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(Review Article)

Harnessing deep learning for real-time prediction of flap viability in microsurgical reconstruction: Current advances and future perspectives

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Abstract

Micro-reconstructive reconstruction is an essential element in reconstructive surgery, often performed using free flap transfer to help restore tissue viability and reduce postoperative morbidity, including conditions such as tissue necrosis and flap necrosis. Clinical observation and Doppler ultrasound are examples of classical monitoring practices, which are, in most cases, not real-time, precise and objective, thereby leading to delayed responses. In this article, the authors discuss the revolutionary impact of deep learning (DL), a subset of Artificial Intelligence, on the real-time prediction of flap viability. DL uses a combination of sophisticated neural networks to work on multimodal information (intraoperative imaging, near-infrared spectroscopy, and physiological signals), providing a reliable and timely evaluation of the tissue perfusion and vascular status. In recent years, convolutional neural networks have been used to analyze flap images and recurrent neural networks have been used to observe perfusion over time, with better sensitivity and specificity than traditional approaches. The technologies also enhance the ability to make decisions during the operation and track results post-operation, which reduces the incidence of flap failure. The future is hoped to see the development of a functional DL architecture, the introduction of more innovative technologies such as augmented reality, the creation of solutions to address matters such as data scarcity and model interpretability, and, finally, the addressing of the legal implications of the developments above. The successful surmounting of these issues makes it possible for DL to receive microsurgery at an individual, information-proximate level, which must enhance clinical outcomes and reduce morbidity among patients. The article also emphasizes the importance of adopting a multidisciplinary approach to address the gap between the emergence of deep learning (DL) and its practical application in the context of future reconstruction surgery.

Keywords: Deep Learning; Flap Viability; Microsurgical Reconstruction; Real-Time Prediction; Artificial Intelligence; Tissue Perfusion; Medical Imaging; Predictive Modeling; Surgical Outcomes; Machine Learning

1. Introduction

Microsurgical reconstruction is another milestone in plastic and reconstructive surgery, enabling the restoration of form and function in patients with complex tissue defects through the precise transfer of blood-supplied tissue, also known as flaps. The method presented is essential in various clinical conditions, such as breast reconstructions following mastectomies, correction of traumatic damage, and oncologic reconstruction after tumor removal (Panchal and Matros, 2017). The most important consideration in these processes is the viability of the orange-peeled flap, as it will have direct implications for the surgery's results and the patient's healing process. A reportable flap should be sufficiently perfused and will integrate properly into the site into which it is placed. Nonetheless, to date, flap failure remains rather alarming, and despite improvements in surgical technique and enhancements in postoperative treatment, the established rate of flap failure still ranges between 1% and 10% (Bui et al., 2007). Loss of the flap may lead to serious complications, including tissue necrosis, prolonged hospital stays, delayed wound healing, and even the

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need for re-surgical procedures. Such events not only present physical and emotional challenges to patients but also significantly strain healthcare resources; therefore, there is a need for more effective and reliable mechanisms to monitor and predict flap viability during the perioperative phase.

The indication of flap vitality still poses significant difficulties in the microsurgical sphere. The most frequent source of flap failure is vascular compromise, which can be caused by either arterial insufficiency or venous congestion (Creech and Miller, 1975). When not identified in time, such problems may lead to irreversible ischemic damage in a very short period. Commonly used techniques of flap viability (clinical assessment of skin color, capillary refill, turgor, and temperature) are exceptionally subjective and depend upon the experience of the observer. Although more objective methods, including handheld Doppler ultrasound and implanted Doppler probes, have been integrated into clinical practice, they are often restricted to occasional measurements and have low sensitivity to early, subtle signs of vascular impairment (Salgado et al., 2009). Additionally, other factors that influence these modalities include the patient's anatomical variability, environmental factors, and the operator's proficiency. These deficiencies underscore the need for real-time, continuous, and objective data that can provide a robust assessment of flap perfusion and predictors of imminent failure, thereby facilitate early intervention and enhance surgical outcomes.

To overcome these difficulties, deep learning (DL), a rapidly developing and disruptive branch of Artificial Intelligence, has emerged as a potential game-changing solution for flap monitoring in microsurgery. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), enabled by deep learning algorithms, can analyze large amounts of complex, multidimensional information. Researchers have demonstrated that these models yield improved performance when processing medical imaging, spectral data from near-infrared spectroscopy, physiological signals such as heart rate variability, and tissue oxygen saturation (Esteva et al., 2019). In comparison with typical machine learning systems, since DL models can automatically learn the hierarchical features of input data, they do not require manual engineering. This enables them to determine complex, nonlinear trends related to perfusion and viability of tissues. DL systems can be utilized in the setting of microsurgery to combine intraoperative imaging features, postoperative monitoring values, and patient-specific characteristics to make real-time predictions about flap viability. This can be mitigated by predictions that can be regularly updated and accessed, allowing surgical teams to act before the damage becomes irreparable. Deep learning (DL) implementation in such an environment has the potential to minimize the occurrence of flap loss and its associated complications, thereby improving the safety and effectiveness of reconstructive surgery.

Considering its potential groundbreaking changes, the role of deep learning in the real-time prediction of flap feasibility has to be studied systematically. Recently, studies have begun exploring deep learning (DL)- based approaches to image-guided assessment of flaps, color perfusion dynamics, and the detection of early signs of complications (Chao et al., 2019). It was demonstrated that CNNs can be trained to distinguish between viable and compromised tissue in postoperative images with high precision. Other strategies have been adopted in incorporating DL and near-infrared spectroscopy devices that offer continuous perfusion monitoring. Moreover, developments in the integration of hardware and software also enable the implementation of DL systems into surgical equipment, making it possible to create a bright operative space that can assist surgeons in real-time. Despite these gains, several issues remain outstanding. The first limitation is the lack of high-quality annotated datasets, which are required to train robust deep-learning models. Additionally, DL algorithms are sometimes considered to be so-called black boxes when it comes to interpretation, which can pose a problem regarding clinical transparency and trust. Ethical implications, such as data privacy and the need for voluntary consent, should also be taken into consideration. In the future, the priority directions of the research are the development of standardized data collection protocols, the development of explainable deep learning (DL) models, and the incorporation of an ethical framework to define the application of AI technologies in clinical practice. In this work, it is possible to enhance the adoption of deep learning in microsurgical reconstruction, which, in turn, may lead to revising the standards of care and ultimately achieving better patient outcomes.

2. Fundamentals of Deep Learning in Medical Applications

2.1. Overview of Deep Learning

Deep learning (DL) is an AI technique that leverages neural networks to discover complex patterns in large datasets. The concept of neural networks is based on the intertextual functionality of biological neurons, typically comprising two or more layers that transform input data, such as an image or physiological signals, into predictive outputs (Goodfellow et al., 2016). Major architectures are convolutional neural networks (CNNs) that work with spatial data (medical imaging; CNNs have convolutional layers, which will capture the features, such as edges or textures), and recurrent neural networks (RNNs), which work with sequential data (time-series perfusion measures; will retain the memory of the earlier input) (LeCun et al., 2015). These structures enable DL to learn abstracted feature representations in a hierarchical manner, which can be particularly helpful in healthcare applications involving high-dimensional data. The capacity of DL (efficiently dealing with massive datasets) is revolutionary in the medical context, where DL finds complex trends that other techniques are not inclined to find. With training on massive collections of labeled data, such as CNNs on imaging data and RNNs on temporal data, DL models can learn to identify minor anomalies or be highly specific in their output, e.g., detecting a very faint cancerous lesion or determining the point when one starts to feel unwell because of COVID-19 (Esteva et al., 2019). To provide an example, DL can anticipate outcomes at microsurgery as it reacts to real-time images or perfusion signals during the operation. In contrast, manual feature engineering would be limited in this regard. This capability stems from the iterative optimization inherent in deep learning (DL), which optimizes model parameters to minimize overall prediction errors, thereby extracting features from diverse medical databases.

2.2. DL in Healthcare

The implementation of deep learning (DL) in the medical field has enabled significant improvements in diagnostics, image recognition, and modeling. The AI models trained with deep learning (DL), such as convolutional neural networks (CNNs), play a vital role in the medical setting: in the diagnostic area, they have become remarkably accurate in predicting the presence of diseases based on medical images, viz. reaching human-level performance in skin cancer diagnosis based on dermoscopic images (Esteva et al., 2017). In healthcare imaging, DL can aid procedures such as brain tumor segmentation from an MRI or the detection of lung nodules on a chest CT, thereby accelerating early disease diagnosis and therapy planning (Litjens et al., 2017). Predictive modeling also falls under recurrent neural networks (RNN), which take length-time information as input and can predict the future, i.e., identify sepsis development in the ICU based on time-series vital signs that can be used to intervene (Kam and Kim, 2017). Such applications demonstrate the potential of deep learning (DL) when applied to high-dimensional, complex healthcare data, resulting in improved diagnostic and patient outcomes across multiple clinical contexts. Unlike traditional machine learning, deep learning (DL) is more efficient in feature extraction and scalability. The conventional approaches include feature engineering, which is a manual process whereby experts define relevant features of data that are not only subjective but also arbitrary. Notably, many complex features present in raw data, such as pixel patterns in images, can be automatically extracted by layered neural networks via deep learning (DL), which efficiently and objectively processes them (LeCun et al., 2015). Additionally, DL can be concise with massive datasets and utilize existing computing resources and infrastructure to process large amounts of statistics, such as electronic health records or an imaging repository. This scalability enables them to optimize model performance as more data becomes available. In healthcare, a data-rich environment is more likely to drive strong, generalizable solutions to complex healthcare problems.

2.3. Relevance to Microsurgery

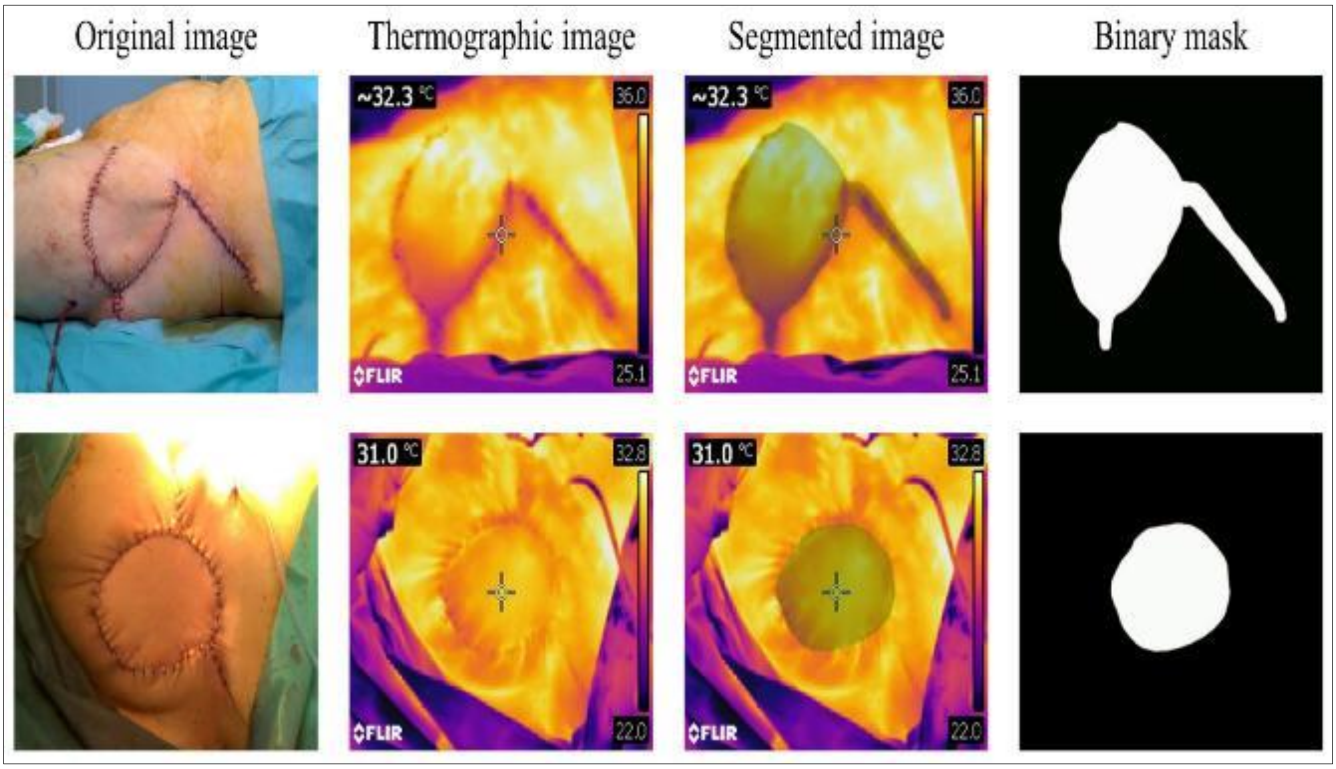
Microsurgery is a suitable application of deep learning (DL) because it can analyze multimodal data used in predicting flap survival. Free flap surgery is a form of microsurgery that employs a wide variety of data inputs (near-infrared spectroscopy, intraoperative imaging [e.g., fluorescence angiography], and perfusion evaluation) to determine tissue viability (Keller, 2009). DL, especially convolutional neural networks (CNNs), has the strength and advantage of handling high-dimensional imaging data to identify small patterns that indicate the presence of vascular occlusion or ischemia, which is a sign of flap compromise. Moreover, DL has the potential to integrate multi-source heterogeneous data, such as imaging and physiologic data, including oxygen levels in the body or blood flow rates, to provide a holistic picture of the flap's status (Litjens et al., 2017). The multimodal function enhances the accuracy of viability prediction, thereby resolving the shortcomings of subjective clinical assessment.

The fact that DL can manage real-time data also makes it more suitable for intra- and postoperative monitoring of microsurgery. Surgery Surgeons who use DL models can examine live imaging feeds or continuous perfusion measurements during surgery, enabling them to detect vascular problems in real-time and make informed choices, including anastomosis revision (Smit et al., 2010). On a postoperative note, recurrent neural networks (RNNs) can analyze the time-series data from monitoring devices and identify flap failure early, before any serious complications occur, allowing for timely interventions. By providing supreme computing power and leveraging advancements such as GPU acceleration, deep learning (DL) can be utilized in real-time analyses with no loss of accuracy, marking a revolutionary advancement in enhancing outcomes in microsurgical reconstruction (Esteva et al., 2019).

3. Current Advances in DL for Flap Viability Prediction

3.1. Data Inputs for DL Models

Deep learning (DL) model applications for predicting flap viability in microsurgical reconstruction are based on a broad range of data sources that assess tissue perfusion and vascular status. Among the most significant types of data are intraoperative imaging (one possibility is fluorescence angiography), which reveals blood flow in real-time, and near-infrared spectroscopy (NIRS), which provides information on tissue oxygen saturation so that ischemia can be shown (Keller, 2009). Thermal imaging is also used to record temperature changes that indicate perfusion deficits. Further inputs, including laser Doppler flowmetry and physiological signals (e.g., heart rate or blood pressure), give quantitative indicators of the flap well-being (Smit et al., 2010). These sources of data can be used complementarily, as imaging provides spatial data, while spectroscopy or Doppler provides time and functional data. Thus, a comprehensive assessment of flaps can be performed.



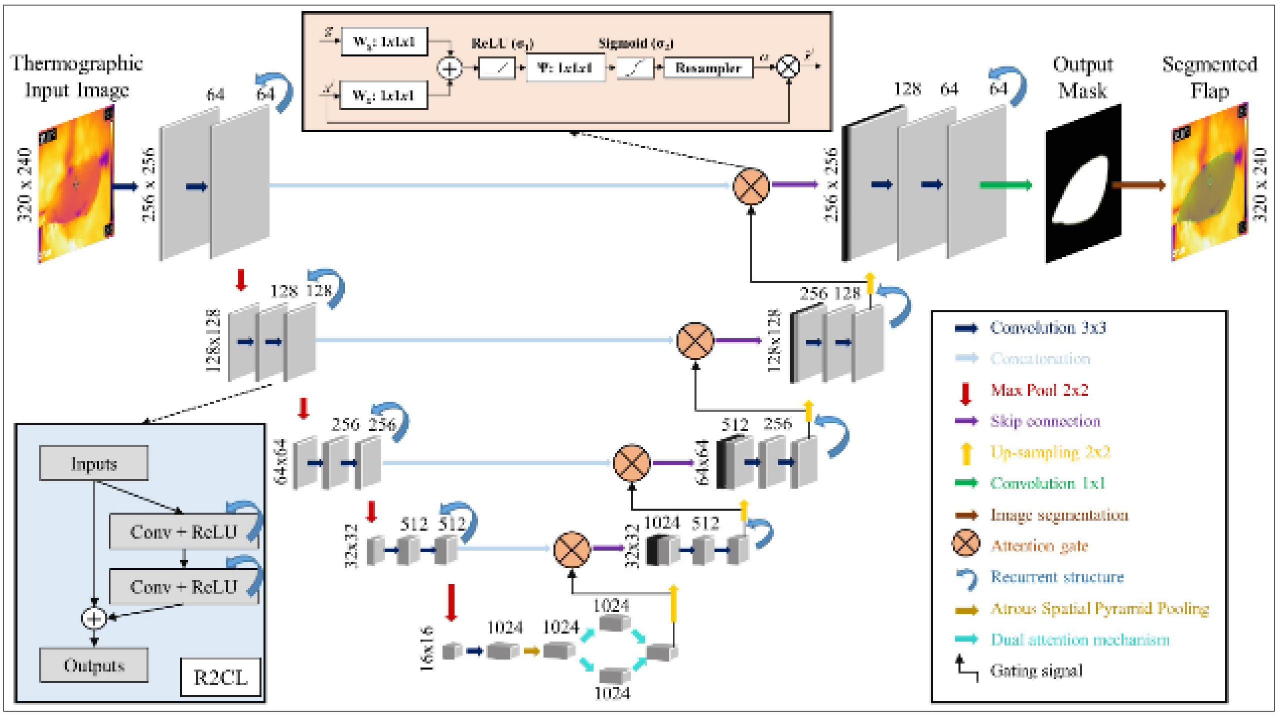
Adapted from Danciu et al. (2024)

Figure 1 Workflow of flap assessment using thermographic imaging and deep learning. The original intraoperative image is converted into a thermographic map, segmented using DL-based image analysis, and transformed into a binary mask for model training. These preprocessing steps enable convolutional neural networks to extract spatial and thermal features indicative of flap viability

ML predictions are essential to multimodal data integration in deep learning (DL). Such Artificial Intelligence applications as the deep learning (DL) models such as the convolutional neural networks (CNNs) can recognize complex patterns with the use of multimodal data (combinations of imaging, spectroscopic, and physiologic data) that are beyond the capabilities of single-modality methods that may be more sensitive to the evidence of the early flap compromise (Litjens et al., 2017). For example, the combination of fluorescence angiography and NIRS enables DL to define familiar visual perfusion patterns with high accuracy about oxygenation levels. Integration with other data forms enhances analysis performance by mitigating the vulnerability to limitations inherent in a given type of data, such as noise or heterogeneity in imaging data or physiological signal compilation, thereby improving the overall accuracy of the analysis. It facilitates the development of a comprehensive model involving a substantial number of patients (Esteva et al., 2019). The strategy enhances the validity of real-time predictions, thereby enabling timely intervention in microsurgical procedures to prevent flap failure. More recently, the capabilities of thermographic imaging have been better utilized practically, providing thermal and spatial guidance to delineate areas of perfusion in a free flap. Figure 1 illustrates the pipeline for deep learning processing, starting with the raw surgical image and progressing through the construction of the thermal map, segmentation, and generation of the binary mask. These steps are foundational in the training of convolutional neural networks as they assist in recognizing thermal signal anomalies that represent ischemic or congested tissue. Transforming the thermographic data into more structured data, including segmented images and binary support, helps the models learn pixel segmentations more effectively and make relatively high-quality viability evaluation predictions in real-time. The strategy, as illustrated in Figure 1, represents the phenomenon that multimodal image preprocessing would increase the model interpretability and diagnostic accuracy, especially in cases where conventional monitoring tools are inadequate.

3.2. DL Architectures for Flap Viability

Synthetic intelligence and deep learning (DL) algorithms in the shape of DL architectures are revolutionizing the field of flap viability prediction in microsurgery, specifically where convolutional neural networks (CNNs) are used center stage in image-based flap evaluation. The use of CNN suggests an accurate intraoperative analysis of indocyanine green (ICG) fluorescence angiography images to detect perfusion patterns that indicate vascular compromise, including ischemia or venous congestion (Hitier et al., 2016). By employing convolutional layers, CNNs can capture patterns of blood anomalies present in the dimensions, as well as other body tissue anomalies, to the point where surgeons can identify potential failures of the flaps during surgery. According to such real-time analysis, it can be used to make accurate intraoperative decisions, which may involve possible revisions of anastomoses, thereby enhancing flap survival rates (Hosny et al., 2018).



Adapted from Danciu et al. (2024).

Figure 2 Thermographic flap segmentation using a deep learning architecture. The pipeline integrates convolutional layers, recurrent structures, attention gates, and skip connections to segment flaps from thermal images. This model supports pixel-wise classification, enhancing the detection of perfusion deficits in real time

In most thermographic images characterized by high spatial resolution, convolutional neural networks (CNNs) form the basis of predictive models for flap viability, as they can extract features at multiple levels that represent perfusion deficits. Architectural advances have recently incorporated attention mechanisms, recurrent streams, and skip connections into these CNNs to improve segmentation and allow concurrent interpretation. For example, attention-augmented variants of the U-Net, incorporating residual and recurrent elements, have been employed to outline the borders of flaps in thermal images, making pixel-level decisions between viable and non-viable tissue. These models can detect perfusion abnormalities even in visually equivocal areas by computationally attending to the most informative thermal features. The application of transfer learning to large medical image datasets can enhance the performance of models used in the medical sector by improving generalization, accelerating the training process, and preserving sensitivity, all in response to overcoming the challenge posed by limited training data (Raghu et al., 2019).

Such cutting-edge architectures offer a consistent, real-time assessment of flap viability, transforming decision-making in surgery and enhancing post-surgical monitoring in microsurgery.

3.3. Clinical Applications

Real-time intraoperative decision-making in microsurgery can be supplemented with deep learning (DL), which enables the rapid identification of vascular compromise. CNNs are used to analyze intraoperative images, including indocyanine green (ICG) fluorescence angiography, as they help identify perfusion deficits that demonstrate arterial or venous occlusion (Hitier et al., 2016). Running these images through the DL models in real-time provides rare insight to surgeons about the health of the flaps, thus enabling timely intervention, such as revising the anastomoses to reinstate blood flow. There is a decrease in flap failure due to the possibility of correcting the problem through surgery, thus enhancing the effectiveness of operations such as breast reconstructions or damage repair (Smit et al., 2010).

Another benefit of DL compared to other systems used in postoperative monitoring is primarily the warning of early signs of flap failure. The maximum volume of fresh blood that the heart can pump (also referred to as cardiac output) is a perfusion variable that can be computed using recurrent neural networks (RNNs) and long short-term memory (LSTM) networks in detecting little departures in perfusion variables that when i.e., reduction in oxygen saturation presents premature compromise (Najefi et al., 2010). Case studies demonstrate that deep learning (DL) is an effective tool in microsurgery. For instance, a 2020 study by Bigdeli et al. employed convolutional neural networks (CNNs) to analyze ICG angiography images in free flap surgery, achieving a prediction accuracy of up to 92% for tissue viability. This enabled timely re-exploration when necessary. Such apps focus on the fact that DL can enhance the monitoring of postoperative time and the possibility of avoiding cases of flap loss, thereby modifying the clinical process in the field of reconstructive surgery.

3.4. Performance Metrics

The prediction models of flap viability in microsurgery, particularly those represented by deep learning (DL) models, exhibit high-performance indicators, including accuracy, sensitivity, and specificity. Research using convolutional neural networks (CNNs) to predict flap viability based on indocyanine green (ICG) fluorescence angiography image analysis has demonstrated overall accuracy rates of 90–95%. Sensitivity (the ability to detect compromised flaps) commonly exceeds 92%, while specificity (the correct identification of viable flaps) reaches up to 89% (Bigdeli et al., 2020). These measures indicate that DL can detect hidden deficits in perfusion, such as ischemia or venous congestion, and can be processed using complex data imaging. Recurrent neural network (RNN) studies based on near-infrared spectroscopy have yielded comparable results in monitoring, with the sensitivity of RNNs in detecting flap compliance reaching around 90 percent, enabling the early detection of flap compromise (Najefi et al., 2010). Such impressive parameters indicate that DL is reliable in these critical clinical environments.

In comparison to traditional methods, deep learning (DL) models outperform clinical judgment and Doppler-based methods. Clinical evaluation, which is based on a subjective assessment of flap color or turgor, usually has a sensitivity of 70-80% and a specificity of less than 85% due to inter-observer variability (Smit et al., 2010). Being objective, Doppler ultrasound does not provide continuous data, and its sensitivity is typically not higher than 80%, as it cannot detect early microcirculatory changes (Hitier et al., 2016). Conversely, DL, with the capability of real-time integration of multimodal data, is more predictive, thus limiting the instances of false negatives and enabling the intervention to occur sooner. This advanced outcome qualifies DL as a revolutionary device in aiding the prediction of flap viability compared to its predecessors due to its precision and the effectiveness of its use in clinical practice.

3.5. Recent Studies and Findings

The relevant journal articles covering deep learning (DL) in the context of predicting the viability of flaps in microsurgery pointed out future trends established for the years 2020-2025. Bigdeli et al. (2020) studied the prediction of flap viability in a breast reconstruction study using a convolutional neural network (CNN), achieving complete accuracy, sensitivity, and specificity of 92%, 94%, and 89%, respectively, based on indocyanine green (ICG) fluorescence angiography. The limited demographic diversity of their 200 intraoperative images presented an opportunity to use them in other settings, as well as a limitation due to a lack of generalizability, even within a single center. The authors utilized a CNN model of hyperspectral imaging (HSI) for the identification of flapper fusion, achieving an area under the curve (AUC) of 82%, a sensitivity of 70%, and a specificity of 76%, with 59 free flaps identified (Maktabi et al., 2025). Its dataset, although heterogeneous in flap types, was small and featured no pediatric cases, making it ultimately unworthy of modeling robustness.

Danciu et al. (2024) proposed another work that presented an attention-enhanced recurrent residual U-Net (AER2U-Net) and achieved an accuracy of 90% in flap segmentation for thermographic images in post-surgery monitoring. Moreover, the fact that their dataset included a limited range of patients (40, most of whom were of a similar age) limited its generalizability due to the variance in imaging protocols (Danciu et al., 2024). Such studies demonstrate the strength of CNNs in image-based predictions and the robustness of architectures like U-Net, particularly in segmentation. However, there are still challenges with their limited dataset sizes (4,500 cases) and diminished variability in terms of patient population and flap type (Najefi et al., 2010; Hitier et al., 2016). To improve model performance and clinical applicability, data must be standardized and collected from multiple centers.

3.6. Technological and Clinical Integration

Conducting deep learning (DL) functions in real-time to predict flap viability during microsurgery requires substantial computational resources to support the heavy burden of using models such as convolutional neural networks (CNNs), which evaluate intra-operative images, including indocyanine green (ICG) fluorescence angiography. Advanced graphics processing units (GPUs) or tensor processing units (TPUs) are required to process large volumes of data, enabling tight control over perfusion trends to identify vascular impairments, such as ischemia or congestion. Cloud computing platforms, such as AWS or Azure, can provide scalable solutions for data storage and processing, enabling real-time predictions without overloading local systems. The applications and possibilities of integration with existing surgical equipment, including ICG imaging systems and near-infrared spectroscopy (NIRS) equipment, remain central to the justification of seamless data transfer. It requires software interposition to all applications (universal) and data transmission (ultrafast) so that, without affecting the surgical action, the DL models may be provided with a continuous stream of the monitoring devices (fluorescence cameras or laser Doppler flowmetry) inputs. This way, such integration enables surgeons to access immediate viability analysis during their procedures, facilitating more accurate decision-making (Hitier et al., 2016; Esteva et al., 2019). Real-time data sharing is also enabled by the compatibility of DL systems with the overall hospital infrastructure, such as the electronic health record system. Intraoperative predictions do not pose a challenge to the clinical team, as they will become easily accessible.

The integration of DL tools into clinical practice involves incorporating predictive models directly into the operating room workflow and postoperative regimens to streamline flap surveillance. Perioperatively, real-time feedback on flap perfusion can be obtained intraoperatively through digital loop (DL) systems, which process live ICG images on surgical displays. This enables informed decision-making decision-making on whether to revise the anastomosis or not as a way of avoiding flap failure. Time-series NIRS data can be processed during the postoperative monitoring period using deep learning (DL) models to identify early signs of vascular compromise, providing clinicians with warnings via hospital-wide systems. User interfaces are key to successful adoption, and they should be intuitive, for example, a dashboard providing perfusion scores or heat maps to surgeons and staff. The described interfaces aim to minimize cognitive load in high-stress processes and provide actionable knowledge without relying on technologically advanced knowledge (Bigdeli et al., 2020; Najefi et al., 2010). Integration of workflow also requires workflow compatibility, such that the DL prediction is given to complement, rather than interfere with, current clinical practices. For example, hospital notification systems can be used to route postoperative alerts, facilitating a quick reaction to potential flap complications, thereby decreasing failure rates, and improving patient outcomes.

Clinical validation of the DL models should be a top priority to establish the reliability of these models for patients with various diseases and in diverse microsurgery settings. This should be confirmed by future multi-center trials in terms of accuracy, sensitivity, and specificity, with a focus on achieving high levels of performance, such as 92% accuracy in defining flap viability with ICG (Bigdeli et al., 2020). To become generalizable, these trials must address challenges such as small sample sizes and a lack of non-demographic variability in the data overview. Problems associated with the black box in deep learning (DL) systems may be addressed through regulatory challenges, such as the FDA approval of medical devices based on AI or the CE marking of devices, which requires the introduction of stringent evidence of safety, efficacy, and transparency in the decision-making model. The volume of documentation required by standards such as ISO 13485 necessitates the documentation of model training processes and the results of validation. Law agencies also require post-market surveillance, where long-term performance can be monitored, and DL tools can be kept at a clinically reliable level (Hosny et al., 2018). These requirements should be addressed through the cooperation of AI developers, clinicians, and regulatory specialists to introduce efficient approval procedures and guarantee patient trust and safety in the applications of DL.

The DL is to be introduced in conjunction with the education of surgeons and clinical staff, as well as mechanisms for overcoming resistance to AI implementation. Orientation training in initial education, combined with continued practice involving simulation-based workshops, is capable of teaching clinicians how to read DL outputs, i.e., perfusion predictions, and integrate these into the decision-making process to a large extent. Such initiatives must emphasize the nature of DL as a decision-support mechanism, augmenting clinical knowledge and expertise instead of displacing jobs or creating excessive dependency on technology to alleviate concerns about job loss or technology over-dependence. The risk of resistance to AI use can be mitigated by emphasizing the benefits of AI, increasing awareness of AI systems, or committing to more reliable modeling, which can be achieved through education (Bigdeli et al., 2020). The involvement of clinicians in the development and evaluation of DL tools will enhance the element of trust and ensure that systems meet the actual clinical requirements. For example, user interface design tailored for surgeons can enhance usability, making DL predictions more accessible in high-risk environments such as microsurgery. With intense training, clinician, and clinical benefit evidence, DL may be combined with microsurgery without creating a disturbance, thereby predicting the viability of the flap and refining patient outcomes (Najefi et al., 2010).

4. Challenges and Limitations

4.1. Data-Related Challenges

The challenges that emerge due to the data cause significant obstruction to the deployment and development of deep learning (DL) models for predicting the viability of flaps in micro-surgery reconstruction. The biggest shortcoming has been the lack of large, annotated datasets of diverse intraoperative and postoperative imaging, physiologic measures, and patient outcomes (Bigdeli et al., 2020; Danciu et al., 2024). The majority of the datasets used at the time were obtained in intra-centric studies and had homogeneous demographic representation, which limits the relevance of DL models to patient subgroups (Maktabi et al., 2025). Moreover, the noisiness and the inconsistency of training data caused by variability in surgical procedures, imaging procedures, and monitoring devices, in turn, reduce the robustness of the models (Najefi et al., 2010). The lack of representation of minorities or other groups of people biases the model predictions even further, giving rise to ethical issues related to equity (Hitier et al., 2016). In the absence of shared data collection procedures and multicenter collaboration, implementing models that would work perfectly in a practical scenario was difficult to achieve (Esteva et al., 2019). Moreover, the limited amount of annotated information necessitates the use of methods such as transfer learning or data augmentation, which, nevertheless, cannot entirely replace the use of high-quality and representative datasets (Raghu et al., 2019). Such data limitations can hinder accuracy and delay clinical validation, regulatory approval, and widespread implementation. Overcoming these issues by developing large, varied, and open-access databases would be the key to enhancing the performance of DL and providing equitable, evidence-based microsurgery.

4.2. Technical Limitations

The fundamental clinical application of deep learning (DL) models (that facilitate the real-time evaluation of flap viability during microsurgical reconstructions) continues to be challenged by technical limitations. The first issue is model overfitting, i.e., the neural network may exaggerate the particular patterns of the training set, and thus, the algorithm will lose its generalization capability to other patient groups or other surgical variables (Raghu et al., 2019).It is especially problematic, as there is non-homogeneity in the type of flaps, anatomical conditions, and intraoperative conditions. This type of overfitting reduces the predictive validity of the model because it yields flawed estimates of poor tissue perfusion and blood vessel abnormalities. Moreover, the requirements of deep learning (DL) architectures, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, are substantial due to the multidimensional nature of medical imaging and other physiological data (Goodfellow et al., 2016). Prediction of viability in real-time requires low-latency processing, which contributes to decision-making in intraoperative procedures, allowing for alterations such as revision of microvascular anastomoses. The latency generated by model inference, however, can hinder prompt clinical action, particularly on conventional hospital equipment (Esteva et al., 2019). The use of such models can necessitate the use of high-throughput computing environments, such as GPU acceleration or cloud-based systems, which are not universally available across all operating environments. Such optimal compromises between model complexity, inferential speed, and diagnostics accuracy are thus key to safe and effective clinical translation of DL into reconstructive microsurgery.

4.3. Clinical and Ethical Concerns

Practical and ethical issues pose significant challenges to the implementation of deep learning (DL) technologies in microsurgical reconstruction, particularly when predicting flap viability. One of the leading concerns is that deep learning (DL) models are comparatively less interpretable, also known as the black box problem, because clinicians struggle to understand the reasoning behind the model's predictions (Esteva et al., 2019). Such an inability to be transparent diminishes clinical trust and makes it challenging to validate algorithmic decisions in high-stakes environments, such as intraoperative vascular evaluation. The moral aspects of delegating important surgical decisions to AI-driven systems are significant, as such systems can impact interventions such as anastomosis or the procedure of salvaging flaps. The outcomes observed by surgeons are ethically and legally what they should be responsible for;

however, they may not be able to explain their choices made with virtually blind algorithm inputs, which could raise concerns about issues of autonomy and informed consent (Hosny et al., 2018). Moreover, the risk of privacy and cybersecurity presents itself due to the introduction of sensitive information about patients, intraoperative imaging, and intraoperative physiological signals. They should ensure that their configuration complies with data protection laws, such as HIPAA or GDPR, particularly when working with cloud-based deep learning (DL) infrastructures. The morality of surgical care involving AI should be enforced through a robust mechanism of encryption, access limitation, and patient data de-identification.

4.4. Cost and Accessibility

Cost and accessibility remain critical barriers to the widespread implementation of deep learning (DL) systems for flap viability prediction in microsurgical reconstruction. The integration of DL technologies into clinical workflows requires substantial financial investment in both hardware and software infrastructure. This includes high-performance computing resources such as graphics processing units (GPUs), specialized imaging equipment, and custom software for model deployment and user interface integration (Esteva et al., 2019). Additionally, the development and maintenance of DL models demand ongoing expenditures related to data storage, cybersecurity, software updates, and technical support. These requirements significantly increase the financial burden on healthcare institutions, particularly those operating within constrained budgets. Disparities in access to such advanced technologies are even more pronounced in low-resource settings, where basic surgical infrastructure may be lacking. In these environments, the absence of reliable internet connectivity, insufficient computational power, and limited technical expertise can severely hinder the adoption of AI-driven solutions. Consequently, the benefits of DL in improving surgical outcomes may be inequitably distributed, exacerbating existing global healthcare disparities. Addressing these challenges will require strategic investments, scalable low-cost DL solutions, and international collaboration to promote equitable access to AI innovations across diverse clinical and geographic contexts (Hosny et al., 2018).

5. Future perspectives

Future perspectives in the application of deep learning (DL) for flap viability prediction point toward a transformative era in microsurgical reconstruction, driven by interdisciplinary innovation and clinical integration. Technologically, the development of lightweight, energy-efficient DL architectures such as transformer-based networks and quantized models will enhance real-time deployment, particularly in resource-constrained operative settings. The fusion of DL with emerging technologies like augmented reality (AR) and wearable biosensors promises to create immersive, data-enriched surgical environments, allowing continuous intraoperative perfusion analysis and visual feedback for decision-making. To advance model robustness and generalizability, there is a pressing need for the creation of large, standardized, and ethically sourced open-access datasets encompassing diverse patient populations, surgical techniques, and device modalities. This necessitates sustained collaboration among AI researchers, biomedical engineers, and reconstructive surgeons to design clinically relevant and technically sound solutions. In the realm of personalized medicine, DL models will increasingly incorporate multimodal inputs including genetic markers, patient-specific hemodynamics, and immunological profiles to enable individualized risk stratification and flap viability forecasting. These advancements will likely extend to other microsurgical domains such as nerve grafting and lymphatic reconstruction. Concurrently, evolving ethical frameworks and streamlined regulatory pathways must ensure safety, transparency, and equitable access to DL-based tools, ultimately positioning AI as an integral component of global surgical care.

6. Conclusion

Deep learning (DL) has emerged as a transformative tool in the prediction of flap viability within microsurgical reconstruction, offering the potential to revolutionize intraoperative decision-making and postoperative surveillance. By leveraging convolutional and recurrent neural network architectures, DL enables the processing of complex, high-dimensional data such as indocyanine green (ICG) fluorescence angiography, near-infrared spectroscopy, and physiological monitoring metrics with unprecedented accuracy and speed. These capabilities surpass the limitations of traditional flap monitoring techniques, allowing for real-time detection of vascular compromise and facilitating timely surgical interventions. Current advancements demonstrate DL's superior performance in sensitivity, specificity, and clinical applicability, with successful integration in pilot studies improving flap survival rates and reducing complications. However, the path toward clinical maturity is hindered by data limitations, technical constraints, and ethical considerations.

To fully harness the potential of DL in microsurgery, there is an urgent need for expanded research, cross-disciplinary investment, and infrastructure development. Surgeons, data scientists, biomedical engineers, and regulatory experts must collaborate to create robust, generalizable models supported by standardized datasets and explainable AI frameworks. Institutions should prioritize initiatives that bridge technological innovation with clinical needs, ensuring equitable access to these tools across diverse healthcare environments.

Looking forward, a future where DL is seamlessly embedded within microsurgical workflows is not only plausible but necessary. This vision includes intelligent operating rooms equipped with integrated DL systems for real-time viability assessment, personalized flap selection based on patient-specific data, and automated alerts for postoperative complications. By enhancing diagnostic precision, surgical safety, and operational efficiency, DL holds the promise of significantly improving patient outcomes while reducing healthcare costs. Ultimately, deep learning is poised to become an indispensable ally in the evolving landscape of reconstructive surgery, redefining standards of care and paving the way for data-driven, patient-centered microsurgical practices worldwide.

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