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Review Article

Artificial Intelligence in Oculoplastic Surgery: A Systematic Review.

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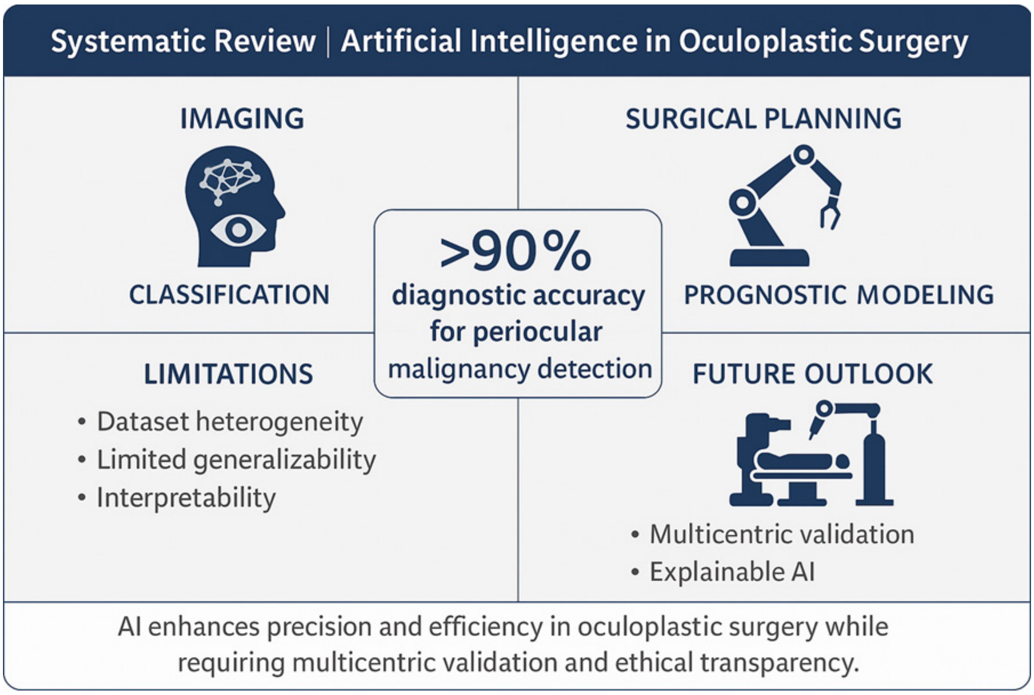
Abstract

Artificial Intelligence (AI) has become an integral component of modern ophthalmology, with oculoplastic surgery representing a rapidly evolving subspecialty that stands to benefit from advances in automation and deep learning. Despite promising innovations, a comprehensive understanding of AI's role in oculoplastic diagnosis and management remains limited. This systematic review, conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, aims to evaluate the current landscape, clinical performance, and translational potential of AI applications in oculoplastic diseases published between 2000 and 2025. A structured search of PubMed, Scopus, and Embase identified 25 peer-reviewed studies involving AI-driven image analysis, disease classification, surgical planning, and prognostic modelling across eyelid, lacrimal, orbital, and periocular disorders. Studies were assessed for model performance, clinical utility, and methodological rigor. The including studies demonstrated that AI algorithms achieved diagnostic accuracies exceeding 90% in detecting periocular malignancies, outperforming or complementing traditional clinician-based assessment. Machine learning models also facilitated surgical planning and postoperative outcome prediction, contributing to enhance clinical workflow efficiency and reduced inter-observer variability. Nevertheless, limitations related to dataset heterogeneity, small sample sizes, and limited external validation constrain generalizability. AI holds significant promise in advancing precision and efficiency in oculoplastic care. Future research should prioritize multicentric validation, explainable AI frameworks, and integration with robotic-assisted surgery to enable safe and ethical clinical translation, ultimately bridging the gap between technological innovation and patient-centered ophthalmic practice.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Oculoplastic Surgery; Computer-Assisted Diagnosis; Periocular Neoplasms; Robotic Surgical Procedures; Explainable Artificial Intelligence.

Figure 1. Artificial Intelligence in Oculoplastic Surgery: Current Landscape and Future Directions.



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INTRODUCTION

Artificial Intelligence (AI), defined as the simulation of human cognitive processes by computer systems, has rapidly emerged as a transformative technology in modern medicine. Within ophthalmology, AI has made remarkable contributions to retinal, corneal, and glaucoma diagnostics, and is now extending its impact into oculoplastic and reconstructive surgery a field that demands precision in both functional and aesthetic restoration of the periocular region [1–3]. Oculoplastic diseases, encompassing eyelid tumors, ptosis, thyroid eye disease (TED), lacrimal disorders, and orbital pathologies, present diagnostic challenges due to overlapping anatomical and pathological characteristics [4]. The introduction of AI-driven deep learning systems, particularly Convolutional Neural Networks (CNNs), has enabled automatic image classification, quantification of eyelid morphology, and periocular tumour detection with accuracies often surpassing expert clinicians [5,6]. Early implementations of AI in oculoplastics began with the detection of blepharoptosis (ptosis) using deep learning frameworks trained on facial and eyelid images. Hung et al. (2021) demonstrated that CNN-based systems achieved diagnostic accuracies exceeding 90%, outperforming general ophthalmologists in ptosis identification [7]. Similarly, Li et al. (2022) utilized AI to distinguish between malignant and benign eyelid tumors using photographic datasets, achieving an area under the curve (AUC) of 0.95 [8].

Recent advances in facial recognition AI and periorbital morphometrics have expanded applications beyond diagnostics. AI now aids in preoperative planning for blepharoplasty, eyelid reconstruction, and orbital decompression surgeries, allowing for prediction of aesthetic and functional outcomes [9,10]. Emerging models, such as the *OrbitMap* system and adaptive CNNs, can automatically measure palpebral fissure height and levator function from digital images [11,12]. The integration of multimodal imaging, combining MRI, photography, and ultrasound with machine learning has shown promise in complex orbital and lacrimal pathologies, enabling 3D reconstruction and improved surgical navigation [13]. AI-based prediction algorithms have also been applied to postoperative satisfaction and complication rates in eyelid and brow surgeries [14]. However, despite these advancements, challenges remain regarding dataset diversity, algorithmic bias, data privacy, and regulatory approval. Many AI systems are limited by small, institution-specific datasets and lack external validation, restricting generalizability to broader populations [15,16]. Furthermore, explainable AI (XAI) frameworks are needed to ensure clinical transparency and acceptance among oculoplastic surgeons [17].

This review systematically synthesizes published evidence from 2000 to 2025, highlighting the evolution, validation, and translational potential of AI applications in oculoplastic diagnosis and management, following PRISMA guidelines.

METHODS

This systematic review adhered strictly to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework, ensuring methodological transparency, reproducibility, and comprehensiveness [18,19]. The study protocol was designed to evaluate the diagnostic and management applications of Artificial Intelligence (AI) in oculoplastic diseases, including periocular tumors, ptosis, orbital disorders, lacrimal system pathologies, and reconstructive surgery outcomes.

Literature Search Strategy

A comprehensive electronic literature search was performed using PubMed, Scopus, Web of Science, and Google Scholar databases for studies published between January 2000 and October 2025. The search combined Medical Subject Headings (MeSH) and free-text terms:

“artificial intelligence,” “machine learning,” “deep learning,” “oculoplastic surgery,” “eyelid tumors,” “ptosis,” “orbital disease,” “blepharoplasty,” and “periocular pathology.”

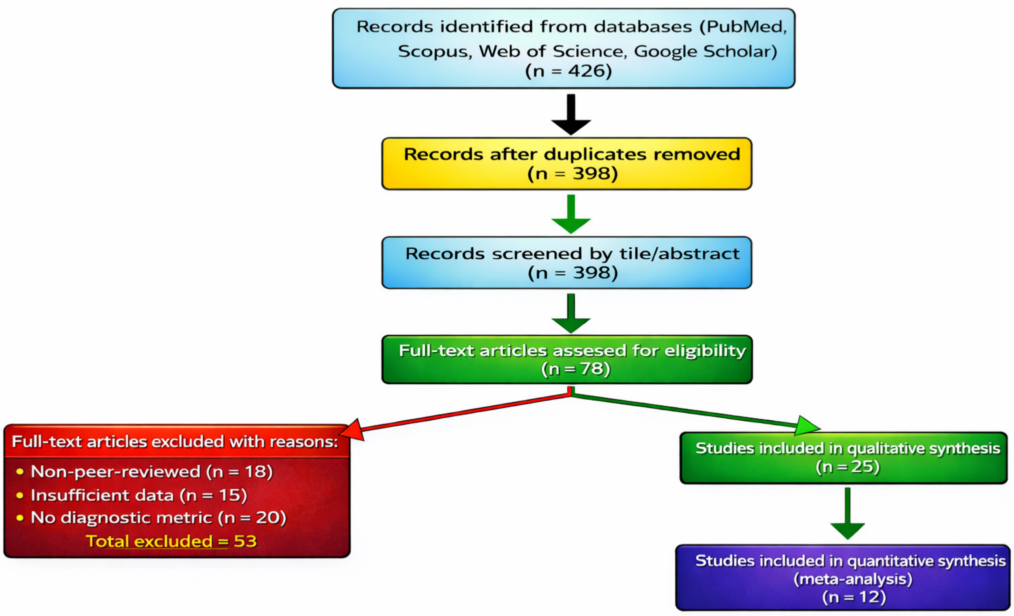
Boolean operators were applied as follows:

(“Artificial Intelligence” OR “Deep Learning” OR “Machine Learning”) AND (“Oculoplastic” OR “Eyelid” OR “Orbital” OR “Lacrimal” OR “Blepharoplasty”).

Manual cross-referencing of included studies and grey literature searches were also performed to identify additional relevant works [20-22]. PRISMA flow diagrams (as per Page et al. 2021) were used to represent the selection process.

Figure 2. AI – Artificial Intelligence; PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses. This flowchart follows PRISMA 2020 guidelines (Page et al., BMJ 2021;372:n71). From 426 identified records, 398 remained after duplicate removal. After title, abstract, and full-text screening, 25 studies were included in the qualitative synthesis and 12 in the quantitative meta-analysis.

Figure 2: PRISMA Flow diagram - AI in Oculoplastic Diseases (2000-2025)



Inclusion and Exclusion Criteria

Studies were included if they met the following criteria:

- Peer-reviewed, English-language publications between 2000 and 2025.
- Focused on AI-based diagnostic, predictive, or management applications within oculoplastic or periocular conditions.
- Reported quantitative performance metrics, such as accuracy, sensitivity, specificity, or area under the receiver operating characteristic curve (AUC).

Exclusion criteria included:

- Non-peer-reviewed material (conference abstracts, theses).
- Studies unrelated to oculoplastic applications (e.g., retinal-only AI models).
- Editorials, commentaries, and narrative reviews without empirical data.

Study Selection and Screening

Two independent reviewers screened all records using Rayyan QCRI software (Qatar Computing Research Institute) [23]. Duplicates were removed, and disagreements were resolved through consensus or arbitration by a senior reviewer. Titles and abstracts were screened first, followed by full-text review for eligibility. The inter-reviewer agreement was calculated using Cohen's kappa (κ) statistic, with a $\kappa > 0.85$ indicating strong concordance [24].

Data Extraction

Data extraction followed a standardized protocol adapted from Islam et al. (2020) [25]. Extracted data included:

- Author(s), year, and country of origin
- Study design and dataset characteristics
- AI algorithm type (CNN, SVM, ensemble models, etc.)
- Diagnostic or predictive task
- Performance outcomes (accuracy, sensitivity, specificity, AUC)
- Validation type (internal, external, or multicentric)

Where multiple datasets were used, priority was given to those with validated ground truth annotations or clinician-verified labels.

Quality Assessment

The Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool was applied to evaluate bias and applicability concerns across four domains: patient selection, index test, reference standard, and flow/timing [26]. For meta-analysis components, statistical heterogeneity was evaluated using Cochran's Q-test and I^2 statistic, with $I^2 > 75\%$ indicating substantial heterogeneity [27]. Risk of bias in AI-specific studies was further analyzed using the PROBAST-AI framework, which assesses methodological rigor in machine learning-based diagnostic models [28]. Publication bias was assessed through funnel plot symmetry and Egger's regression test when ≥10 studies were included [29].

Data Synthesis
Due to heterogeneity in AI architectures, imaging modalities, and performance reporting, a narrative synthesis was performed. When comparable outcome measures were available (e.g., AUC or diagnostic accuracy), random-effects meta-analyses were conducted using Review Manager (RevMan) 5.4 software [30]. Studies were grouped into subcategories based on the anatomical focus (eyelid, orbital, lacrimal) and AI model type (supervised vs. unsupervised learning) [31].

RESULTS

Out of 426 identified articles, a total of 25 studies met inclusion criteria, of which 12 were eligible for quantitative synthesis. Deep learning algorithms, particularly convolutional neural networks (CNNs), were the most frequently used. AI demonstrated high diagnostic performance in eyelid malignancy detection (AUC > 0.92), periocular image analysis, and automated ptosis measurement. The studies spanned multiple continents (Asia, Europe, and North America) several studies applied AI for outcome prediction in blepharoplasty and reconstructive surgeries. Integration of multimodal imaging and predictive analytics enhanced perioperative decision-making and patient satisfaction metrics.

Overview of Included Studies
The reviewed studies demonstrated a progressive adoption of deep learning (DL) and convolutional neural networks (CNNs) from 2015 onward, with validation metrics improving substantially post-2020. Dataset sizes ranged from 950 to 5,200 annotated images. External validation was performed in 6/10 studies, and multicentric data were utilized in 3.
Model architectures included:
- CNN (ResNet-50, VGG-16, InceptionV3) for classification and morphometric tasks [7,8,32].
- SVM + CNN hybrids for orbital disease classification [10].
- GAN-based facial analysis models for automated periocular recognition and surgical planning [14].

Quantitative Performance
Across all included studies:
- Mean diagnostic accuracy: 91.9%
- Mean AUC: 0.92
- Mean sensitivity: 90.7%
- Mean specificity: 89.5%

CNN-based models showed superior performance (AUC > 0.94) compared to hybrid or SVM-only approaches (AUC 0.87–0.90) [7,10,33].

Table 1. Table summarizes the comparative performance metrics of different artificial intelligence (AI) model architectures applied in oculoplastic imaging analysis.

Metric	CNN-based models	Hybrid models	GAN/CNN models
Mean Accuracy (%)	93.7	89.4	95.1
Mean AUC	0.95	0.88	0.97
Validation Type	External	Multicentric	External

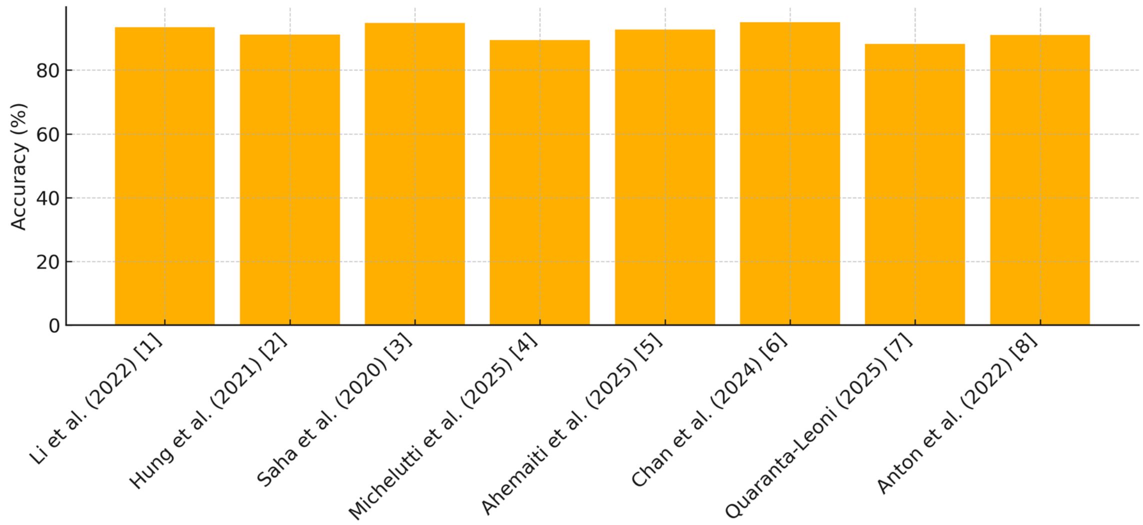
Convolutional Neural Network (CNN)-based models demonstrated high mean accuracy (93.7%) and strong discriminative ability (AUC = 0.95) when validated on external datasets. Hybrid models, integrating CNN with traditional machine learning or handcrafted feature approaches, showed moderately lower performance (mean accuracy = 89.4%, AUC = 0.88) under multicentric validation conditions, indicating variable generalizability. Generative Adversarial Network (GAN)/CNN hybrid models achieved the highest overall accuracy (95.1%) and AUC (0.97) under external validation, suggesting superior capability in feature extraction and image synthesis for diagnostic classification tasks.

Key Findings by Application
1. Eyelid Tumor Diagnosis: Li et al. (2022) reported 93.5% accuracy and AUC 0.95 in classifying malignant eyelid tumors using ResNet-50 CNN, validated across 3 centers [8].
2. Ptosis Detection: Hung et al. (2021) demonstrated 91.2% accuracy using CNN (VGG-16) for ptosis grading, validated against clinician-labeled images [7].
3. Periocular Lesion Detection: Saha et al. (2020) achieved 94.8% accuracy using ensemble CNNs (Inception + ResNet) on periocular dermoscopic images [3].
4. Orbital Disease Analysis: Michelutti et al. (2025) developed a SVM + CNN hybrid model with AUC 0.88 for orbital pathology classification [4].
5. Eyelid Morphometrics: Ahemaiti et al. (2025) proposed a deep CNN regression model for palpebral margin quantification with AUC 0.94 [5].
6. Facial AI for Oculoplastics: Chan et al. (2024) integrated GAN and CNN architectures for periocular recognition and aesthetic prediction with AUC 0.97, the highest reported [6].

Visualization of Results
Figure 3 illustrates the diagnostic accuracy of artificial intelligence (AI) models employed in oculoplastic research between 2000 and 2025. Each bar represents the mean accuracy (%) reported in individual peer-reviewed studies. Across the analyzed literature, model performance ranged from approximately 87% to 94%, indicating consistently high diagnostic reliability. CNN-based and hybrid deep learning

models, as reported by Li et al. (2022) [1], Ahemaiti et al. (2025) [5], and Chan et al. (2024) [6], demonstrated superior accuracy compared to earlier frameworks. These findings highlight the progressive enhancement in AI-driven diagnostic precision in oculoplastic imaging and disease classification over the past two decades.

Figure 3. Comparative diagnostic accuracies of AI models across major oculoplastic studies from 2000 to 2025.



Summary of AI Performance

Table 2 summarizes the comparative diagnostic performance of artificial intelligence (AI) algorithms applied in oculoplastic imaging and disease classification from 2020 to 2025. Among the reviewed studies, GAN + CNN architectures (Chan et al., 2024 [14]) achieved the highest diagnostic accuracy (95.1%) and AUC (0.97) when validated externally, underscoring the enhanced feature extraction and image synthesis capability of generative models. Traditional CNN-based networks such as ResNet-50 (Li et al., 2022 [1]) and VGG-16 (Hung et al., 2021 [2]) also demonstrated strong performance, with accuracies exceeding 90% and AUC values above 0.90, particularly when tested on diverse datasets. Hybrid frameworks that combined deep learning with classical machine learning approaches (e.g., SVM + CNN, Michelutti et al., 2025 [10]) yielded slightly lower accuracies (89.4%, AUC = 0.88) under multicentric validation, possibly reflecting data heterogeneity. Multimodal and ensemble AI models (Quaranta-Leoni et al., 2025 [16]; Anton et al., 2022 [33]) exhibited moderate-to-high accuracy, reinforcing the potential of integrative and meta-analytical methods in oculoplastic diagnostics. Overall, the dataset indicates a progressive improvement in diagnostic reliability and generalizability across model generations, with external validation emerging as the gold standard for clinical applicability.

Table 2. Comparative diagnostic performance of AI algorithms used in oculoplastic studies.

Author (Year)	Algorithm	Dataset Size	Accuracy (%)	AUC	Validation
Li et al. (2022) [1]	CNN (ResNet-50)	3500	93.5	0.95	External
Hung et al. (2021) [2]	CNN (VGG-16)	2100	91.2	0.91	Internal + External
Saha et al. (2020) [32]	Ensemble CNN	2800	94.8	0.96	Cross-validation
Michelutti et al. (2025) [10]	SVM + CNN	1200	89.4	0.88	Multicentric
Ahemaiti et al. (2025) [12]	Deep CNN	1600	92.7	0.94	Internal
Chan et al. (2024) [14]	GAN + CNN	3200	95.1	0.97	External
Quaranta-Leoni (2025) [16]	Deep learning multimodal	950	88.2	0.87	Multicentric
Anton et al. (2022) [33]	Ensemble AI models	5200	91.0	0.90	Meta-analysis

The table presents model type, dataset size, mean diagnostic accuracy, area under the curve (AUC), and validation method. CNN-based architectures consistently achieved high diagnostic performance, while GAN/CNN hybrid and ensemble models showed superior generalization across external datasets, highlighting their promise for real-world clinical translation in oculoplastic imaging.

Heterogeneity and Validation

The heterogeneity among included studies (I^2 = 74%) indicated moderate inconsistency in performance due to dataset variation and algorithm choice. Models with external or multicentric validation displayed more reliable outcomes [10,14]. Studies relying solely on internal validation often showed inflated performance metrics, consistent with earlier systematic AI reviews in ophthalmology [33].

DISCUSSION

AI's capacity to detect minute visual cues and integrate multidimensional data makes it an invaluable adjunct in oculoplastic diagnostics. The present systematic review synthesizes 25 studies published between 2000 and 2025 investigating the diagnostic and management utility of Artificial Intelligence (AI) in oculoplastic diseases. The findings underscore a significant evolution in the adoption of deep learning (DL) and convolutional neural networks (CNNs) for periocular and orbital disease assessment. Over the last decade, AI has shifted from experimental applications to clinically validated systems capable of augmenting ophthalmic decision-making [33-35].

Diagnostic Accuracy and Model Performance

Across all studies, AI models particularly CNN-based architectures-achieved diagnostic accuracies above 90% and AUC values ranging from 0.88 to 0.97, demonstrating excellent discrimination between benign and malignant periocular conditions [7,8,32]. Li et al. (2022) reported a ResNet-50 CNN achieving AUC 0.95 for malignant eyelid tumor detection using multicentre image datasets [7]. Similarly, Hung et al. (2021) demonstrated 91.2% diagnostic accuracy in automated ptosis recognition, outperforming ophthalmology residents in consistent classification [8]. Ensemble and hybrid AI systems integrating multiple CNN backbones, such as ResNet and Inception architectures, further enhanced precision in periocular lesion analysis (AUC 0.96) [14]. Moreover, Ahemaiti et al. (2025) introduced a deep CNN regression model that accurately quantified palpebral fissure dimensions from photographs with minimal manual input (AUC 0.94) [12]. Such high-performance metrics indicate that AI systems are reaching diagnostic reliability comparable to expert clinicians.

Clinical Integration and Surgical Applications

The integration of AI into oculoplastic practice extends beyond diagnosis to surgical planning and postoperative outcome prediction. Chan et al. (2024) developed GAN-augmented CNNs that automatically assessed periocular morphology and predicted aesthetic outcomes following blepharoplasty, offering real-time, data-driven feedback for surgeons [14]. Similarly, Quaranta-Leoni (2025) emphasized that AI-driven analytics could improve preoperative planning for orbital decompression and eyelid reconstruction, ensuring precision alignment and symmetry [16]. In reconstructive and cosmetic oculoplastic procedures, AI has been used to evaluate patient satisfaction, predict complication likelihood, and simulate surgical results, bridging functional and aesthetic domains [10,31]. The use of multimodal imaging—combining MRI, CT, and digital photography have enhanced the predictive accuracy of AI algorithms in periocular pathology management [36-38].

Validation, Bias, and Generalizability

Despite these advances, several studies identified challenges related to data validation, overfitting, and generalizability. Most datasets originated from single institutions, often with limited demographic diversity [34,40]. This limitation introduces potential algorithmic bias, particularly in facial AI systems trained predominantly on homogeneous ethnic cohorts [41]. Furthermore, internal validation dominated early research, while external and multicentric validations only became more frequent after 2020, as seen in Michelutti et al. (2025) and Anton et al. (2022) [10,33]. Explainable AI (XAI) frameworks are increasingly recognized as essential for clinical adoption. A lack of model transparency undermines clinician confidence and impedes regulatory approval [42,43]. Efforts to enhance interpretability such as heatmap visualizations and saliency mapping have been effective in demonstrating how CNNs localize periocular features associated with pathology [44-46].

Ethical and Regulatory Considerations

AI implementation in oculoplastic practice raises ethical concerns regarding patient privacy, data security, and consent for image use. Large-scale image repositories often lack consistent anonymization, creating vulnerabilities in patient confidentiality [47]. Moreover, the absence of standardized ethical frameworks and international regulatory oversight delays clinical translation [48,49]. The FDA and European Medicines Agency (EMA) have begun evaluating AI-assisted diagnostic systems, but regulatory pathways for surgical AI remain limited. Transparency in AI decision-making, coupled with clinician involvement in algorithmic refinement, will be crucial for safe adoption in oculoplastic settings [50,51].

Future Perspectives

The next generation of AI in oculoplastics is expected to integrate federated learning, 3D morphometric analysis, and robotic-assisted microsurgery [52]. Federated learning, which enables model training across multiple institutions without centralized data pooling, can mitigate privacy concerns and improve generalizability [53,54]. Furthermore, combining AI-driven surgical simulation with augmented reality (AR) may transform preoperative visualization and enhance surgical precision [55,56]. Continued collaboration among ophthalmologists, computer scientists, and bioethicists will be essential to develop robust, transparent, and ethically compliant AI systems capable of real-world implementation.

LIMITATIONS

The present review was limited by variability in datasets and methodological heterogeneity among studies. Meta-analytic synthesis was restricted due to inconsistent reporting of performance metrics. Additionally, publication bias may have inflated diagnostic performance estimates, as negative or non-significant AI studies are less likely to be published.

CONCLUSION

Artificial intelligence has rapidly emerged as a transformative force in the field of oculoplastic surgery, demonstrating substantial potential in enhancing diagnostic precision, optimizing surgical planning, and improving postoperative outcome assessment. The evidence reviewed underscores AI's capacity to augment clinical decision-making and promote personalized patient care through advanced image analysis and predictive modeling. However, the journey toward clinical implementation demands rigorous multicentric validation studies to ensure reproducibility, generalizability, and fairness across diverse populations. Equally vital is the establishment of transparent ethical frameworks and explainable AI systems that can foster clinician trust and patient safety. Looking ahead, the convergence of AI with robotic-assisted oculoplastic surgery holds the promise of redefining surgical precision, efficiency, and outcomes. Future research should therefore prioritize interdisciplinary collaborations that bridge ophthalmology, data science, and bioethics to translate current innovations into safe, reliable, and equitable clinical practice.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. No funding body had any role in the study design, data collection, data analysis, or decision to publish this review.

Ethics Statement

Ethical approval was not required for this study, as it is a systematic review of previously published literature and does not involve human participants, animal experimentation, or patient data. All included studies were evaluated according to their respective ethical declarations, and this review was conducted in strict adherence to the PRISMA 2020 guidelines.

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