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Deep Learning-Based Image Fusion: A Systematic Literature Review on Trends, Datasets, Evaluation Methods, and Research Challenges

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Abstract

Advances in digital image processing technology have increased the need for image fusion techniques to produce more accurate and high-quality visual information. This study aims to analyze methodological developments, research trends, datasets, evaluation methods, and challenges in image fusion research through a Systematic Literature Review (SLR) using the PRISMA framework. The literature selection process resulted in 335 papers being included for analysis. The findings indicate that deep learning-based methods, particularly Convolutional Neural Networks (CNNs), have become the dominant approach in modern image fusion research. Furthermore, recent studies have increasingly explored Generative Adversarial Networks (GANs), Transformers, and hybrid methods to improve fusion performance. The most significant challenges identified include the need for large-scale datasets, high computational complexity, the lack of standardized evaluation frameworks, and limitations in model generalization. These findings provide a comprehensive overview of current developments and highlight future research opportunities in deep learning-based image fusion.

***Keywords**: Convolutional Neural Network; Deep Learning; Digital Image Processing; Image Fusion; Systematic Literature Review*

1. Introduction

Advances in digital image processing technology have driven the need for more accurate and comprehensive visual information. In many applications, a single image is often unable to represent all required information due to limitations in sensors, lighting conditions, and acquisition perspectives. To address these limitations, image fusion has emerged as an effective technique for integrating complementary information from multiple images into a single image with enhanced quality and information content [1]

Image fusion has been widely applied in various domains, including medical imaging, remote sensing, surveillance systems, and computer vision applications. By combining information from different sensors or modalities, image fusion can improve visual quality, feature representation, and decision-making processes. Early image fusion approaches primarily relied on mathematical transformation techniques, such as Wavelet Transform and Pyramid-based methods. Although effective in preserving image details, these conventional approaches often struggle to extract complex features and maintain critical information from source images [2].

With the rapid advancement of artificial intelligence, deep learning-based approaches have become the dominant paradigm in image fusion research. In particular, Convolutional Neural Networks (CNNs) have demonstrated superior capability in automatically extracting hierarchical features and generating higher-quality fusion results. More recently, advanced architectures such as Generative Adversarial Networks (GANs), Transformers, and hybrid models have shown promising performance improvements and have become emerging research trends in the field [3].

Despite these advancements, several challenges remain. Existing methods often require large-scale datasets, substantial computational resources, and complex training procedures. Furthermore, image fusion evaluation still relies heavily on objective metrics such as Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR), while standardized evaluation frameworks have not yet been established [4]. Another important limitation is the domain-specific nature of many studies, which restricts the generalization capability of developed models across different application scenarios.

Given the rapid evolution of image fusion techniques and the increasing adoption of deep learning approaches, a comprehensive synthesis of existing studies is required. Therefore, this study conducts a Systematic Literature Review (SLR) based on the PRISMA framework to examine developments, research trends, datasets, evaluation methods, and research challenges in image fusion studies published between

2015 and 2025. Through the analysis of 335 selected studies, this review aims to provide a comprehensive overview of the current state of image fusion research and identify future research opportunities in the field.
The main contributions of this study are as follows:
1. To systematically review image fusion studies published between 2015 and 2025 using the PRISMA framework.
2. To identify and analyze the dominant deep learning approaches employed in image fusion research.
3. To examine the datasets and evaluation metrics commonly used in image fusion studies.
4. To identify research challenges, research gaps, and potential future directions in the field of image fusion.

2. Related Works

2.1. Fundamentals of Image Fusion

Image fusion is a digital image processing technique that combines two or more images from different sources into a single image containing more comprehensive and informative visual content. The primary objective of image fusion is to enhance image quality, reduce information loss, and integrate complementary features from multiple sensors or modalities. Due to its ability to improve visual representation, image fusion has been extensively applied in various domains, including medical imaging, remote sensing, surveillance systems, and computer vision applications [2], [5].
In general, the effectiveness of image fusion depends on several factors, including the characteristics of source images, the fusion algorithm employed, and the evaluation techniques used to assess fusion quality. Therefore, selecting an appropriate fusion method is essential for achieving optimal results in different application scenarios.

2.2. Classification of Image Fusion Methods

Image fusion methods can generally be categorized into three main groups: transform-domain methods, spatial-domain methods, and deep learning-based methods.
Transform-domain methods represent some of the earliest approaches to image fusion and include techniques such as Wavelet Transform and Laplacian Pyramid. These methods operate by transforming images into the frequency domain, fusing important information, and then reconstructing the fused image. Although effective in preserving image details, they often struggle to capture complex feature relationships [2].
Spatial-domain methods perform fusion directly on image pixels without additional transformations. Popular techniques include Principal Component Analysis (PCA) and Intensity-Hue-Saturation (IHS). These approaches are computationally efficient and relatively simple to implement; however, they are susceptible to information loss and visual distortion, particularly in multimodal image fusion tasks [1].
Recent developments have shifted toward deep learning-based methods, which utilize neural networks such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to automatically extract and fuse image features. These approaches generally outperform conventional methods in terms of fusion quality, although they require substantial computational resources and large training datasets [3], [6].

2.3. Evolution of Deep Learning-Based Image Fusion

The evolution of image fusion research demonstrates a significant transition from traditional signal-processing approaches toward artificial intelligence-based techniques. Early studies primarily focused on transform-domain methods, while subsequent research increasingly adopted machine learning and deep learning frameworks.
Among deep learning approaches, CNN-based architectures have become the most widely used due to their capability to automatically learn hierarchical feature representations from source images. More recently, researchers have explored GAN-based methods, Transformer architectures, and hybrid models that combine conventional image fusion techniques with deep learning frameworks. These approaches have shown promising improvements in image quality, robustness, and generalization capabilities [3].
The emergence of Transformer-based architectures further indicates a shift toward global feature representation and long-range dependency modeling. Consequently, modern image fusion research increasingly focuses not only on improving visual quality but also on enhancing computational efficiency, real-time performance, and cross-domain adaptability.

2.4 Research Gap

Although numerous review studies have discussed image fusion techniques and deep learning-based approaches, most existing reviews focus on specific application domains, such as medical imaging, remote sensing, or infrared-visible image fusion. Furthermore, many studies provide limited analysis of datasets, evaluation metrics, and research challenges across different domains. There is still a lack of comprehensive reviews that systematically examine the evolution of image fusion methods, dominant datasets, evaluation frameworks, and emerging research trends over the last decade. Therefore, this study aims to fill this gap by conducting a PRISMA-based systematic literature review covering image fusion research published between 2015 and 2025.

3. Research Method

3.1. Research Design

This study employed a Systematic Literature Review (SLR) approach to comprehensively analyze developments, trends, datasets, evaluation methods, and research challenges in image fusion research. The SLR methodology was selected because it provides a structured, transparent, and reproducible process for identifying, evaluating, and synthesizing relevant scientific literature [7].
The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which consists of four stages: identification, screening, eligibility assessment, and inclusion.

3.2. Research Questions

To guide the review process, five research questions (RQs) were formulated:

- RQ1: What are the dominant methods used in modern image fusion research?
- RQ2: How have image fusion methods evolved over time?
- RQ3: Which datasets are most frequently used in image fusion studies?
- RQ4: What evaluation metrics are commonly employed to assess image fusion performance?
- RQ5: What are the major challenges and research gaps in current image fusion research?

3.3. Search Strategy

The literature search was conducted using several major scientific databases, including Google Scholar, IEEE Xplore, ScienceDirect, and Scopus. The search process focused on studies published between 2015 and 2025.
The following search string was used:
("image fusion") AND ("deep learning" OR "CNN" OR "GAN" OR "Transformer")
The search was performed to identify studies related to image fusion methods, datasets, evaluation techniques, and emerging research trends.

3.4. Inclusion and Exclusion Criteria

The selected studies were filtered according to predefined inclusion and exclusion criteria.

Table 1: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Published 2015–2025	Duplicate studies
Related to Image Fusion	Unrelated topics
Full-text available	No full-text
Contains evaluation results	No methodology

3.5. Data Extraction and Analysis

A data extraction form was developed to collect relevant information from each selected study. The extracted data included:

Table 2: Data Extraction Items

Data Category	Description
Publication Year	Year of publication
Method	CNN, GAN, Transformer, etc.
Dataset	IR-VIS, Medical, Remote Sensing
Evaluation Metrics	SSIM, PSNR, MI, Entropy
Findings	Main contribution
Limitations	Research limitations

The collected data were analyzed using descriptive synthesis to identify dominant methods, research trends, commonly used datasets, evaluation approaches, and emerging research challenges.

3.6. PRISMA Flow Diagram

The article selection process was documented using the PRISMA framework. Initially, relevant studies were identified from multiple databases. After removing duplicates and irrelevant records, eligible studies were assessed based on the predefined criteria. The final selection resulted in 335 articles included in the systematic review.

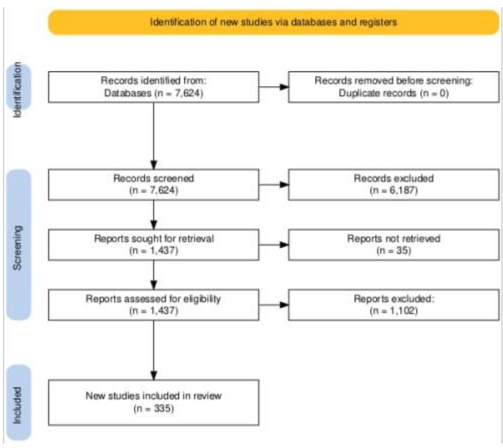

Figure 1: PRISMA flow diagram of the study selection process.

4. Results and Discussion

4.1. Dominant Methods in Image Fusion Research

The analysis of 335 selected studies indicates that deep learning-based approaches have become the dominant paradigm in modern image fusion research. Among these approaches, Convolutional Neural Networks (CNNs) represent the most frequently adopted architecture due to their ability to automatically extract hierarchical spatial features and generate high-quality fused images.
Compared with traditional approaches such as Wavelet Transform, Principal Component Analysis (PCA), and Scale-Invariant Feature Transform (SIFT), CNN-based methods demonstrate superior performance in preserving image details and integrating complementary information from multiple image sources.
In addition to CNNs, recent studies have increasingly explored Generative Adversarial Networks (GANs), Transformer-based architectures, and hybrid approaches. These methods aim to improve fusion quality, feature representation, and model robustness. The growing adoption of advanced deep learning techniques reflects a significant paradigm shift from conventional mathematical transformation methods toward data-driven approaches.

4.2. Trends in Deep Learning-Based Image Fusion

The evolution of image fusion research reveals a gradual transition from conventional signal-processing techniques to deep learning-based methods. Prior to 2015, most studies focused on transform-domain and spatial-domain approaches.
Following the rapid development of artificial intelligence technologies, CNN-based image fusion methods became increasingly dominant due to their ability to learn complex feature representations automatically. More recently, research has expanded toward GANs, Transformers, and hybrid architectures that combine multiple fusion strategies.
Another important trend is the increasing emphasis on computational efficiency, real-time implementation, and model generalization. Contemporary studies are not only concerned with improving visual quality but also with developing practical solutions suitable for real-world applications.

4.3. Datasets Used in Image Fusion Studies

The review identified three major categories of datasets commonly used in image fusion research:

1. Infrared-Visible (IR-VIS) datasets
2. Medical imaging datasets (MRI-CT, MRI-PET)
3. Remote sensing datasets

Among these categories, IR-VIS datasets were the most frequently utilized because of their relevance to surveillance, security monitoring, and target detection applications.
Medical image fusion datasets are primarily used to improve diagnostic accuracy by integrating complementary anatomical and functional information. Meanwhile, remote sensing datasets support environmental monitoring, land-use analysis, and geographical information systems.
Despite their importance, dataset-related challenges remain significant. Common issues include limited dataset availability, variations in image quality, insufficient dataset standardization, and the lack of reliable ground truth references.

4.4. Evaluation Metrics for Image Fusion

The analysis shows that image fusion performance is predominantly evaluated using objective metrics, including:

- Structural Similarity Index (SSIM)
- Peak Signal-to-Noise Ratio (PSNR)
- Entropy
- Mutual Information (MI)

Among these metrics, SSIM is the most widely adopted because it better reflects human visual perception when assessing image quality.
Many studies employ multiple evaluation metrics simultaneously to provide a more comprehensive assessment of fusion performance. In addition, visual inspection remains a common subjective evaluation approach, particularly for comparing perceptual image quality.
Recent studies have also begun investigating deep learning-based evaluation methods and task-oriented evaluation frameworks. However, no universally accepted evaluation standard currently exists, making direct comparisons between image fusion methods challenging.

4.5. Research Challenges and Future Directions

The review identified several major challenges in contemporary image fusion research.
First, deep learning-based methods require large-scale datasets and substantial computational resources, limiting their applicability in resource-constrained environments.
Second, the absence of standardized evaluation frameworks creates difficulties when comparing the performance of different methods across studies.
Third, many image fusion models exhibit limited generalization capabilities because they are trained and evaluated on domain-specific datasets.
Fourth, the interpretability of deep learning models remains a significant concern. Most fusion systems function as black-box models, making it difficult to understand the reasoning behind fusion decisions.

Based on these findings, several future research directions are recommended:

- Development of lightweight image fusion architectures.
- Real-time image fusion systems.
- Transformer-based fusion frameworks.
- Explainable Artificial Intelligence (XAI) for image fusion.
- Cross-domain generalization techniques.
- Standardized evaluation protocols and benchmark datasets.

These directions provide promising opportunities for advancing image fusion research and improving the practical applicability of future image fusion systems.

Table 3. Summary of Findings Based on Research Questions

Research Question	Summary Findings
RQ1	CNN-based architectures are the dominant approaches in contemporary image fusion research.
RQ2	Research has evolved from traditional methods toward GAN, Transformer, and hybrid architectures.
RQ3	Infrared-visible, medical imaging, and remote sensing datasets are the most frequently utilized datasets.
RQ4	SSIM, PSNR, entropy, and mutual information are the most widely adopted evaluation metrics.
RQ5	Major challenges include dataset limitations, computational complexity, evaluation standardization, and model generalization.

Table 3 summarizes the findings of this systematic literature review based on the five research questions formulated in this study. The results indicate that deep learning approaches dominate contemporary image fusion research, while several challenges remain regarding evaluation standardization, computational efficiency, and model generalization.

5. Conclusion

This study presented a Systematic Literature Review (SLR) based on the PRISMA framework to investigate developments, trends, datasets, evaluation methods, and research challenges in deep learning-based image fusion research published between 2015 and 2025. A total of 335 studies were selected and analyzed to provide a comprehensive overview of the current state of image fusion research.

The findings indicate that deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have become the dominant methods in modern image fusion due to their superior feature extraction and fusion capabilities. Recent studies have increasingly explored Generative Adversarial Networks (GANs), Transformer-based architectures, and hybrid approaches to further improve fusion performance. The review also identified infrared-visible, medical, and remote sensing datasets as the most frequently used datasets, while SSIM, PSNR, entropy, and mutual information remain the most commonly adopted evaluation metrics.

Despite significant progress, several challenges remain, including dataset limitations, high computational complexity, the absence of standardized evaluation frameworks, and limited model generalization. Future research should focus on lightweight architectures, real-time implementation, explainable artificial intelligence, and robust cross-domain fusion systems. These directions are expected to enhance both the effectiveness and practical applicability of image fusion technologies in various domains.

The findings of this review indicate that image fusion research is rapidly evolving toward more intelligent, efficient, and application-oriented solutions. Emerging technologies such as Transformers, hybrid architectures, and explainable artificial intelligence are expected to play a significant role in future developments. Moreover, the establishment of standardized benchmark datasets and evaluation frameworks will be essential to ensure fair comparison and reproducibility across image fusion studies.

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