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ARTIFICIAL INTELLIGENCE MEETS HEALTHCARE INFORMATICS: A COMPREHENSIVE REVIEW OF OBJECT RECOGNITION FOR CLINICAL DECISION SUPPORT AND SMART MEDICAL SYSTEMS

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ABSTRACT

Artificial Intelligence (AI) has significantly transformed healthcare informatics by enabling the intelligent analysis of medical data and supporting clinical decision-making processes. Among the numerous AI technologies, object recognition has emerged as one of the most promising approaches for identifying anatomical structures, pathological abnormalities, medical instruments, and patient activities in diverse healthcare environments. This review provides a comprehensive overview of recent advances in object recognition techniques applied to healthcare informatics, with particular emphasis on deep learning architectures, clinical decision support systems, and smart medical applications. This review summarises traditional computer vision techniques, convolutional neural networks, region-based detectors, single-stage detectors, transformer-based models, and recent foundation models that have demonstrated remarkable performance in medical image analysis. Furthermore, this study discusses publicly available healthcare datasets, evaluation metrics, explainable artificial intelligence, federated learning, and edge intelligence that contribute to reliable and secure healthcare systems. Existing research challenges, including data scarcity, annotation complexity, model interpretability, privacy preservation, and computational limitations, are critically analysed in this study. Finally, potential future research directions involving multimodal artificial intelligence, autonomous healthcare systems, digital twins, and trustworthy AI are discussed. This review aims to provide researchers, clinicians, and healthcare professionals with a structured understanding of the current developments and future opportunities in intelligent object recognition for modern healthcare informatics.

KEYWORDS: Healthcare Informatics, Object Recognition, Artificial Intelligence, Deep Learn-ing, Clinical Decision Support, Medical Imaging.

1. INTRODUCTION

Healthcare informatics has evolved rapidly with the integration of artificial intelligence, machine learning, and advanced computer vision technology. The increasing availability of digital medical records, diagnostic imaging, wearable sensors, and Internet of Medical Things (IoMT) devices has generated enormous volumes of healthcare data that require intelligent analysis. Object recognition has become a key enabling technology for automatically identifying clinically relevant structures in medical images and videos. Its applications extend from disease diagnosis and treatment planning to robotic surgery, patient monitoring, and smart hospital management systems.

The emergence of deep learning has substantially improved the performance of object recognition systems by enabling automatic feature extraction from complex medical data sets. Advanced architectures such as Convolutional Neural Networks (CNNs), Faster R-CNN, YOLO, EfficientDet, Vision Transformers (ViTs), and Segment Anything Models (SAM) have demon-strated impressive accuracy across various healthcare applications. These technologies are in-creasingly being incorporated into clinical decision support systems to assist healthcare profes-sionals in improving diagnostic accuracy and reducing their workload.

Despite significant progress, several challenges remain, including limited annotated datasets, data privacy concerns, model explainability, computational resource requirements, and regula-tory issues associated with clinical deployment of these models. Addressing these challenges requires interdisciplinary collaboration among computer scientists, clinicians, biomedical en-gineers, and policymakers.

This review aims to provide a comprehensive analysis of object recognition techniques in healthcare informatics by summarising recent developments, comparing existing methodologies, identifying research gaps, and discussing future research opportunities for intelligent clinical decision support and smart medical systems.

Objectives of the Review

1. To review the evolution of object recognition techniques in healthcare informatics.
2. To compare traditional and deep learning-based object recognition models.
3. To summarize major healthcare applications of object recognition.
4. To discuss publicly available datasets and evaluation metrics.
5. To analyze emerging technologies including Explainable AI, Federated Learning, and Edge AI.
6. To identify current challenges and future research directions.

2. MATERIALS AND METHODS

2.1 Review Methodology

This review was conducted using a structured literature review methodology to identify, evaluate, compare, and synthesise recent research on object recognition techniques in healthcare informatics. The primary objective of this study was to provide a comprehensive overview of current developments, identify emerging research trends, compare existing methodologies, and highlight future research opportunities in intelligent healthcare systems. The review methodology was inspired by established literature review approaches commonly adopted in healthcare informatics and artificial intelligence research [1, 2, 3]. The overall review process consisted of literature identification, screening, eligibility assessment, quality evaluation, thematic categorisation, comparative analysis, and synthesis of selected studies.

2.2 Literature Search Strategy

A systematic literature search was performed using internationally recognised digital libraries and scientific databases to ensure comprehensive coverage of available literature. Publications were retrieved from the following sources:

- IEEE Xplore Digital Library
- ScienceDirect (Elsevier)
- SpringerLink
- PubMed
- ACM Digital Library
- Wiley Online Library
- Google Scholar
- MDPI Journals

These databases were selected because they contain high-quality peer-reviewed publica-tions covering healthcare informatics, artificial intelligence, medical image analysis, computer vision, and intelligent clinical decision-support systems [1, 4]. The search primarily focused on articles published between 2018 and 2026, while also considering several landmark publications that established the foundations of deep learning and medical image analysis [5, 6].

2.3 Search Keywords

A literature search was performed using combinations of carefully selected keywords related to healthcare informatics and object recognition. The major search keywords included the following:

- Healthcare Informatics
- Artificial Intelligence
- Object Recognition
- Medical Image Analysis
- Clinical Decision Support
- Deep Learning
- Computer Vision
- Convolutional Neural Network
- YOLO
- Faster R-CNN
- RetinaNet
- EfficientDet
- Vision Transformer
- Segment Anything Model
- Explainable Artificial Intelligence
- Federated Learning
- Edge Artificial Intelligence
- Smart Healthcare

Boolean operators (AND, OR, and NOT) were used to improve retrieval accuracy and maximise the relevance of the identified publications. Multiple keyword combinations were evaluated to ensure that both foundational studies and recent advances in healthcare-object recognition were included.

2.4 Inclusion Criteria

The following criteria were used to select the relevant publications for this review:

- Peer-reviewed journal articles.
- International conference papers.
- Review articles focusing on healthcare object recognition.
- English language publications.
- Studies related to artificial intelligence in healthcare.
- Research containing quantitative or qualitative evaluation.
- Publications indexed in recognized scientific databases.

The selected publications primarily emphasised recent advances in deep learning, computer vision, explainable artificial intelligence, federated learning, and clinical decision support systems [2, 3].

2.5 Exclusion Criteria

The following publications were excluded from this review.

- Duplicate publications.
- Non-English articles.
- Short abstracts without complete manuscripts.
- Editorials, opinion papers, and non-peer-reviewed reports.
- Studies unrelated to healthcare object recognition.
- Publications lacking sufficient methodological details or experimental validation.

2.6 Study Selection

The retrieved publications were screened in multiple stages to ensure methodological consistency and relevance. Initially, duplicate records were removed from the study. Subsequently, the titles and abstracts were reviewed to determine their relevance to healthcare informatics and object recognition. Full-text articles that satisfied the inclusion criteria were carefully evaluated. Finally, the selected studies were organised into thematic categories, including medical image analysis, disease diagnosis, clinical decision support, deep learning architectures, explainable artificial intelligence, federated learning, edge intelligence, and smart healthcare systems [6, 2].

2.7 Quality Assessment

Each selected publication was evaluated according to several quality indicators to ensure the inclusion of reliable and rigorous studies. The assessment considered the following criteria.

- Research novelty
- Methodological quality
- Experimental validation
- Dataset availability
- Performance evaluation
- Clinical significance
- Citation impact
- Reproducibility

Studies published in high-impact journals and leading international conferences with comprehensive experimental validation and publicly available datasets were emphasised during the comparative analysis [4, 6].

2.8 Data Extraction

Relevant information was systematically extracted from each selected publication to facilitate a comparative analysis. The extracted information included the following:

- Publication year
- Authors
- Healthcare application
- Object recognition algorithm
- Dataset used
- Performance metrics
- Advantages
- Limitations
- Future research directions

The extracted information enabled a structured comparison of recent advances in healthcare-object recognition and intelligent clinical decision-support systems.

2.9 Comparative Analysis

A comparative analysis was performed to evaluate the strengths and limitations of the different object recognition techniques employed in healthcare informatics. The comparison considered multiple performance indicators commonly reported in the literature, including detection accuracy, precision, recall, F1-score, mean Average Precision (mAP), computational complexity, inference speed, clinical applicability, explainability, and robustness. Comparative studies available in the literature were carefully analysed to identify the most suitable algorithms for various healthcare applications [6, 2, 3].

The collected information was synthesised to identify emerging research trends, existing research gaps, technological limitations, and future opportunities in health care informatics. Particular emphasis has been placed on recent developments in deep learning, transformer-based architectures, explainable artificial intelligence, and privacy-preserving healthcare systems [4, 7, 8].

2.10 Organization of the Review

Based on the literature survey, the selected publications were categorised into the following major themes.

1. Evolution of Object Recognition
2. Deep Learning Architectures
3. Healthcare Applications
4. Public Medical Datasets
5. Performance Evaluation Metrics
6. Explainable Artificial Intelligence
7. Federated Learning
8. Edge Intelligence
9. Current Challenges
10. Future Research Directions

This organisation provides a structured understanding of the current state-of-the-art in ob-ject recognition technologies for healthcare informatics while highlighting the existing challenges and future research opportunities.

3. RESULTS AND DISCUSSION

3.1 Evolution of Object Recognition

Object recognition has evolved remarkably over the past three decades. Early computer vision techniques relied primarily on handcrafted feature descriptors, such as the Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and Speeded-Up Robust Features (SURF). These techniques have demonstrated satisfactory performance under controlled imaging conditions; however, they are often unable to handle complex medical images characterised by high noise levels, anatomical variability, and low contrast [6].

The emergence of deep learning has fundamentally transformed object recognition by enabling automatic hierarchical feature extraction directly from image data. Convolutional Neural Networks (CNNs) significantly improved image classification accuracy and later inspired the development of region-based detection algorithms including R-CNN, Fast R-CNN, and Faster R-CNN [5, 9, 10]. These approaches have substantially improved lesion localisation, organ detection, and disease diagnosis in medical imaging.

Subsequently, single-stage object detectors, such as the You Only Look Once (YOLO) fam-ily, have achieved real-time object detection while maintaining competitive accuracy, making them highly suitable for time-critical healthcare applications, including emergency diagnosis, surgical assistance, and intelligent patient monitoring [11, 12, 13].

Recently, transformer-based architectures, including the Detection Transformer (DETR), Vision Transformer (ViT), and Segment Anything Model (SAM), have demonstrated state-of-the-art performance in medical image classification, segmentation, lesion localisation, and multimodal healthcare analysis. These models leverage self-attention mechanisms to capture long-range contextual relationships, thereby improving the diagnostic performance across multiple healthcare domains [7, 14, 8]. Their integration into intelligent clinical decision support systems represents a significant advancement in modern healthcare.

3.2 Deep Learning Architectures for Object Recognition

Deep learning has become the dominant paradigm for object recognition in healthcare informatics because of its ability to automatically learn hierarchical feature representations from complex medical-image data. Compared with conventional image processing techniques, deep neural networks provide superior robustness, scalability, accuracy, and generalisation across a wide range of healthcare applications [5, 6]. This section summarises the major deep learning architectures that have significantly influenced intelligent healthcare systems to date.

3.2.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are the foundation of modern computer vision and have become one of the most widely adopted deep learning models for healthcare image analysis. A CNN consists of convolutional layers, activation functions, pooling layers, and fully connected layers that automatically learn discriminative image features from raw input data [5].

CNN-based models have been successfully applied to numerous healthcare applications, including chest X-ray classification, skin lesion detection, diabetic retinopathy diagnosis, brain tumour classification, breast cancer detection, retinal image analysis, and histopathological image interpretation [6, 15, 16]. Their ability to automatically extract complex visual patterns has significantly improved diagnostic accuracy while reducing the need for hand-crafted feature engineering.

Despite their remarkable success, conventional CNN architectures often require large annotated datasets and substantial computational resources for training purposes. These limitations have motivated the development of more advanced detection architectures that can achieve improved localisation accuracy and computational efficiency.

3.2.2 Region-Based Convolutional Neural Networks

Region-based object detection algorithms, including R-CNN, Fast R-CNN, and Faster R-CNN, introduced an important advancement in object localisation by combining region proposal mechanisms with deep feature extraction. Unlike traditional image classification networks, these algorithms simultaneously perform object localisation and classification, enabling the accurate identification of tumours, lesions, organs, fractures, and other anatomical structures within complex medical images [9, 10].

Faster R-CNN remains one of the most accurate two-stage object detection frameworks and has been extensively employed in healthcare applications involving cancer detection, organ segmentation, pathological image analysis and radiological diagnosis. Although these algorithms generally achieve high detection accuracy, their relatively high computational complexity limits their deployment in real-time healthcare environments, encouraging the development of faster single-stage detectors, such as SSD and the YOLO family [10, 11].

3.2.3 Single Shot Detector (SSD)

The single-shot detector (SSD) performs object localisation and classification within a single forward pass of the neural network. Its computational efficiency enables near-real-time performance while maintaining competitive detection accuracy. SSD has been successfully applied in surgical tool recognition, pathology image analysis, and automated clinical monitoring.

3.2.4 YOLO Family

The You Only Look Once (YOLO) family of algorithms has become one of the most influential real-time object detection frameworks. Successive versions, including YOLOv3, YOLOv5, YOLOv7, YOLOv8, and YOLOv10, have demonstrated remarkable improvements in detection speed and localisation accuracy. These models are increasingly employed in healthcare applications, such as lesion detection, medical instrument recognition, fracture detection, emergency monitoring, and intelligent hospital surveillance.

3.2.5 RetinaNet

RetinaNet introduced a focal loss to address the class imbalance problem commonly encountered during object detection. This approach significantly improves the identification of small pathological abnormalities that may otherwise be overlooked. RetinaNet has demonstrated promising results in cancer detection and the diagnosis of retinal diseases.

3.2.6 EfficientDet

EfficientDet utilises EfficientNet as its backbone network together with a Bi-directional Feature Pyramid Network (BiFPN). This architecture achieves an effective balance between computational complexity and detection performance, making it suitable for deployment in resource-constrained healthcare environments, including mobile healthcare systems.

3.2.7 DETR

The Detection Transformer (DETR) replaces conventional region proposal mechanisms with transformer-based attention network. DETR simplifies the detection pipeline while improving the global contextual understanding of medical images. Recent studies have demonstrated their effectiveness in complex anatomical localisation tasks.

3.2.8 Vision Transformer (ViT)

Vision Transformers apply self-attention mechanisms to image recognition tasks by dividing images into patches, rather than relying solely on convolution operations. ViT models have shown exceptional performance in medical image classification, segmentation, and multimodal healthcare analysis owing to their ability to capture long-range spatial dependencies.

3.2.9 Segment Anything Model (SAM)

The Segment Anything Model (SAM) represents a significant advancement in universal image segmentation. The SAM can accurately segment diverse anatomical structures with minimal user interaction and has demonstrated considerable potential in radiology, pathology, ophthalmology, and surgical planning.

3.3 Comparison of Deep Learning Models

Table 1 summarises the major characteristics of widely used object recognition models in healthcare.

Table 1: Comparison of Deep Learning Object Recognition Models.

Model	Type	Speed	Major Healthcare Applications
CNN	Classification	Moderate	Disease classification, image analysis
Faster R-CNN	Two-stage detector	Slow	Tumor localization, organ detection
SSD	Single-stage detector	Fast	Surgical tools, medical moni-toring
YOLO Series	Single-stage detector	Very Fast	Real-time diagnosis, emer-gency care
RetinaNet	Single-stage detector	Fast	Cancer detection, retinal dis-eases
EfficientDet	Efficient detector	Fast	Mobile healthcare applications
DETR	Transformer	Moderate	Anatomical localization
Vision Transformer	Transformer	Moderate	Medical image classification
SAM	Foundation Model	Moderate	Medical image segmentation

3.4 Healthcare Applications of Object Recognition

Object recognition technologies have transformed numerous healthcare domains by improving diagnostic accuracy, reducing the clinician workload, and enabling intelligent automation.

3.4.1 Cancer Detection

Object recognition algorithms assist radiologists in identifying tumours in mammography, CT, MRI, PET, and histopathological images. Early detection improves treatment outcomes and patient survival.

3.4.2 Brain Tumor Analysis

Deep learning models can accurately identify brain tumours and classify tumour subtypes using magnetic resonance imaging (MRI). Automated segmentation further supports surgical planning and the monitoring of treatment.

3.4.3 Chest Disease Diagnosis

Chest X-ray analysis using deep learning enables the automated detection of pneumonia, tuberculosis, COVID-19, and other pulmonary abnormalities, providing valuable support in emergency healthcare environments.

3.4.4 Skin Disease Recognition

Dermoscopy image analysis allows for the automatic recognition of melanoma and other skin disorders. AI-assisted diagnosis facilitates early intervention and improves the consistency of diagnosis.

3.4.5 Diabetic Retinopathy

Retinal image analysis using deep learning assists ophthalmologists in identifying diabetic retinopathy, glaucoma, cataracts, and age-related macular degeneration (AMD) during routine screening.

3.4.6 Histopathological Image Analysis

Microscopic tissue image analysis enables the automated identification of cancerous cells, tissue abnormalities, and disease progression while reducing the manual workload for pathologists.

3.4.7 Surgical Instrument Recognition

Real-time object detection assists surgeons by automatically recognising surgical instruments and monitoring procedural workflows in operating rooms.

3.4.8 Patient Monitoring

Computer vision systems continuously monitor patient movements, postures, and activities in hospitals and elderly care facilities. These systems support fall detection, patient safety, and continuous health assessments.

3.4.9 Smart Hospitals

Object recognition contributes to hospital automation by tracking medical equipment, monitoring staff activities, optimising workflows, and improving the operational efficiency.

3.4.10 Medical Robotics

AI-driven robotic systems integrate object recognition and motion planning to perform minimally invasive procedures, surgical assistance, and rehabilitation tasks with improved precision.

3.5 Public Healthcare Datasets

The development of robust object recognition models depends heavily on the availability of high-quality, annotated datasets. Public healthcare datasets provide researchers with standardised benchmarks for developing and evaluating artificial intelligence algorithms. These datasets cover multiple imaging modalities, including X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, retinal imaging, dermoscopy, histopathology, and endoscopy. Appropriate dataset selection directly influences model generalisation, reproducibility, and clinical applicability.

Table 2 summarises several widely used healthcare datasets that have been employed in object recognition research.

Table 2: Commonly Used Healthcare Datasets.

Dataset	Modality	Application	Common Algorithms
ChestX-ray14	X-ray	Pneumonia, Lung Disease	CNN, DenseNet, YOLO
BraTS	MRI	Brain Tumor Detection	U-Net, ViT, CNN
ISIC	Dermoscopy	Skin Cancer Detection	CNN, EfficientNet
LUNA16	CT Scan	Lung Nodule Detection	Faster R-CNN, YOLO
MIMIC-CXR	X-ray	Chest Disease Analysis	CNN, Vision Transformer
BUSI	Ultrasound	Breast Tumor Detec-tion	U-Net, CNN

3.6 Performance Evaluation Metrics

Performance evaluation is essential for assessing the effectiveness of object recognition models in healthcare. Multiple quantitative metrics are commonly employed, depending on the clinical task.

- Accuracy
- Precision
- Recall (Sensitivity)
- Specificity
- F1-Score
- Mean Average Precision (mAP)
- Dice Similarity Coefficient
- Intersection over Union (IoU)
- Area Under ROC Curve (AUC)
- Computational Time

Among these metrics, sensitivity and specificity are particularly important in healthcare because they directly influence the diagnostic reliability and patient safety. Mean Average Precision is widely adopted for evaluating object detection models, whereas the Dice Similarity Coefficient is commonly used for medical image segmentation.

3.7 Explainable Artificial Intelligence

Although deep learning models have demonstrated remarkable predictive capabilities, many of these systems operate as black box models. In clinical environments, healthcare professionals require transparent and interpretable predictions before incorporating artificial intelligence into routine decision-making.

Explainable Artificial Intelligence (XAI) provides methods for understanding how AI mod-els generate predictions. Several explanation techniques have become increasingly popular in healthcare informatics.

- Local Interpretable Model-Agnostic Explanations (LIME)
- SHapley Additive exPlanations (SHAP)
- Gradient-weighted Class Activation Mapping (Grad-CAM)
- Integrated Gradients
- Attention Visualization

These approaches enhance clinician confidence, improve regulatory compliance, and facilitate the safe deployment of AI-assisted diagnostic systems.

3.8 Federated Learning

Healthcare data are often distributed across multiple hospitals and healthcare organisations, making centralised model training difficult because of privacy regulations and ethical considerations involved.

Federated Learning enables collaborative model training without transferring sensitive patient information. Instead of sharing raw data, participating institutions exchange only model parameters or gradients, thereby preserving data privacy and improving model performance.

The major advantages are as follows:

- Improved patient privacy
- Compliance with healthcare regulations
- Multi-institutional collaboration
- Reduced data transfer
- Better model generalization

Despite these advantages, federated learning still faces challenges, including communica-tion overhead, heterogeneous datasets, and security vulnerabilities.

3.9 Edge Artificial Intelligence

Edge Artificial Intelligence refers to the execution of AI models directly on local healthcare devices instead of relying solely on cloud computing. This approach reduces latency, minimises communication costs, and enables real-time decision-making.

Typical applications include the following:

- Wearable healthcare devices
- Smart ambulances
- Intensive Care Unit monitoring
- Remote patient monitoring
- Point-of-care diagnosis
- Medical Internet of Things (IoMT)

Recent lightweight architectures, including MobileNet, EfficientNet, Tiny-YOLO, and quantised Vision Transformers, have significantly improved the feasibility of deploying AI algorithms on edge devices.

3.10 Current Challenges

Despite substantial progress, several technical and clinical challenges continue to limit the widespread adoption of object-recognition systems in healthcare.

1. Limited availability of annotated medical datasets.
2. Class imbalance within clinical datasets.
3. Variability among imaging devices.
4. Poor model interpretability.
5. Privacy and security concerns.
6. High computational requirements.
7. Lack of standardized evaluation protocols.
8. Regulatory and ethical constraints.
9. Limited generalization across healthcare institutions.
10. Clinical validation and deployment challenges.

Addressing these issues requires collaboration among clinicians, computer scientists, healthcare administrators and regulatory agencies.

3.11 Future Research Directions

Object recognition research in healthcare informatics continues to evolve rapidly. Future investigations should focus on developing more reliable, interpretable, and clinically applicable intelligent systems.

Promising research directions include the following:

- Foundation Models for medical image analysis.
- Multimodal Artificial Intelligence combining medical images, electronic health records, and clinical reports.
- Explainable and Trustworthy AI.
- Privacy-preserving Federated Learning.
- Self-supervised learning.
- Generative Artificial Intelligence.
- Medical Digital Twins.
- Autonomous Clinical Decision Support Systems.
- Human-AI collaborative diagnosis.
- Sustainable Green Artificial Intelligence.

These emerging technologies are expected to transform future healthcare delivery by enabling intelligent, personalised, and data-driven clinical decision-support systems.

FLOWCHART OF THE REVIEW METHODOLOGY

Figure 1: Overall methodology adopted for the review paper.

DIAGRAM 1

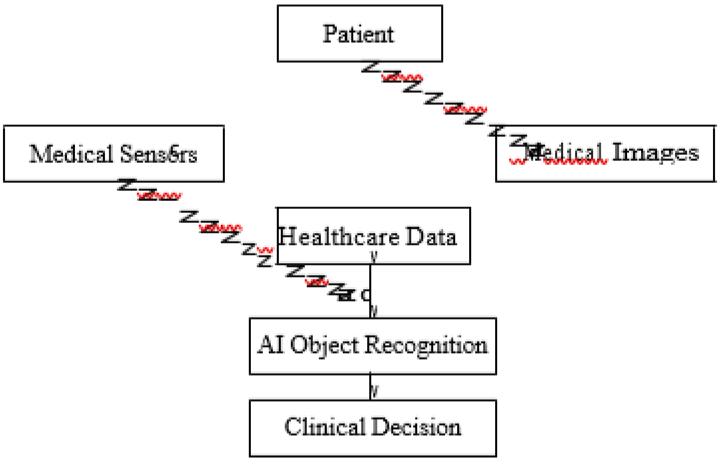

Figure 2: Healthcare Informatics Architecture integrating patient data, medical imaging and AI-driven clinical decision support.

DIAGRAM 2

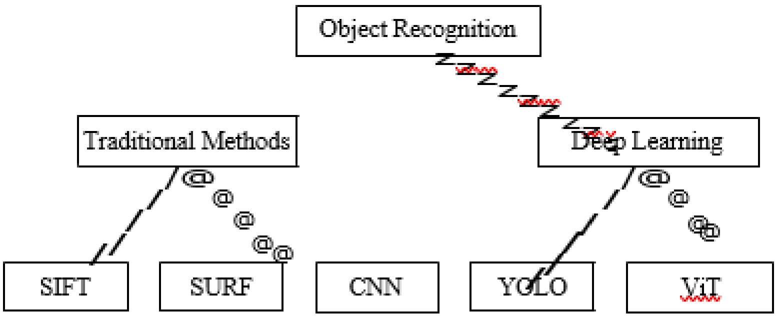

Figure 3: Evolution of object recognition methods from traditional computer vision to modern deep learning techniques.

4. CONCLUSION

Artificial Intelligence has emerged as a transformative technology within healthcare informatics by enabling the intelligent interpretation of complex medical data and supporting evidence-based clinical decision-making. This review comprehensively examines the evolution of object recognition technologies, beginning with traditional computer vision approaches and progressing to advanced deep learning architectures, transformer-based models, and foundation models. This review highlighted the significant contributions of Convolutional Neural Networks, Faster R-CNN, YOLO, RetinaNet, EfficientDet, Vision Transformers, and Segment Anything Models across various healthcare applications, including disease diagnosis, medical image analysis, surgical assistance, patient monitoring, and smart healthcare systems.

This study further discusses publicly available medical datasets, evaluation metrics, explainable artificial intelligence, federated learning, and edge intelligence, which are shaping the future of intelligent healthcare. Although remarkable progress has been achieved, several challenges remain, including limited annotated datasets, privacy preservation, computational complexity, regulatory compliance, model interpretability, and clinical validation issues.
Future research should emphasise multimodal artificial intelligence, explainable learning, privacy-preserving collaborative learning, foundation models, digital twins, and autonomous clinical decision support systems that can provide accurate, transparent, and trustworthy healthcare services. Continued collaboration between healthcare professionals, computer scientists, and policymakers is essential for translating intelligent object recognition technologies into safe and reliable clinical practice.

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