Artificial Intelligence in Free Flap Monitoring: A Systematic Review and Meta-Analysis

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Abstract: *Background: Postoperative free flap monitoring is critical for early detection of vascular compromise and successful flap salvage. Artificial intelligence (AI)–based monitoring systems have recently emerged as potential adjuncts to conventional clinical assessment. Methods: A systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. PubMed/MEDLINE, Scopus, and Google Scholar were searched for studies evaluating AI-based postoperative free flap monitoring. Original clinical studies involving human subjects were included. Extracted data included study characteristics, AI model type, input modality, monitoring outcomes, and reported diagnostic performance metrics. Due to heterogeneity in study design and outcome reporting, narrative synthesis was performed, with limited quantitative analysis of reported accuracy and area under the curve (AUC). Results: Eight studies met the inclusion criteria. AI models primarily employed deep learning and machine learning techniques applied to clinical photographs or hyperspectral imaging. Reported diagnostic accuracy ranged from 95.3% to 98.7%, with AUC values between 0.96 and 0.99. Sensitivity and specificity were inconsistently reported across studies. Overall, AI-based systems demonstrated earlier and more reliable detection of flap perfusion compromise compared with conventional clinical monitoring. Conclusion: AI-based free flap monitoring demonstrates high diagnostic performance and promising clinical utility. However, heterogeneity in study methodology and outcome reporting limits formal meta-analysis. Standardized reporting and multicentre prospective validation studies are required before widespread clinical adoption.*

Keywords: Artificial Intelligence, Free Flap, Microsurgery, Post-Operative Monitoring, Machine Learning

1. Introduction

Postoperative monitoring of free flaps is a cornerstone of microsurgical reconstruction, as early detection of vascular compromise is essential for flap salvage. Conventional monitoring relies on serial clinical examination, including assessment of colour, capillary refill, temperature, and bleeding characteristics, which is subjective and dependent on clinical expertise. Recent advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have enabled automated analysis of complex visual and physiological data. AI-based systems have been proposed as adjunctive tools for free flap monitoring, aiming to improve diagnostic accuracy, reduce interobserver variability, and facilitate early detection of perfusion abnormalities.

This systematic review aims to synthesize current evidence on AI-based postoperative free flap monitoring, evaluate reported diagnostic performance, and assess the feasibility of quantitative meta-analysis.

2. Methods

Study Design
This study was conducted as a systematic review with a limited meta-analysis in accordance with the PRISMA 2020 guidelines.

Literature Search Strategy
A comprehensive literature search was performed in PubMed/MEDLINE, Scopus, and Google Scholar from database inception to the most recent search. Search terms included combinations of "artificial intelligence," "machine learning," "deep learning," "free flap," "microsurgery," and "monitoring." Reference lists of relevant articles were manually screened for additional eligible studies.

Eligibility Criteria

Inclusion criteria:
- Original clinical or diagnostic studies
- Human subjects
- AI/ML-based systems applied to postoperative free flap monitoring
- Reported clinical or diagnostic outcomes

Exclusion criteria:
- Review articles, editorials, and opinion pieces
- Animal or simulation-only studies
- AI models not applied to flap monitoring
- Studies without clinically relevant outcomes

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Study Selection
Titles and abstracts were screened, followed by full-text review of potentially eligible studies. Disagreements were resolved by consensus.

Data Extraction
Data were extracted using a standardized form, including:
- Author, year, and country
- Study design and sample size
- Type of free flap and anatomical site
- AI model and input modality
- Monitoring outcome
- Diagnostic performance metrics (accuracy, AUC, sensitivity, specificity, where reported)

When sensitivity or specificity were not explicitly reported, these values were recorded as not reported.

Quality Assessment
Risk of bias and applicability concerns were assessed using the QUADAS-2 tool.

Data Synthesis
Due to heterogeneity in AI models, input modalities, and outcome reporting, narrative synthesis was performed. Limited quantitative analysis was conducted for studies reporting comparable accuracy or AUC values.

3. Results

Study Selection and Characteristics
Eight studies met the inclusion criteria. Seven were original clinical studies, and one was a narrative review included for contextual discussion. Studies were published between 2023 and 2024 and conducted primarily in East Asia. Sample sizes ranged from 122 to 305 patients, with image datasets comprising up to 11,112 clinical photographs. Flap types included head and neck, intraoral, and extraoral free flaps.

AI Model Performance
Most studies employed deep learning architectures, including convolutional neural networks, while others utilized supervised machine learning classifiers. Input modalities included smartphone-based clinical photographs, intraoral images, and hyperspectral imaging.

Reported diagnostic performance was consistently high. Accuracy ranged from 95.3% to 98.7%, and AUC values ranged from 0.96 to 0.99. Sensitivity and specificity were inconsistently reported, limiting formal pooled diagnostic accuracy analysis.

Narrative Synthesis
AI-based systems demonstrated reliable detection of vascular compromise and, in several studies, outperformed conventional clinical monitoring. Smartphone-based AI applications showed particular promise due to accessibility and ease of integration into clinical workflows. Hyperspectral imaging and ordinal classification models showed potential but lacked sufficient quantitative data for meta-analysis.

Table 1: Summary of Included Studies

Study	AI Model	Input Modality	Sample Size	Key Performance Metric
Kim et al., 2024	DenseNet + FS-Net	Smartphone images	305 patients	AUC 0.96
Hsu et al., 2023	Deep learning iOS application	Smartphone images	122 patients	Accuracy 95.3%
Huang et al., 2023	Random forest classifier	Images + clinical data	805 flaps	Accuracy 98.4%
Kim H et al., 2024	Balanced deep learning model	Intraoral images	131 patients	Accuracy 98.7%
Hyperspectral imaging study	Machine learning	Hyperspectral imaging	Not reported	Narrative synthesis
Flap takeback prediction model	Machine learning	Clinical data	Not reported	Narrative synthesis

4. Discussion

Artificial intelligence–based postoperative free flap monitoring has demonstrated consistently high diagnostic performance across recent clinical studies. Most included investigations reported accuracy exceeding 95% and area under the curve values approaching or exceeding 0.96, suggesting strong discriminative capability in detecting early flap perfusion compromise. These findings indicate that AI systems may function as reliable adjuncts to conventional clinical assessment in microsurgical reconstruction.

A major advantage of AI-driven monitoring lies in its ability to objectively analyse subtle visual and perfusion-related changes that may not be readily detected by routine bedside examination.

Smartphone-based deep learning applications, in particular, offer a cost-effective and scalable solution, enabling frequent monitoring without the need for specialized equipment. Such systems may reduce interobserver variability and facilitate earlier recognition of venous congestion or arterial insufficiency, potentially improving flap salvage outcomes.

However, several limitations warrant consideration. Significant heterogeneity was observed among studies regarding AI model architecture, input modalities, outcome definitions, and reported diagnostic metrics. Sensitivity and specificity were inconsistently reported, precluding robust pooled diagnostic accuracy meta-analysis. Furthermore, most studies were retrospective and single-centre in nature, raising concerns regarding external validity and the risk of algorithm overfitting.

Another important limitation relates to clinical integration. While diagnostic performance was high, few studies assessed the impact of AI-assisted monitoring on clinical decision-making, time to re-exploration, or overall flap survival rates. Ethical considerations, data security, and the requirement for clinician oversight also remain important barriers to widespread implementation.

Future research should emphasize prospective, multicentre validation studies with standardized reporting of diagnostic metrics. Evaluation of clinical outcomes, workflow integration, and cost-effectiveness will be essential before routine adoption of AI-based free flap monitoring can be recommended.

5. Conclusion

Artificial intelligence–based postoperative free flap monitoring demonstrates high diagnostic accuracy and promising clinical utility as an adjunct to conventional monitoring methods. Despite encouraging results, heterogeneity in study design and reporting limits definitive conclusions.

Standardized methodologies, external validation, and prospective clinical trials are required to establish the role of AI in routine microsurgical practice.

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