability, data efficiency and computational cost. The development of hybrid models incorporating both traditional methods and existing deep learning models can provide a practical and high-performing computer vision system capable of being applied in the real-world for domains such as medical imaging, remote sensing and autonomous systems, with the added benefits of explainability. Additionally, some of the challenges at the core of computer vision, such as data limitations and labeling can also be addressed with hybrid methods as traditional techniques can be added for augmenting or synthesizing data. Additionally, researchers could address issues related to the energy efficiency of models that may aid in on-device real-time processing and deployment in energy-constrained settings. Altogether, the development of these hybrid methodologies in the future will create more robust, scalable systems in computer vision and address real-world challenges in connected domains.

9. Conclusion

In this paper, combining the traditional image processing methods with deep learning architectures are becoming a promising trend in the domain of computer vision. The need for such conventional approaches—filtering, gradient edge detection, morphological operations and contrast enhancement—would form a critical backbone for image filtering, refining features, or even model interpretability that can be achieved through a simple intuition paired with the power of deep learning methods such as convolutional neural networks (CNNs), U-Nets and ResNets. From a review of the newest literature and use cases in medical imaging, remote sensing, industrial inspection, and document analysis, it is clear relevance for hybrid models to outperform single-deep learning techniques, especially where there is noise in data or the images are at very low resolution or the datasets themselves are limited. This paper is mainly focused in synthesizing the state-of-the-art research trends and highlighting some of the advantages and disadvantages of hybrid methods. This led to the identification of key challenges faced, such as integration complexity, data alignment, and computational cost, as well as an urgent need for modular, interpretable, and energy-efficient model architectures. Moreover, the review points out the potential for hybrid systems to improve the trustworthiness and practical application of AI in sensitive or high-stakes settings. Future research should explore on standard cross-domain model design frameworks for hybridization, hybrid automated fusion by neural architecture search (NAS), and explainable AI based on traditional feature cues from both domains. This will allow researchers to create more powerful, adaptable, and interpretable intelligent vision systems that can respond to the increasing requirements of real-world applications, bridging between classical and modern approaches.

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