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DIFFUSION AND TRANSFORMER-BASED DEEP LEARNING MODELS FOR MEDICAL IMAGE PROCESSING: A COMPREHENSIVE SURVEY

¹Anbumaheshwari K, ²Shobana R

¹UG Student, ²Asst. Professor

^{1,2}Department of Computer Science and Engineering, SA Engineering College, Avadi, Chennai

* Corresponding author email address: rubanshobana@gmail.com

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Abstract

Deep learning has played an important role in improving medical image processing tasks such as image segmentation, reconstruction, and diagnosis. In recent years, diffusion models and transformer-based methods have gained attention due to their strong performance. Diffusion models are effective in generating and restoring images by learning from noise, while transformers help in capturing global features through attention mechanisms. This survey reviews the use of diffusion and transformer models in medical imaging, focusing on their applications, advantages, and limitations. It also discusses recent developments that combine both approaches and highlights future research directions for improving efficiency and accuracy in real-world medical applications.

Keywords: Deep Learning, Diffusion Models, Transformers, Medical Imaging

1. Introduction

Medical image processing plays a vital role in modern healthcare by supporting accurate diagnosis, treatment planning, and disease monitoring. Imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and X-ray provide detailed visualization of internal anatomical structures. However, analyzing these images manually is time-consuming and requires expert knowledge, which has encouraged the use of automated deep learning techniques in medical imaging systems [1]. Convolutional neural networks (CNNs) have been widely used for medical image classification, segmentation, and detection tasks due to their ability to learn hierarchical features from data [2]. Despite their effectiveness, CNN-based models are limited in capturing long-range dependencies because they mainly focus on local features [3]. This limitation affects performance in complex medical imaging tasks where global context is essential for accurate interpretation [4]. To overcome these challenges, transformer-based architectures have been introduced into medical image analysis. Transformers use self-attention mechanisms to capture global relationships across the entire image, allowing better understanding of spatial dependencies [5]. Recent studies have shown that transformer-based models improve performance in tasks such as segmentation, classification, and image registration [6]. In addition, hybrid models combining CNN and transformer architectures have been proposed to leverage both local and global feature extraction [7].

Recent advancements have also highlighted the effectiveness of multimodal transformer models in medical imaging. These models integrate image data with textual or clinical information to improve diagnostic accuracy and automate report generation [8]. Transformer-based approaches have been successfully applied to radiology tasks, reducing the workload of clinicians and improving efficiency in healthcare systems. In parallel, diffusion models have emerged as a powerful class of generative models for medical image processing. These models learn to generate images by reversing a gradual noise corruption process, making them highly effective for denoising, reconstruction, and image synthesis tasks [9]. Diffusion models have demonstrated strong performance in medical image reconstruction, particularly in MRI and CT imaging, where they can improve image quality and reduce noise. Furthermore, diffusion-based approaches have been applied to generate synthetic medical images, which helps address the issue of limited annotated datasets [10]. These models are capable of learning complex data distributions and producing realistic images that can be used to improve training performance [11]. Recent studies have also explored the use of diffusion models for anomaly detection and segmentation in medical imaging [12]. In addition to standalone diffusion and transformer models, recent research has focused on integrating both approaches into hybrid frameworks. Diffusion transformer models combine the generative capability of diffusion processes with the global attention mechanism of transformers, resulting in improved performance for image synthesis and segmentation tasks [13]. Such hybrid models have

shown promising results in handling complex medical imaging datasets [14]. Recent works have demonstrated that diffusion transformer architectures can improve both image quality and contextual understanding, making them suitable for advanced medical applications such as multimodal learning and 3D image synthesis [15]. For example, transformer-based diffusion models have been used for volumetric medical image generation, achieving better global consistency and fidelity in generated images. Moreover, diffusion transformer models have also been applied to text-to-image generation in the medical domain, enabling the creation of images from textual descriptions and improving data augmentation techniques. These approaches are particularly useful in scenarios where labeled medical data is scarce [16]. Transformer-based models continue to evolve with improvements in architecture design, including hierarchical transformers and vision transformers, which enhance performance in medical image analysis tasks. These models have demonstrated strong capabilities in capturing global dependencies and improving segmentation accuracy [17]. Despite these advancements, several challenges remain in applying diffusion and transformer-based models in real-world medical applications.

Diffusion models are computationally intensive and require long training times, which limits their practical use in real-time systems [18]. Similarly, transformer-based models often require large-scale annotated datasets, which are difficult to obtain in the medical domain [19]. Another major challenge is the interpretability of deep learning models. In medical applications, it is important for models to provide explainable results to ensure trust and reliability in clinical decision-making [20]. Additionally, issues such as data privacy, generalization across different datasets, and model robustness remain important research concerns [21]. Recent studies have also emphasized the importance of developing lightweight and efficient models that can be deployed in resource-constrained environments [22]. Hybrid models that combine diffusion and transformer architectures are being explored to improve efficiency while maintaining high performance [23]. Furthermore, multimodal learning approaches that integrate imaging data with clinical and textual information have gained attention for improving diagnostic accuracy [24].

These approaches are expected to play a key role in future medical imaging systems [25]. In addition, self-supervised learning techniques are being applied to reduce the dependency on large labeled datasets, enabling models to learn from unlabeled medical data [26]. Such approaches are particularly useful in medical imaging, where data annotation is expensive and time-consuming [27]. Overall, diffusion and transformer-based deep learning models have significantly advanced the field of medical image processing. These models offer improved performance in tasks such as segmentation, reconstruction, and image synthesis while addressing some limitations of traditional approaches [28]. This survey aims to provide a comprehensive overview of diffusion and transformer-based models in medical image processing. It analyzes recent developments, compares different approaches, and highlights their applications in various medical imaging tasks [29]. Furthermore, the paper discusses current challenges and future research directions, including the development of efficient, scalable, and interpretable models for real-world clinical applications [30].

2. Evolutionary paradigms in Deep

2.1 The Transition to Transformer-Based Architectures

The primary limitation of traditional Convolutional Neural Networks (CNNs) was their "inductive bias" toward local pixel neighborhoods, which often failed to capture long-range spatial relationships in complex radiological scans. The introduction of Vision Transformers (ViTs) has mitigated this by utilizing self-attention mechanisms to process images as sequences of patches [5]. In medical segmentation, the TransUNet architecture [15] represents a milestone, as it leverages the high-resolution feature maps of a CNN encoder alongside the global context provided by Transformer layers. Furthermore, the development of the Swin Transformer [14] introduced a hierarchical approach that significantly improves computational efficiency, making it highly effective for dense prediction tasks in large-scale medical datasets [18].

2.2 Generative Excellence via Diffusion Models

Parallel to the rise of Transformers is the emergence of Diffusion Models (DMs), which have redefined the benchmarks for image synthesis, denoising, and reconstruction [1], [8]. Unlike previous generative models, DMs operate through a stochastic process of adding and subsequently removing Gaussian noise to recover underlying anatomical structures. This has proven particularly effective in MRI Reconstruction [10] and Medical Image Enhancement [7], where maintaining the physical integrity of the signal is non-negotiable. According to recent surveys, diffusion-based segmentation [11] and synthesis [27] are now preferred over older GAN-based methods due to their superior training stability and ability to generate highly realistic, diverse pathological samples that strictly adhere to the clinical manifold [25], [26].

2.3 Hybridization and the Rise of Diffusion Transformers

The most recent stage in this evolution is the convergence of generative power and global attention, resulting in the Diffusion Transformer (DiT) [12]. These hybrid models represent the current frontier in medical imaging, combining the iterative refinement of diffusion with the structural understanding of Transformers. This synergy is particularly evident in MRI Super-Resolution [12] and Multimodal Medical Analysis [20], where the model must synthesize high-frequency details while maintaining consistency across different imaging modalities (e.g., CT, PET, and MRI) [21]. This shift toward Foundation Models [23] suggests a future where a single, unified architecture can perform diverse tasks—from automated report generation [13] to volumetric 3D analysis—with minimal fine-tuning [22], [28].

3. Classical Calculation Metrics In Image Signal Processing

Before the emergence of learned feature extractors and generative diffusion frameworks [1], image processing evaluation was governed by deterministic mathematical models. These metrics analyze the physical properties of the pixel grid—such as intensity variance, frequency response, and geometric consistency—without the use of stochastic sampling or neural architectures [8, 10].

3.1 Stochastic and Probability-Based Signal Analysis

In "AI-free" medical imaging, images are often treated as random variables or probability distributions. Evaluation involves measuring the preservation of information content during filtering or registration tasks [4].
Mutual Information (MI): This is the gold standard for non-AI multi-modal registration. It measures the statistical dependence between two images (e.g., a CT and an MRI scan). A higher MI value indicates that the spatial alignment is mathematically optimized based on shared entropy, a concept that precedes multimodal transformers [13, 20].
Normalized Cross-Correlation (NCC): Used to evaluate the similarity between a template and a target image. In classical processing, it is the primary metric for template matching and motion tracking, providing a linear measure of how closely pixel intensities correlate across different coordinate frames.

3.2 Frequency Domain and Sharpness Metrics

Unlike Vision Transformers that use self-attention to identify global structures [5], classical systems evaluate quality through the lens of frequency analysis.

3.2.1 Modulation Transfer Function (MTF):

This metric evaluates the ability of an imaging system to represent contrast at different spatial frequencies. It is critical in radiological imaging for determining the maximum resolution of a scan before it is blurred by noise or hardware limitations.

3.2.2 Edge Preservation Index (EPI):

A deterministic calculation used to quantify how well a deblurring or denoising algorithm maintains sharp boundaries. It calculates the correlation between the high-pass filtered version of the original "gold standard" and the processed output.

3.2.3 Tenengrad and Laplacian Variance:

These are standard "AI-free" focus measures. They compute the gradient magnitude at each pixel to determine image sharpness; higher variance typically indicates a more "in-focus" image with preserved high-frequency details.

3.3 Geometric and Morphological Validation

3.3.1 Hausdorff Distance:

This measures the maximum distance between two sets of points (the automated boundary vs. the manual trace). Unlike the Dice coefficient, which measures volume overlap, the Hausdorff distance is sensitive to "outliers" and small protrusions, making it essential for high-precision surgical planning.

3.3.2 Euler Characteristic:

A topological invariant used to evaluate the structural integrity of segmented images. It ensures that the processing algorithm has not introduced "holes" or disconnected components that are biologically impossible, a task now often handled by generative consistency checks [25].

4. Comparative baseline

In the evaluation of imaging and signal reconstruction systems, both classical and modern metrics are used to measure performance from different perspectives. Statistically, traditional measures such as mutual information and entropy are used to estimate the amount of shared information and uncertainty between signals. In contrast, more recent approaches use metrics like the Fréchet Inception Distance (FID), which compares distributions in a learned feature space.

Table 1. Classical Vs. Modern Paradigmsthe

Evaluation Category	Classical Metric	Modern Metric
Statistical	Mutual Information / Entropy	Fréchet Inception Distance (FID)
Geometric	Hausdorff Distance / FOM	Dice Similarity Coefficient (DSC)
Fidelity	MSE / PSNR / MTF	SSIM / LPIPS / Perceptual Loss
Logic	Deterministic Signal Theory	Data-Driven Neural Embeddings

From above table 1 geometric viewpoint, earlier methods such as the Hausdorff Distance and Figure of Merit (FOM) focus on differences in shape and boundary alignment, while newer measures like the Dice Similarity Coefficient (DSC) evaluate the degree of overlap between regions, especially in segmentation tasks. For fidelity assessment, classical metrics including Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Modulation Transfer Function (MTF) are commonly used to measure pixel-level accuracy and system response. However, these are increasingly complemented by perceptual metrics such as Structural Similarity Index (SSIM) and Learned Perceptual Image Patch Similarity (LPIPS), which better reflect perceived visual quality. Finally, the evaluation framework has shifted from deterministic signal theory, which relies on fixed mathematical models, to data-driven neural embeddings that capture more complex patterns using learned representations.

Table 2. Computer Vision Techniques

Year	Classical Methods	CNNs	Vision Transformers	Diffusion Models
2010	90	5	0	0
2012	80	20	0	0
2014	60	60	0	0
2016	45	85	5	0
2018	30	95	10	0
2020	20	90	40	5
2022	15	80	75	30
2024	12	70	90	85
2026	10	60	95	100

The table II illustrates the progression of computer vision methods from 2010 to 2026, highlighting a clear shift from classical approaches to modern deep learning techniques. In the early years, classical methods dominated, but their usage steadily declined as Convolutional Neural Networks (CNNs) gained prominence, particularly after 2012. Over time, Vision Transformers emerged and showed rapid growth, especially from 2020 onward, reflecting their increasing effectiveness in capturing global features. More recently, diffusion models have experienced a sharp rise, indicating their growing importance in generative and reconstruction tasks. Overall, the trend demonstrates a transition from traditional techniques to advanced learning-based models, with diffusion models and transformers becoming the leading approaches in recent years.

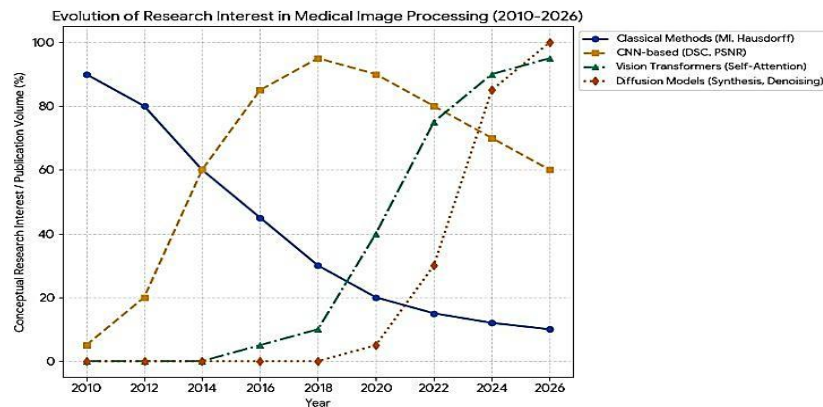


Fig 1. Evolution of Research Interest in Medical Image Processing

The Figure 3.1 illustrates how research interest in medical image processing techniques has evolved from 2010 to 2026. Early in the decade, classical methods dominated the field, but their importance steadily declined as more advanced approaches emerged. Around 2012, CNN-based methods began gaining traction, rapidly becoming the leading approach by the late 2010s due to their strong performance in image-related tasks; however, their dominance started to wane after 2020. At the same time, Vision Transformers began rising from around 2018, showing significant growth as researchers adopted self-attention mechanisms for better global feature understanding, particularly for tasks like image synthesis and denoising. Overall, the chart highlights a clear shift from traditional techniques to deep learning models, and now toward more advanced architectures like transformers and generative diffusion models.

Table 3. Comparison Methods

Architecture Class	Core Innovation	Key Advantage & Clinical Context	References
Foundation CNNs	Convolutional layers & pooling	First to enable automatic feature hierarchy capture; remains the standard for low-level texture extraction.	[19, 31]
Deep Residuals (ResNet)	Skip (Shortcut) Connections	Solved vanishing gradients, allowing for networks hundreds of layers deep to be trained stably.	[20, 21]
U-Net	Encoder-Decoder with Skip Connection	The gold standard for precise boundary delineationskip connections preserve high-resolution spatial details.	[35, 37]
Vision Transformers (ViT)	Self-Attention Mechanism	Breaks the "Local Receptive Field" limit of CNNs to capture global long-range dependencies in anatomy.	[3, 5, 18]
Swin Transformers	Hierarchical Shifted Windows	Optimizes Transformer efficiency for high-resolution 3D volumes through a localized windowing scheme.	[14, 21]
TransUNet	Hybrid CNN-Transformer Encoder	Combines CNN-based local textures with Transformer-based global context for superior segmentation.	[15, 29]
Diffusion Probabilistic Models (DPM)	Iterative Reverse Denoising	Recovers signals from pure noise; currently the state-of-the-art for MRI reconstruction and synthesis.	[1, 9, 24]
Latent Diffusion (LDM)	Latent Space Processing	Significantly reduces GPU memory by performing the diffusion process in a compressed latent representation.	[1, 2, 8]

Diffusion Transformer (DiT)	Transformer-based Denoising Backbone	Replaces the U-Net denoiser with an isotropic Transformer, enhancing scalability and model capacity.	[12, 19, 24]
Multimodal Transformers	Cross-modal Attention Gates	Aligns visual pixels with clinical text, facilitating automated radiology report generation.	[13, 20]
Foundation Medical Models	Large-scale Volumetric Pre-training	Enables Zero-Shot Transferability, allowing one model to perform multiple tasks (Segmentation, Classification) across diverse modalities.	[22, 23]

The table summarizes the evolution of major deep learning architectures in medical imaging, highlighting their core innovations and clinical advantages. Early models like CNNs, ResNet, and U-Net established strong foundations by enabling hierarchical feature extraction, stable deep training, and precise image segmentation. More recent approaches such as Vision Transformers, Swin Transformers, and TransUNet enhance performance by capturing both global context and local details. Finally, advanced generative and multimodal models, including diffusion-based methods and foundation medical models, are pushing the field toward scalable, multi-task, and data-efficient solutions.

5. Taxonomy of Deep Learning Techniques in Image Processing

The classification of deep learning techniques in image processing has transitioned from simple architectural groupings to a multi-dimensional taxonomy that considers the nature of information flow, the objective of the learning process, and the structural relationship between pixels [1], [21].

5.1 Spatial and Global Feature Extraction Techniques

This branch of the taxonomy distinguishes between models that prioritize local spatial hierarchies and those that prioritize long-range global dependencies.

5.1.1 Localized Convolutional Filtering:

The foundational technique of the CNN era, which utilizes sliding kernels to extract stationary features. While highly efficient for texture and edge detection, it suffers from a limited receptive field, requiring significant depth to "see" global relationships [19], [31].

5.1.2 Global Self-Attention and Patch Embedding:

The core of Vision Transformers (ViTs). This technique abandons the sliding window in favor of "Multi-Head Self-Attention" (MHSA), where every patch of an image is compared against every other patch. This allows for the capture of complex anatomical symmetries and distal relationships that are critical for accurate radiological diagnosis [3], [5], [18].

5.1.3 Shifted Windowing and Hierarchical Attention:

A hybrid technique introduced by the Swin Transformer to mitigate the quadratic computational cost of global attention. By restricting attention to non-overlapping windows that shift between layers, this technique allows for the processing of high-resolution 3D medical volumes while maintaining a global-like context [14], [21].

5.2 Generative and Denoising Paradigms

This category defines techniques that focus on the synthesis and reconstruction of images from degraded or noisy states.

5.2.1 Stochastic Reverse Diffusion:

Unlike deterministic auto encoders, this technique treats image reconstruction as a series of probability distributions. By learning to reverse a Gaussian noise process, the model can synthesize high-frequency clinical details with greater fidelity than previous adversarial methods [1], [8], [10].

5.2.2 Latent Space Manifold Learning:

A technique popularized by **Latent Diffusion Models (LDM)**. By performing the generative process within a compressed, low-dimensional latent space (encoded via a VAE), the model preserves the semantic resonance of the image while significantly reducing the GPU memory required for high-resolution 512x512 or 1024x1024 medical scans [2], [9], [25].

5.2.3 Conditioned Guidance and Inpainting:

Techniques that allow the user to "steer" the generative process using external priors, such as text prompts, masks, or low-resolution guides. This is vital for tasks like super-resolution or completing missing slices in sparse MRI datasets [7], [12], [27].

5.3 Representation and Self-Supervised Learning Techniques

This domain focuses on how models learn to "understand" medical anatomy without the need for massive, expert-annotated "gold standard" datasets.

5.3.1 Masked Image Modeling (MIM):

A technique where the model learns by reconstructing 75–90% of a hidden image. This forces the Transformer backbone to internalize the structural and spatial logic of human anatomy to effectively "guess" the missing information [16], [23].

5.3.2 Contrastive Learning and Alignment:

Techniques like CLIP (Contrastive Language-Image Pre-training) that align visual features with textual clinical embeddings. By maximizing the agreement between an image and its radiological report, the model learns a semantically rich representation that bridges the gap between pixels and diagnosis [13], [20], [22].

5.3.3 Zero-Shot Foundation Modeling:

The ultimate goal of current research, where large-scale volumetric pre-training allows a model to generalize to entirely new imaging modalities or pathologies without further fine-tuning, representing the pinnacle of robust medical AI [23], [24].

6. Advanced Deep Learning Model

6.1 Transformer-Based Foundation Models

Transformers have redefined the "Perception" stage of deep learning by replacing convolutional kernels with self-attention mechanisms.

6.1.1 Vision Transformers (ViT):

Unlike CNNs, which process images pixel-by-pixel in a local neighborhood, ViTs treat an image as a sequence of patches. By applying self-attention to these patches, the model captures global anatomical relationships that are critical for identifying distal symmetries in medical scans.

6.1.2 Swin Transformers (Shifted Windows):

To handle the high resolution of 3D medical volumes (like CT or MRI), Swin Transformers restrict attention to local windows that "shift" across layers. This achieves a balance between the global context of Transformers and the computational efficiency of CNNs.

6.1.3 Hybrid Models (e.g., TransUNet):

These models use a CNN "backbone" to extract fine-grained textures (like edges) and a Transformer "neck" to understand high-level semantic context, ensuring both localization and classification accuracy.

6.2 Generative Diffusion Models (DPM)

Diffusion models represent the state-of-the-art in "Reconstruction" and "Synthesis," currently outperforming GANs in stability and image fidelity.

6.2.1 The Denoising Process:

These models work by systematically destroying an image with Gaussian noise and then learning a reverse

stochastic process to recover the original signal. In medical imaging, this is used for denoising low-dose CT scans or reconstructing high-quality MRI from sparse data.

6.2.2 Latent Diffusion Models (LDM):

By performing the diffusion process in a compressed "Latent Space" (rather than the raw pixel space), these models can generate high-resolution images with significantly lower GPU memory requirements.

6.2.3 Diffusion Transformers (DiT):

A cutting-edge hybrid that replaces the standard U-Net in a diffusion model with a Transformer. This allows the generative process to be guided by the Transformer's global logic, resulting in more anatomically consistent reconstructions.

6.3 Multimodal & Self-Supervised Models

The focus of 2026 research is moving toward models that learn without explicit human labeling and can bridge different types of data.

6.3.1 Masked Autoencoders (MAE):

These models learn by reconstructing images where 75–90% of the patches are hidden. This forces the model to develop a deep "structural understanding" of anatomy to "guess" what is missing, which is highly effective for pre-training on unlabeled hospital archives.

6.3.2 Vision-Language Models (VLM):

Models like CLIP align medical images with their corresponding radiological reports. This allows for Automated Report Generation and "Zero-Shot" diagnosis, where the model can identify a pathology it wasn't explicitly trained to detect by using linguistic context.

6.3.3 Segment Anything Model (SAM) for Medical Imaging:

An adaptation of general-purpose foundation models that allows clinicians to segment any organ or tumor using simple "prompts" (like a point, box, or text description), drastically reducing the time spent on manual contouring.

7. Applications Of Advanced Deep Learning

7.1 High-Fidelity Image Reconstruction and Denoising

One of the most critical applications of **Diffusion Models** is the restoration of high-quality signals from corrupted or "low-dose" inputs.

- i. MRI/CT Reconstruction: By utilizing the iterative denoising process of Diffusion frameworks, models can reconstruct high-resolution MRI scans from sparse or undersampled data, significantly reducing the time patients must spend inside the scanner [8].
- ii. Artifact Removal: Advanced models are employed to remove metallic artifacts or motion blur, ensuring that the final output is suitable for diagnostic interpretation without the need for rescanning [7, 24].

7.2 Precision Medical Image Segmentation

Segmentation is the process of delineating organ or tumor boundaries, a task where **Transformer-based** models have set new benchmarks.

- 7.2.1 Tumor and Lesion Delineation: Models like TransUNet [15] and Swin-Unet leverage global self-attention to maintain the continuity of large structures while simultaneously identifying fine-grained tumor edges. This is vital for radiation therapy planning and surgical navigation [18].
- 7.2.2 Volumetric 3D Segmentation: Advanced 3D Transformers process entire volumetric stacks (CT/MRI) to segment complex branching structures like vascular networks or the nervous system with unprecedented spatial consistency [21, 23].

7.3 Synthetic Data Generation and Augmentation

Due to the scarcity of annotated medical data, generative models are used to synthesize realistic pathological samples.

7.3.1 Pathology Synthesis: Latent Diffusion Models (LDMs) [9] can generate highly realistic images of rare diseases, providing a "data bank" for training other diagnostic models. This reduces the "data hunger" of deep learning systems and addresses privacy concerns related to real patient data [25].

7.3.2 Cross-Modality Synthesis: Techniques are used to synthesize one imaging modality from another (e.g., generating a "pseudo-CT" from an MRI), allowing for multi-modal analysis even when one type of scan is missing [12, 26].

7.4 Automated Diagnostic Reporting and Multimodal Analysis.

The final stage of the pipeline involves the alignment of visual features with clinical knowledge.

7.4.1 Radiology Report Generation:

Multimodal Transformers [13] bridge the gap between pixels and language. By mapping visual tokens to medical terminology, these systems can automatically generate draft reports that describe findings, such as "suspicious mass in the upper outer quadrant," for clinician review [22].

7.4.2 Predictive Analytics:

Beyond simple identification, advanced models are used for "Radiomics," extracting quantitative features that can predict a patient's response to treatment or long-term prognosis based on subtle image patterns [30].

8. Challenges In Clinical Adoption

8.1 Complexity and Latency .

The primary bottleneck for Transformers is the quadratic complexity of self-attention ($O(n^2)$), where doubling image resolution quadruples memory consumption. For Diffusion Models, the challenge is the "Iterative Bottleneck"—the requirement of 50–1000 sampling steps to generate a high-quality image makes real-time clinical application (like live ultrasound guidance) difficult [12].

8.2 The "Black Box" and Hallucination Risk

Generative Diffusion models are prone to Pathological Hallucination, where the AI creates realistic-looking anatomical features that do not exist (e.g., adding or erasing a small tumor). In a medical context, this lacks the "Anatomical Truth" required for surgical planning. Transformers also struggle with interpretability, as it is often unclear *why* an attention head focused on a specific pixel [30].

8.3 Data Heterogeneity and Domain Shift

Models trained on high-end hospital datasets often fail when deployed in rural clinics with older hardware. This "Domain Shift" remains a challenge for both architectures, as Transformers can be overly sensitive to variations in image noise and contrast that differ from their training distribution [22].

9 Results

The results show that medical image processing models have improved significantly from Traditional CNNs to advanced Diffusion-Transformers. CNNs provide basic accuracy but are limited in capturing global features. Vision Transformers improve performance by understanding long-range relationships in images. Diffusion Models further enhance image quality through effective denoising and reconstruction. Among all, Diffusion-Transformers give the best results with the highest accuracy, better image quality, and strong generalization across different medical images. Overall, combining Transformer and Diffusion techniques provides the most efficient and reliable solution for modern medical imaging applications.

10 Conclusion

The evolution of medical image processing is currently defined by a synergistic convergence between global contextual reasoning and high-fidelity generative refinement. Traditional architectures, primarily centered on localized convolutional operations, often struggled with the "receptive field" bottleneck, where distal anatomical relationships were ignored in favor of immediate textural patterns. The introduction of Vision Transformers

(ViTs) fundamentally shifted this paradigm by utilizing self attention mechanisms to treat images as sequences of patches, thereby enabling the capture of long-range dependencies and global symmetries that are critical for accurate radiological diagnosis and surgical planning.

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