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Review Article

Artificial intelligence in embryo selection: enhancing precision and overcoming traditional limitations in *in vitro* fertilization

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ABSTRACT

Identification of embryos with the highest potential for successful implantation is a key step in in-vitro fertilization (IVF). Traditionally, embryologists visually grade embryos by assessing their morphology and developmental stages. However, these assessments can differ between embryologists (inter-observer variability) and even when the same embryologist reviews the same embryo again (intra-observer variability), leading to inconsistent grading and potential misjudgement of embryo grading. Recent advancements in artificial intelligence (AI) offer a more standardized and objective approach to human embryo grading. By using machine learning models, AI systems can analyze embryo images and detect subtle developmental patterns that may not be apparent through visual assessment alone. This review explores original research studies from 2012 to 2024, that developed AI-driven embryo assessment methods that apply machine learning models, such as Convolutional Neural Networks (CNNs), which are deep learning models, while excluding studies involving animal embryos and non-english papers. Our findings from the review indicate that AI can reduce human error and improve embryo grading consistency for successful IVF. However, integrating AI into clinical practice presents challenges such as data variability, regulatory barriers, and the need for transparent, explainable AI models. Future directions include refining AI models to handle diverse datasets ensuring model interpretability for clinicians, and validating AI systems through large-scale clinical trials to establish their reliability and clinical utility in embryo selection.

Keywords: Assisted reproductive technology, *In vitro* fertilization, Artificial intelligence, Deep learning, Convolutional neural networks, Embryo grading, Predictive analytics

INTRODUCTION

Embryo development is a step-by-step process that plays a pivotal role in determining the success of in-vitro fertilization (IVF). Following fertilization in vitro, embryos progress through distinct stages, each characterized by specific structural and developmental features that indicate their potential for successful implantation.[1] The zygote is the initial single-cell structure formed after fertilization, containing the genetic material from both the sperm and egg. It undergoes its first mitotic division, marking the beginning of embryonic development. During the first 2-3 day's post-fertilization, the zygote undergoes a series of mitotic divisions, forming a multicellular structure with symmetrical blastomeres. Symmetrical cell division at this stage is a key indicator of a healthy embryo.[1] Around day 4, the embryo forms a compact ball of 16-32 cells called morula. Minimal fragmentation and consistent cell compaction are essential for advancing to the blastocyst stage. By day 5-6, the blastocyst forms a fluid-filled cavity, with two distinct structures - the inner cell mass (ICM), which will develop

into the foetus, and the trophectoderm (TE), which contributes to placental formation. Well-defined ICM and TE structures are crucial markers of embryo viability.[1]

A healthy embryo typically exhibits symmetrical cell division, minimal fragmentation, and well-defined structures such as the inner cell mass (ICM) and trophectoderm (TE), which are key indicators of implantation success.[2] Figure 2 illustrates the progressive stages of embryo development, from the zygote to the hatching blastocyst. Accurate assessment of these features is essential for selecting embryos with optimal developmental potential.[3] Embryo grading is a structured assessment process conducted to evaluate morphological characteristics at specific developmental stages to determine the implantation potential of embryos. Typically, embryos are graded on Days 3 and 5, corresponding to the cleavage and blastocyst stages, respectively. On Day 3, grading focuses on the number of cells, symmetry, and fragmentation Figure 3 Embryos with optimal cell division, minimal fragmentation, and well-formed blastomeres are classified as high-grade and are prioritized for transfer.[4] In contrast, embryos with severe fragmentation or irregular cell sizes are assigned lower grades, potentially reducing their implantation potential.[1]

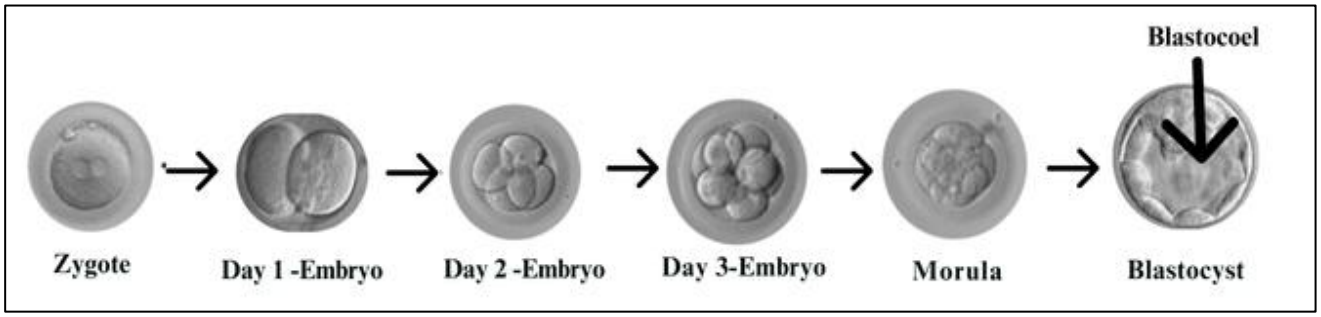

Figure 1: Morphological stages of embryo development studied in IVF.

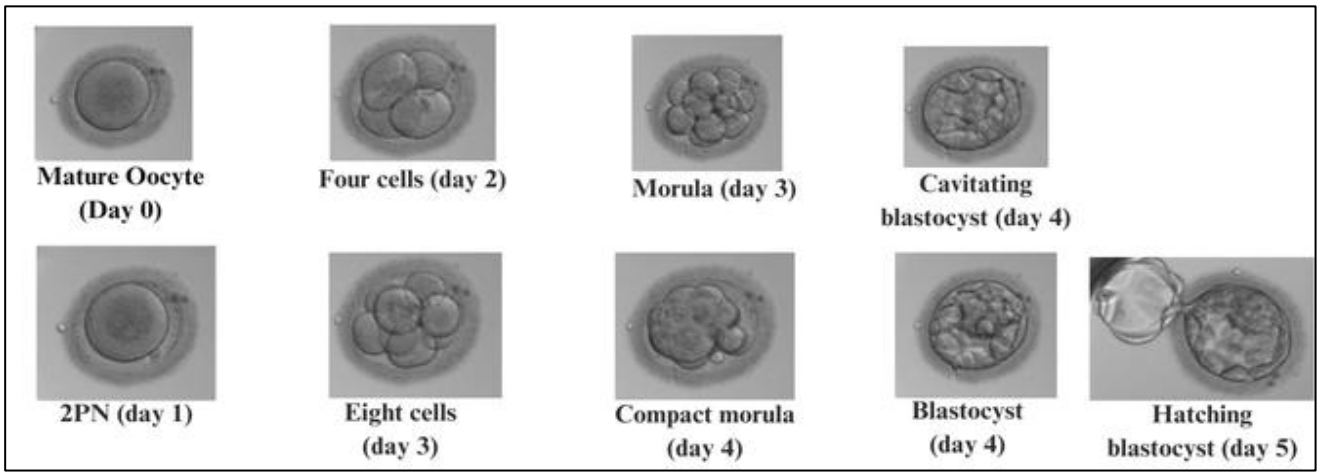

Figure 2: Day wise visualization of embryo development: from oocyte to blastocyst.

Day 5 grading figure 4 is more comprehensive, assessing the blastocoel cavity, inner cell mass (ICM), and trophectoderm (TE). The blastocoel cavity is evaluated based on its size and expansion, ranging from partially filled is Grade 1(lower grade) to fully expanded or hatching is Grade 6 (highest grade). The ICM is graded based on the density and compaction of the cells, with tightly packed, numerous cells considered Grade A (highest grade), while fewer, loosely packed cells are graded lower. Similarly, the TE is assessed based on cell number and uniformity, with densely packed cells classified as Grade A (highest grade) and sparse or unevenly distributed cells classified as Grade C. Embryos with optimal morphology, minimal fragmentation, and well-defined ICM and TE are considered high-grade and are selected for transfer. The goal is to identify embryos with the best implantation potential to increase the likelihood of successful pregnancy outcomes. Two widely recognized grading systems in embryo assessment are the Gardner grading system and the Istanbul consensus grading system. The Gardner grading system is primarily used for blastocyst evaluation, assessing parameters such as inner cell mass (ICM) quality, trophectoderm (TE) quality, and blastocoel expansion. In contrast, the Istanbul consensus grading system[6] provides a comprehensive framework for assessing embryos at all developmental stages, incorporating criteria like cell symmetry, fragmentation, and blastocoel development.[7] Traditionally, grading is performed visually by embryologists, assessing morphological features under a

microscope. However, this method is highly subjective and susceptible to variability between different observers (inter-observer variability) and even when the same observer re-evaluates the same embryo (intra-observer variability), leading to inconsistent grading outcomes.[8]

Inconsistencies in embryo grading can result in the selection of suboptimal embryos, potentially lowering implantation success rates and increasing the emotional and financial burden on couples.[9] AI refers to the use of computer systems capable of simulating human intelligence to perform tasks such as image recognition, data analysis, and decision-making.[10] In the context of embryo grading, AI systems utilize machine learning algorithms, like Convolutional Neural Networks (CNNs), to analyze embryo images, detect subtle morphological patterns, and provide consistent grading assessments.[11] Unlike traditional visual grading methods that are prone to subjective variability, AI systems can objectively assess features such as cell symmetry, fragmentation, and ICM and TE structure, thereby reducing inter-observer and intra-observer variability.[12] Figure 5 illustrates the comprehensive AI-based grading pipeline, starting from raw microscopy images to multi-label classification, where images undergo processes like labeling, annotation, preprocessing, and feature extraction through deep neural networks.[13] The final output includes a multi-label blastocyst grade (eg.5AB), which portrays blastocoel expansion, inner cell mass (ICM) and trophectoderm (TE) quality, providing a more objective and consistent evaluation framework.[14] Advanced imaging algorithms like IDA Score v 2.0 have been developed to further enhance grading accuracy by detecting complex morphological markers that may not be apparent through conventional assessments.[15]

This review systematically explores AI-driven methods for embryo grading, analyzing studies published between 2012 and 2024. The review consolidates findings from original research, with a focus on algorithm development, grading criteria, and the clinical integration of AI-based systems for embryo evaluation.

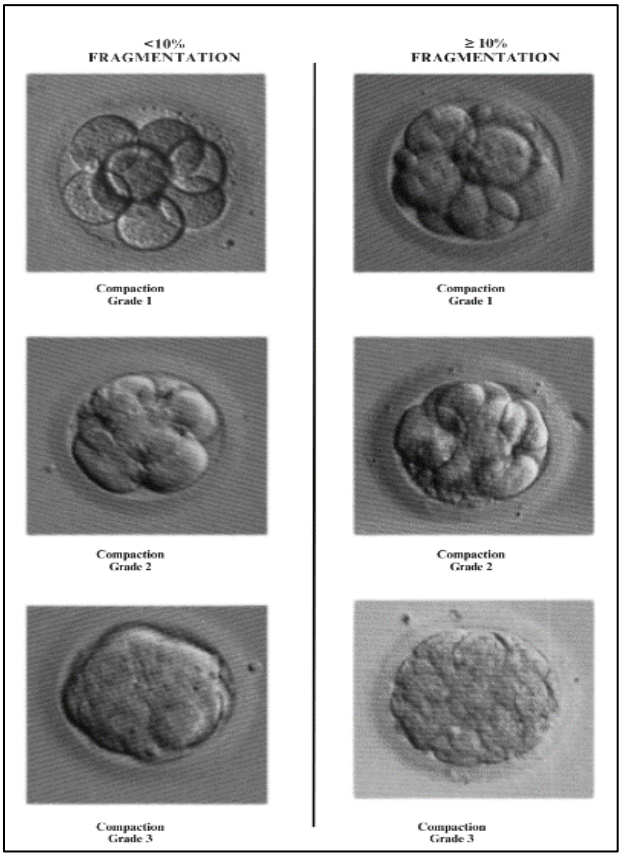

Figure 3: Visual representation of day 3 embryo grading.

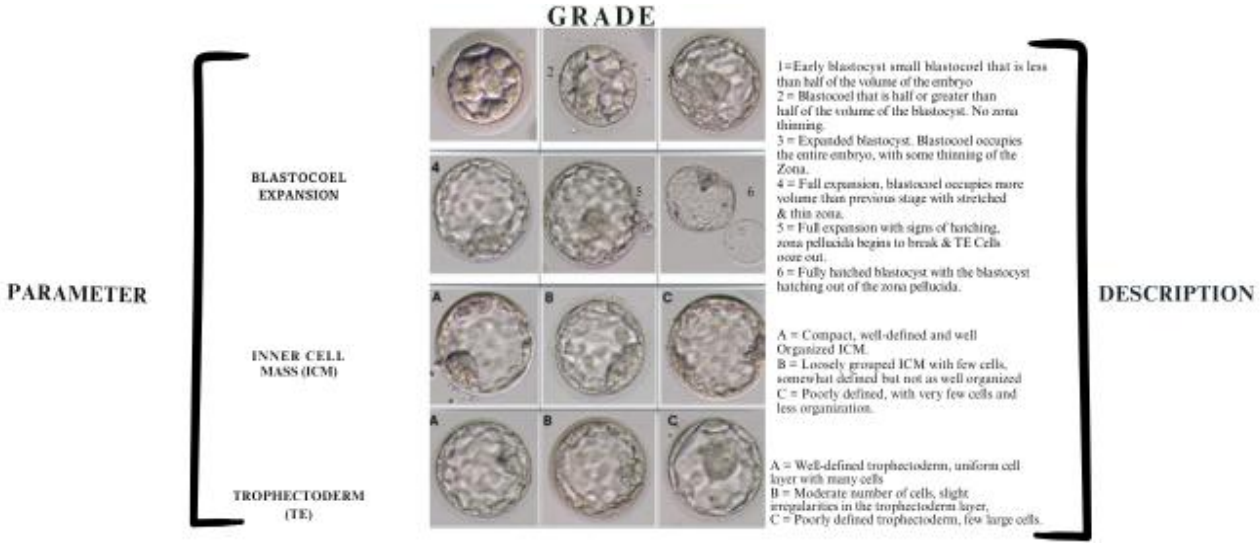

Figure 4: Visual representation of day 5 embryo grading.

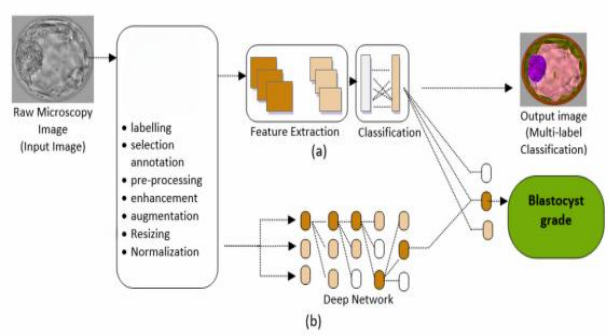

Figure 5: AI-based embryo grading pipeline: from image input to blastocyst grade prediction.

METHODS

Search strategy

A systematic review was conducted by collecting related articles from 2012 to 2024. The terms used for collecting articles were automated embryo selection, automated embryo grading, embryo classification using deep learning (DL) and embryo classification using machine learning (ML) models. A Boolean search query — ("embryo grading" OR "blastocyst grading") AND ("deep learning" OR "CNN") AND ("IVF" OR "ART")—filtered relevant studies as mentioned in Table 1.

Table 1: Search keywords and boolean operators.

Category	Keywords used	Boolean operators
Embryo grading	"Embryo grading," "Blastocyst grading," "Embryo assessment"	Or
Machine learning	"Deep learning," "Machine learning," "Artificial intelligence"	Or
Computer vision	"Image analysis," "Convolutional neural networks (CNN)," "Automated segmentation"	Or
IVF	"In vitro fertilization," "Assisted reproductive technology (ART)"	Or
Final query	("Embryo grading" or "Blastocyst grading") and ("Deep learning" or "CNN") and ("IVF" or "ART")	And

Selection process

Collected articles were screened in stages based on inclusion criteria: published between 2012–2024, focused on AI-driven embryo grading (DL/ML), reported metrics (accuracy, sensitivity, specificity, AUC), and AI methods. Excluded were non-human/animal embryo studies, non-English papers, reviews, meta-analysis, and studies lacking original data or metrics.

Machine learning to cutting-edge deep learning models

Machine learning (ML) is a branch of artificial intelligence (AI) that enables systems to learn patterns from data and make predictions or decisions without explicit programming.[16] Deep learning (DL) is a specialized subset of ML that uses artificial neural networks with many layers (deep neural networks, or DNNs) to automatically extract features from raw data removing the need for manual feature engineering. While some define DL as networks with 3-4 layers, modern models often have dozens or hundreds of layers. Among DL architectures, Convolutional Neural Networks (CNNs) are especially popular for image processing, their ability to learn spatial hierarchies and patterns.[17] However, DL for image analysis is not limited to CNNs. Emerging non-CNN models have shown competitive or superior performance in many tasks. Vision Transformers (VIT) apply transformer architectures to image patches, achieving state-of-the-art classification results.[18] MLP-based models like MLP-Mixer replace convolutions entirely with fully connected layers. Capsule Networks (Caps Nets) aim to capture spatial hierarchies without relying on traditional pooling.[19] Together, these advances highlight the evolving landscape of deep learning in computer vision and beyond.[20]

Deep learning applications in embryo image analysis

Deep learning has emerged as a powerful tool in human embryo image analysis, aiming to improve selection accuracy in assisted reproductive technologies.[18] Researchers have explored a wide range of models, dataset sizes, and stages of embryonic development.[19] used Efficient Net variants, Swin Transformers, STORK, and Alex Net on 20,000 blastocyst and cleavage-stage images, achieving ~99.5% accuracy. Charnpinyo et al applied a deep learning model to blastocyst-stage images with 65% accuracy, 74.29% sensitivity, and an AUC of 0.72. Ahlström et al (2023) used Ida Score v2.0 on 1,786 cleavage-stage images, reporting AUCs around 0.627, while Theilgaard Lassen et al used the same model on 181,428 images, achieving AUCs up to 0.954 on later developmental days. Arsalan et al developed MASS-Net for segmenting blastocyst regions, reporting mean Jaccard indices ranging from ~79% to ~89%. Loewke et al achieved an AUC of 0.74 on 5,923 images with a deep learning model, while Wang et al used VGG-16 with Grad-

CAM on 11,275 images to reach an AUC of 0.936, highlighting interpretability. Septiandri et al achieved 91.79% accuracy using ResNet50 on 1,084 images. Rad et al used a hierarchical neural network (HiNN) on 235 images, achieving 95.6% accuracy with strong precision and recall. Saeedi et al reported accuracies over 86% for specific blastocyst regions on 211 images, while earlier work like Yee et al and Filho et al showed early promise, with the latter achieving 92% accuracy using SVMs on 93 images. Liao employed Faster R-CNN with Crowd-NMS on 94 images, achieving precision of 99.4%, recall of 91.21%, and mAP of 95.31%. Alkindy combined ResNet50 and Xception to achieve 98% accuracy on cleavage-stage embryos. Farias used Dice coefficients to segment over 2,000 blastocyst images, achieving values from 0.54 to 0.96 across regions. Ishaq developed FSBS-Net, achieving 87.26% accuracy on 200 images. Wang introduced I2 C Net with 94.14% accuracy and an 85.25% Jaccard index. Berntsen applied Ida Score v1.0 to 115,832 images, with AUCs of 0.63–0.69. Arsalan also proposed SSS-Net, though detailed metrics were not provided. Other studies include Bormann achieving 70% accuracy on 1,231 images with a CNN; VerMilyea using the Life Whisperer AI model with 64.3% accuracy on 8,886 images; Au (2020) developing Blast-Net; and Rad using U-Net on 592 images for 96.9% accuracy. Rad (2019) also reported 82.85% with Blast-Net, while Wu achieved 74.14% accuracy on 3,601 cleavage-stage images. Harun used DNNs to segment ICM and TE regions with exceptional accuracy over 98%, plus high precision, recall, Dice, and Jaccard scores. Kragh applied RNNs on 851 images, achieving 97.5% accuracy. Kheradmand used Fully Convolutional Networks on 8,460 images but with a lower Jaccard index of 28%, showing early challenges. Lagalla and Singh also contributed, with Singh reporting segmentation accuracy up to 91.7% by grade. Altogether, these studies highlight the diverse architectures from classic CNNs and U-Nets to cutting-edge transformers and object detection models used to analyze embryo images. By improving classification accuracy, segmentation precision, and interpretability, these models support embryologists in making consistent, data-driven decisions, ultimately aiming to improve IVF success rates and patient outcomes.

Table 2: Comparative table of DL approaches for embryo image analysis.

Author (year)	Model	Embryo images	Embryo stage	Reported metrics
Ou et al[28] (2023)	Efficientnet variant, swin transformer, stork, alexnet	20,000	Blastocyst and cleavage	Accuracy: ~99.5%
Charnpinyo et al[29] (2023)	DL model	Na	Blastocyst	Accuracy: 65%, sensitivity: 74.29%, AUC: 0.72
Ahlström et al[30] (2023)	IDAscore v2.0	1,786	Cleavage	AUC: 0.627 and 0.607
Theilgaard Lassen et al[31] (2023)	IDAscore v2.0	181,428	Blastocyst and cleavage	AUC: day 2: 0.861, day 3: 0.872, day 5+: 0.954
Arsalan et al[32] (2022)	MASS-net	Na	Blastocyst	TE: 79.08%, ZP: 84.69%, ICM: 85.88%, BL: 89.28%
Loewke et al[33] (2022)	DL model	5,923	Blastocyst	AUC: 0.74
Wang et al[34] (2021)	VGG-16, grad-CAM	11,275	Blastocyst	AUC: 0.936
Septiandri et al[35] (2020)	Resnet50	1,084	Blastocyst	Accuracy: 91.79%
Rad et al[36] (2018)	HINN	235	Blastocyst	Accuracy: 95.6%
Saeedi et al[37] (2017)	DL model	211	Blastocyst	Accuracy: 86.6% (TE), 91.3% (ICM)
Yee et al[38] (2013)	DL model	20	Blastocyst	—
Filho et al[39] (2012)	SVM	93	Blastocyst	Accuracy: 0.92
Liao et al[40] (2024)	Faster R-CNN, crowd-NMS	94	Blastocyst	Precision: 0.9940, recall: 0.9121
Alkindy et al[41] (2023)	Resnet50, xception	—	Cleavage	Accuracy: 98.00%
Farias et al[42] (2023)	Dice-based segmentation	2,132	Blastocyst	DSC: all pixels 0.87
Ishaq et al[43] (2023)	FSBS-net	200	Blastocyst	Accuracy: 87.26%
Wang et al[44] (2022)	I2CNET	—	Blastocyst	Accuracy: 94.14%
Berntsen et al[45] (2022)	IDAscore v1.0	115,832	Blastocyst and cleavage	AUC: 0.63, 0.69
Arsalan et al[46] (2022)	SSS-net	—	Blastocyst	—

Continued.

Author (year)	Model	Embryo images	Embryo stage	Reported metrics
Bormann et al[47](2020)	CNN	1,231	Blastocyst	Accuracy: 0.70
Vermilyea et al[48] (2020)	Life whisperer AI	8,886	Blastocyst	Accuracy: 64.3%
Au et al[49](2020)	Blast-net	415	Blastocyst	—
Rad et al[50] (2020)	U-net	592	Blastocyst	Accuracy: 96.9%
Rad et al[51] (2019)	Blast-net	—	Blastocyst	Accuracy: 82.85%
Wu et al[52] (2021)	DL	3,601	Cleavage	Accuracy: 74.14%
Harun et al[53] (2019)	DNN	249	Blastocyst	Dice (ICM): 94.3%
Kragh et al[54] (2019)	RNN	851	Blastocyst	Accuracy: 97.5%
Kheradmand et al[55] (2017)	FCN	8,460	Blastocyst	Jaccard: 28%
Kheradmand et al[56] (2016)	Neural network	—	Blastocyst	—
Lagalla et al[57] (2015)	Xception	124	Blastocyst	—
Singh et al[58] (2014)	DL	85	Blastocyst	Segmentation accuracy: 84.6–91.7%

Ethical considerations

AI in embryo grading brings ethical issues. Firstly, dataset bias is a problem—many datasets miss out on diverse patient groups, so AI might work well only for some and flop for others, making it less accurate and unfair. This can widen gaps in fertility treatment. We need varied, all-inclusive datasets for fairer, stronger AI models. Secondly, patient privacy is at risk. Embryo images and records are super personal, but studies often skip how they hide identities or lock data safely with things like encryption. Weak protection can break trust in IVF, so strict safety steps are a must. Lastly, patients need clear consent and understanding they should know how AI picks embryos, keep control over choices, and not just follow a mystery "black box" AI. Fairness, privacy, consent, and clear explanations are key for using AI responsibly in embryo grading.[25]

Clinical applicability issues

AI could transform embryo grading in IVF, but bringing it to clinics is not easy. Regulatory roadblocks, like FDA approval, demand on solid trials linking AI's grading accuracy to live births, etc. may slow the progress. Doubt of clinicians and embryologists whether AI can beat their skill sets, or adapt to each patient's quirks, and its "black box" nature and narrow datasets fuel the hesitation. In an article reviewed, it is highlighted that real-world results are patchy, with a trial across three clinics showing an AI model matching embryologists' picks over 83% consistent grading, while two clinics successfully used AI with time-lapse data for reliable outcomes. Still, these are small steps. Most AI tools boast lab accuracy but lack the big, real-clinic evidence tying them to pregnancies.[26] For AI to hit the mainstream, it needs tougher validation, clinician trust, and clear, outcome driven studies.[27]

Future directions

The future of AI in embryo grading depends on sharper tech and solid clinical proof. Boosting tools like Convolutional Neural Networks (CNNs) past their 99.5% accuracy making them faster and adaptable to diverse data which is key, but so are randomized controlled trials (RCTs) to show AI-picked embryos up to live birth rates, not just lab scores. As of March 2025, the focus tilts toward tech upgrades over clinical validation but both need equal push. Patient trust also matters; studies focusing on people's confidence level on AI for something as personal as embryo selection are thin. Research into clear communication and patient involvement could lift confidence, and without it, adoption of AI might stall the progress. Better algorithms, hard clinical evidence, and keeping patients on board with AI's role is the need of the hour.[48]

DISCUSSION

This review highlights the growing role of AI in embryo grading and selection, demonstrating its potential to address long-standing limitations of conventional morphological assessment in IVF. Across studies published between 2012 and 2024, AI-based systems particularly deep learning models such as convolutional neural networks (CNNs) consistently showed improved objectivity, reproducibility, and predictive performance compared to traditional visual grading by embryologists.

A key finding of this review is that AI-driven embryo assessment significantly reduces inter- and intra-observer variability, a major drawback of conventional morphology-based grading. Traditional embryo evaluation relies heavily on subjective interpretation of features such as cell symmetry, fragmentation, inner cell mass (ICM), and trophectoderm (TE) quality, leading to inconsistencies even among experienced embryologists.[30] In contrast, studies such as Bormann et al and Ver Milyea et al demonstrated that AI systems provide consistent grading across large datasets, supporting earlier observations that algorithmic assessments can outperform human consistency without fatigue or bias.[31]

Another important observation is the progressive improvement in predictive performance as AI models evolved from early machine learning approaches to

modern deep learning architectures. Early studies, including Filho et al and Yee et al relied on relatively small datasets and conventional classifiers such as support vector machines, achieving promising but limited accuracy. Subsequent advances in CNN-based models enabled automatic feature extraction from raw embryo images, resulting in substantially higher performance. For example, Khosravi et al and Wang et al reported high AUC values (>0.90) for blastocyst viability prediction, while recent large-scale implementations such as Ida Score v 2.0 demonstrated strong discriminatory power across different developmental stages when trained on hundreds of thousands of images.[33]

The review also reveals that AI performance improves markedly with increased dataset size and diversity. Models trained on large, multicenter datasets generally showed superior generalizability compared to those developed using small, single-center image collections. This finding aligns with previous work emphasizing that limited and homogeneous datasets restrict the external validity of AI tools in reproductive medicine.[34] Recent efforts to incorporate synthetic data and annotated benchmark datasets represent important steps toward overcoming data scarcity and improving model robustness.[35]

Despite these advances, this review identifies a persistent gap between laboratory-level AI performance and demonstrated clinical benefit. While many studies report high accuracy, sensitivity, or AUC values, relatively few link AI-based embryo grading directly to clinically meaningful outcomes such as implantation, pregnancy, or live birth rates. This concern has been echoed in earlier evaluations of AI in IVF, which caution that predictive accuracy alone is insufficient without prospective clinical validation.[36] The limited number of randomized or multicenter clinical trials remains a significant barrier to widespread clinical adoption.

In comparison with conventional and time-lapse-based embryo assessment, AI appears to complement rather than replace embryologist expertise. Several studies suggest that AI-assisted grading performs comparably to expert embryologists and may serve as a decision-support tool rather than an autonomous selector.[40] This hybrid approach aligns with the Istanbul Consensus updates, which emphasize standardized assessment frameworks while acknowledging the evolving role of automated technologies in embryology laboratories.[42]

Overall, the findings of this review are consistent with previous literature indicating that AI has the potential to enhance precision, standardization, and scalability in embryo selection. However, translating these technical advances into routine clinical practice requires robust prospective trials, transparent and explainable AI models, and careful consideration of ethical and regulatory challenges. Addressing these issues will be essential to ensure that AI-based embryo grading not only improves laboratory metrics but also leads to tangible improvements in IVF outcomes.

CONCLUSION

This review consolidates and critically evaluates over a decade of original research on artificial intelligence driven embryo grading, demonstrating that AI has the potential to substantially enhance precision, objectivity, and consistency in embryo selection compared with conventional morphology-based assessment in IVF. By synthesizing evidence from diverse deep learning architectures, developmental stages, and dataset scales, this study advances current understanding by highlighting not only the technical strengths of AI systems such as reduced observer variability and improved predictive performance but also the translational gaps that limit their routine clinical adoption. Importantly, the review underscores that while AI models increasingly achieve expert-level grading accuracy, their true clinical value depends on robust validation against meaningful outcomes such as implantation and live birth, along with transparency, ethical safeguards, and clinician trust. By integrating technical performance, clinical applicability, and ethical considerations into a unified framework, this review provides a comprehensive reference for researchers, clinicians, and policymakers, and offers a clear roadmap for the responsible integration of AI into embryo selection to improve IVF outcomes.

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