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REVIEW ARTICLE

Integrating artificial intelligence in surgical sperm retrieval techniques: A narrative review

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Abstract

Nonobstructive azoospermia (NOA) is a serious form of male infertility with therapeutic options limited to trials of endocrine manipulations and repertoire of surgical interventions, also known as surgical sperm retrieval (SSR) procedures. Despite its invasive nature, SSR remains crucial in the management of NOA, offering infertile males the opportunity of fathering their biological children using assisted reproductive technologies. Success rates of SSR are variably governed by several factors including the genetic background, preoperative endocrine optimization, testicular histopathology, surgeon's microsurgical expertise, and laboratory technological and technical team's capability. This paper explores the significant role of artificial intelligence (AI) in the process of sperm retrieval among NOA patients. The role of AI has evolved from basic predictive models used for outcome assessment and patient counseling, to advanced image processing capabilities for assessing sperm parameters, and now to cutting-edge applications in identifying the rare sperm present in the azoospermic microdissection testicular sperm extraction tissue samples.

KEYWORDS

artificial intelligence, micro-TESE, nonobstructive azoospermia, sperm retrieval

1 | INTRODUCTION

Male infertility is a serious medical condition affecting males worldwide and is on the rise; with nearly 1 in 20 men suffering from reduced fertility[1,2]. The clinical profile varies according to the severity of the condition, with nonobstructive azoospermia (NOA) considered the most serious form of male infertility[3]. Defined as the absence of sperm in the ejaculate due to failure of production, NOA occurs in approximately 1% of the general population and 15% of patients with infertility[4]. Despite its poor prognosis, NOA could still be managed with variable degrees of success. With the advent of artificial reproductive techniques (ART), many infertile men are given the chance to father their biological children, and as the number of sperm required for ART is minimal, introducing surgical sperm retrieval (SSR) procedures in patients with NOA is crucial. Once sperm are retrieved, they can be used in ART[5]. A growing number of SSR techniques can be offered to NOA patients, with microdissection testicular sperm extraction (micro-TESE) being the most up-to-date and the gold standard approach[5]. Despite its significant role in management, the outcome of micro-TESE is subject to multiple factors that are not only limited to the surgeon's expertise, but also the optimal laboratory techniques and environment[6,7].

Recently, the healthcare industry has been grappling with the adoption of artificial intelligence (AI), which has disrupted contemporary healthcare. AI refers to the process of developing computer systems that are capable of efficiently performing complex tasks that usually require human intelligence and dexterity[8] and is defined as the capability of the engineered systems to acquire, process and apply knowledge and skills according to the International Organization for Standardization/International Electrotechnical Commission technical report[9]. AI has revolutionized NOA management, offering a wide range of innovative solutions, from numerous sophisticated predictive models to guide physicians in counseling their patients, to the implementing of ground-breaking laboratory innovations that utilize complex computational algorithmic models to accurately assess semen samples, eliminating human error and subjectivity[10]. The most up-to-date and innovative measures include image recognition technology, which is used to analyze micro-TESE tissue samples, significantly improving the capability of retrieving the rare sperm within a sample[11]. However, there remains a significant challenge in identifying rare sperm in the complex micro-TESE testicular specimens, with an existent possibility of false-negative results, which could result from human error or limited laboratory capabilities[7]. By leveraging AI, healthcare providers can potentially transform the landscape of male infertility treatment, offering improved outcomes and personalized care for patients suffering from this complex condition[12,13]. This will potentially revolutionize this aspect of management, yet its universal applicability and affordability remain uncertain.

2 | CONVENTIONAL SSR PROCEDURES

SSR is defined as the group of surgical procedures that are used to retrieve sperm from the testis or the epididymis[14]. This approach is generally indicated where no viable sperm are present in the semen and hence, commonly offered in the context of ART when sperm are absent in the ejaculate, either due to an obstructive or nonobstructive pathology[15]. Moreover, SSR may also be considered in patients with an adequate number of ejaculated sperm, yet intratesticular sperm, which commonly exhibit better DNA quality is preferred especially in the context of elevated sperm DNA fragmentation and severe seminal parameters abnormalities[16].

In cases of obstruction, such as obstructive azoospermia (OA), for example, after vasectomy, SSR is more commonly indicated and rates of retrieval may reach up to 100%, as obstructed testes can remain functional and produce enough sperm to make SSR procedures less challenging[17]. In the clinical context of testicular failure, that is, NOA, the testes fail to produce sperm, commonly due to genetic aberrations, for example, Klinefelter syndrome, Y-chromosome microdeletion and translocations[18]. Acquired causes can also contribute to the development of NOA, including undescended testis, mumps orchitis and chemotherapy-induced testicular failure[19].

Considering the different nature, NOA is associated with the considerably less favorable outcomes when it comes to sperm retrieval, compared to OA, primarily because of the underlying testicular failure where sperm production is either severely compromised or totally absent[17,20]. One of the most performed SSR procedures is fine needle aspiration-testicular sperm aspiration (FNA-TESA), which is a less invasive and less technically demanding procedure, entailing percutaneous tissue aspiration using an 18 gauge needle to retrieve testicular tissues and subsequent examination for the presence or absence of sperm[21] (Figure 1). FNA-TESA is commonly indicated in OA or in those who have sperm in their ejaculate, while aiming to retrieve better-quality sperm for ART. Conversely, FNA-TESA is less indicated in NOA, except in the context of testicular mapping, which is performed to outline active sperm-harboring regions within the testis[22].

Another conventional SSR technique is conventional testicular sperm extraction (cTESE), which is the surgical excision of testicular specimens under nonmagnified visual control[23] (Figure 2).

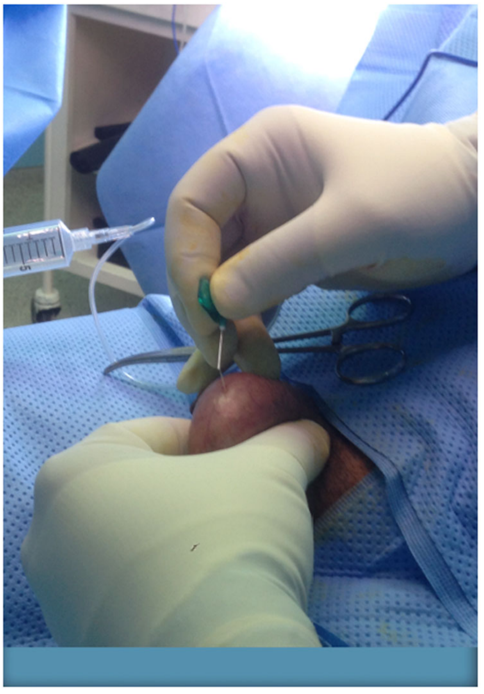

FIGURE 1 FNA-TESA is a minimally invasive procedure in which a fine needle is used to aspirate tissue from the testes, allowing sperm to be extracted. FNA-TESA, fine needle aspiration-testicular sperm aspiration.

FIGURE 2 Conventional testicular sperm extraction, in which testicular tissue is retrieved from the testes without optical magnification.

To improve SSR rates in the context of NOA, Schlegel introduced an advanced and widely adopted technique known as micro-TESE, which utilizes the magnifying power of the surgical microscope[6] (Figure 3). Micro-TESE entails an extensive surgical exploration of the testes, exposing the seminiferous tubules after bivalving the testes and undergoing a series of delicate microdissections under the guidance of the surgical microscope, aiming for morphologically distinct seminiferous tubules, which may appear opaquer and more dilated seen under high-power magnification, suggesting the presence of active spermatogenesis[5] (Figure 4).

Following the surgical microdissection, the tissues are gently handled to the ART lab team for examination. The laboratory procedures used in handling the seminiferous tubules involve a complex process of either mechanical tissue maceration, or enzymatic processing using collagenase and centrifugation that would result in releasing the testicular sperm into the field for proper visualization and isolation[24–26].

Over the years, micro-TESE has become the gold standard SSR technique for patients with NOA despite its inherent technical challenges, requiring advanced microsurgical expertise and a steep learning curve[27]. In a systematic review, SSR ranged from 42.9% to 63% for microsurgical retrievals compared to 16.7%–45% in conventional biopsies[28], with variable degrees of SSR success in Sertoli cell only syndrome (22.5%–41%), early maturation arrest (27%–40%), late maturation arrest (27%–86%), and hypospermatogenesis (73%–100%)[5,28–32]. In a systematic review and meta-analysis by Bernie et al., pooled

FIGURE 3 A microsurgeon using the operating microscope while performing micro-TESE procedure, which enables better assessment of testicular parenchyma. micro-TESE, microdissection testicular sperm extraction.

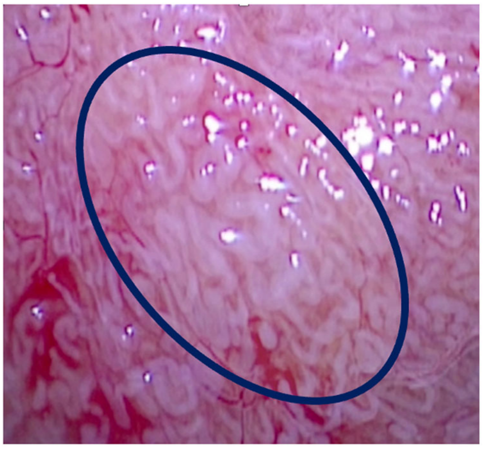

FIGURE 4 A magnified image captured through the operating microscope during the micro-TESE procedure reveals seminiferous tubules with a focal area of dilation, indicating a potential site of active spermatogenesis. micro-TESE, microdissection testicular sperm extraction.

data from 1890 patients included in 15 studies, it was shown that micro-TESE resulted in 1.5 times higher sperm retrieval rate compared to cTESE, while TESA was two times less likely to retrieve sperm compared to cTESE[32]. SSR success rates can be influenced by several factors, including the necessity of the optimal laboratory techniques, advanced technology and skilled staff, which can yield a false-negative result if not properly controlled, potentially skewing the outcome[7].

3 | AI IN REPRODUCTIVE MEDICINE

Recently, the healthcare industry has witnessed an unprecedented disruption due to the rapid adoption of AI, which has up-scaled progressively to involve diverse contemporary medical domains[33]. Being an innovative tool, AI is a comprehensive term referring to the computer utility in performing tasks that generally require reasoning and learning[34]. Such innovative applications are pioneered to assist physicians in various healthcare settings and to deliver a tailored and personalized patient-centered care[35]. AI is regarded as a machine learning (ML) process, which after a series of training sessions, can acquire learning and problem-solving capabilities. Previously, available computational models were confined to a predictive functionality, helping healthcare professionals identify undetectable patterns to facilitate diagnosis and management[36,37]. Subsequently, more complex computational algorithms were introduced and developed advancing ML with more sophisticated and profound capabilities, which facilitated diagnosis and management[38].

In essence, ML is conceptualized around the software algorithms performing training sessions where they analyze statistical outcomes from labeled test sets and compare against a specific outcome to identify a correlation or a discernible pattern[39]. ML can be categorized as supervised when the used training data is compared against a specified outcome. Conversely, it is unsupervised when no labeling data or human interference exist, and the model is left to recognize patterns[40]. ML is not confined to learning, recognizing patterns or problem solving, but also being able to automatically undergo improvements[41].

In the field of andrology, supervised ML models have been developed to assist in the diagnosis and management of male infertility. Krenz et al. developed a prediction model used on azoospermic patients to identify patients with Klinefelter syndrome[42], while Ory et al. developed a random forest model that can predict improvement in semen parameters following varicocele repair[43]. Furthermore, AI has become increasingly engaged in various pathological realms, leveraging the "-omics" data to explore more complex biological realms. With that being said, the innovative cloud-based technology and high-speed data transfer have rendered the application and utility of AI models more seamless and accessible with significant feasibility of monitoring and improvements[35,44].

For instance, in the field of radiomics, where medical images are more profoundly processed and analyzed using complex algorithms, a more precise characterization of the image is obtained, but can help in patient stratification according to the different risk groups[45]. Deep learning (DL) as a subtype of AI uses multiple layers of data, for example, neural networks, which can analyze and identify intricate patterns existing in complex and detailed data models[46]. Neural networks are used for different forms of data, for instance, in a type of DL model, convolutional neural networks (CNNs) are used to analyze spatial data arranged in a grid pattern, rendering them particularly effective for image processing[47], while in recurrent neural networks, where inputs are memorized, sequential data are used instead (e.g., time)[48].

4 | AI PREDICTIVE MODELS IN REPRODUCTIVE MEDICINE

In the field of reproductive medicine, several factors influence the outcome, that is, healthy live births. Male factor contributes to around 30%–40% of the couple's overall infertility, with female factors contributing at nearly similar rates[49]. Currently, semen parameters are commonly assessed using the conventional semen analysis (SA), which is an unreliable tool, incapable of discerning between fertile and infertile males and subject to significant variability that warrants a need for repeated testing[50]. Sperm DNA and chromatin structural studies have emerged as a supporting tool in assessing the fertilizing capacity of the human sperm[51]. Genetic and epigenetic background can significantly be involved in the different sperm abnormalities including sperm maturation, acrosome reaction, and fertilization[52–54].

Furthermore, normal spermatogenesis is highly dependent on normal endocrine function, essentially follicle stimulating hormone and testosterone[55]. Consequently, multiple factors interact to influence male fertility, and addressing each factor individually is insufficient to fully understand male fertility potential. In this context, AI predictive models provide a valuable tool by analyzing existing data to predict and anticipate outcomes more effectively. Moreover, numerous clinical decision support algorithms have been offered to assist in diagnosis and management. Artificial neural networks (ANNs) can be sought in evaluating in vitro fertilization (IVF) data, aiming to predict treatment success, as they are highly effective in handling complex data with high levels of variability[56].

In a study by Vogiatzi et al., 12 statistically significant parameters were collected from 426 IVF/intracytoplasmic sperm injection cycles and used in the construction of ANN that resulted in a 76.7% sensitivity and 73.4% specificity, which was further cross validated to establish a sensitivity and specificity of 69.2% ± 2.36% and 69.19% ± 2.8%, respectively[57]. In a study by Yi et al., sperm morphology was classified using ANNs as either normal or abnormal[58]. In another study by Wang et al., images of sperm in a training set were used in a linear and nonlinear regression models to predict DNA fragmentation from sperm morphology ($r = 0.558$, and 0.62, respectively)[59]. Kandel et al. used computational methods to predict IVF pregnancy outcomes according to sperm ultrastructure[60].

In the context of NOA, an ANN model was developed to predict the odds of sperm retrieval before micro-TESE, utilizing data from 1026 patients performing micro-TESE. This model was capable of predicting the outcome in approximately 60% of cases, with a receiver operating characteristic (ROC) area of 0.641. Furthermore, a nomogram was produced for such purpose with an AUC of 0.59[61]. These values, though promising for future applications, yet require further refinement. Table 1 summarizes key AI-based algorithms that enhance the role of ML across various medical fields.

5 | AI-ENHANCED SPERM IMAGE RECOGNITION

In the context of sperm detection, previous algorithms dedicated to sperm detection used several image processing techniques, including, for example, using the combined Lambertian optical model of light reflection and a mathematical morphologic image processing framework used in segmenting sperm cell images[64], or using an adaptive local threshold and ellipse detection, which entails applying locally adjusting thresholds to manage uneven illumination in a specimen and identifying objects with elliptical shape (i.e., sperm head) in the thresholded images[65]. Unfortunately, the intensive computational demands for image processing, eventually limit the number of samples that can be processed in a given time (throughput)[66].

With advancements in predictive models, AI has evolved beyond numerical data-based processing and analysis to image recognition, achieving high precision and accuracy in detecting intricate structures and shapes. Image processing is challenged by the capability of attaining powerful resolution, a fact that requires large data training sets, and powerful computational capabilities to minimize the blurriness of the image. For this purpose, Dobrovolny et al. proposed a supervised generative adversarial network system, which can generate high-resolution images from low-resolution input, without interfering with the pathological invariance[67]. Furthermore, in an attempt to reduce the subjectivity of conventional SA results, a study by Dobrovolny et al., developed a deep neural network algorithm using a dataset comprised of World Health Organization SA data, live sperm video captures, spermatic fatty acid profile, serum phospholipid fatty acid composition and demographic characteristics, from 85 distinct male subjects, to detect healthy sperm, which resulted in a highly precise and rapid model with a mean average precision of 72.15[68].

Sperm motility is considered pivotal in the assessment of sperm vitality and function, yet in the most advanced measuring systems, the multisperm tracking is lacking, possibly due to the large sperm count, challenging the ability to identify the sperm path along the field[69,70]. This was addressed by numerous projects, for instance, Su et al. used a lens-free on-chip device to undergo sperm tracking in a three-dimensional fashion and was capable in identifying trajectory patterns while imaging appropriately 34 000 sperm trajectories at a rate of 90–140 frames per second[69].

6 | TECHNOLOGICAL INNOVATIONS IN AI FOR SPERM IDENTIFICATION DURING SSR

Searching for and identifying sperm in azoospermic samples is a critical and challenging process, as the outcome is paramount in the decision-making process of whether the patient should or should not move forward with sperm retrieval surgery. Ensuring the identification of existing sperm is prudent to prevent undergoing unnecessary surgical retrieval[7,13]. Moreover, sample processing in the laboratory following the delivery of the specimen may take up to 4 h–6 h[71]. The extended lapse of time during sample processing and examination holds a significant risk on the sperm viability[72]. With that being said, the surgical retrieval itself is not the sole determining factor for success in identifying sperm, in fact, laboratory-related factors have a profound impact on sperm retrieval[73]. In one study, sperm were identified in the laboratory in 7% of samples where no sperm had been identified intraoperatively[74].

To address these challenges, Goss et al. trained an AI model to identify sperm within complex tissue sample. They demonstrated that sperm was detected significantly faster per field of examination using the AI model compared to manual identification by trained embryologists ($0.019 \pm 1.4 \times 10^{-4}$ s vs. 22.87 ± 0.98 s, $p < 0.0001$), with a significant difference in accuracy favoring the AI model over the trained embryologist ($89.88 \pm 1.56\%$ vs. $83.22 \pm 2.02\%$, $p = 0.017$)[12].

As previously mentioned, the process of tissue analysis and sperm identification in surgically retrieved azoospermic samples is extremely challenging and is governed by several factors that dictate the success of sperm recovery. False-negative results are common due to the presence of crowded collateral cell density, lack of experience or simply human fatigue. Such an error could have a devastating outset on the patient and the couple[7,74]. Wu et al. developed a computer-aided sperm analysis system, which is based on a DL model, trained to identify sperm in testicular tissue specimens. The model used data generated from images from 702 testicular specimens across 30 patients divided into training, validation, and testing sets (80%, 10%, and 10%, respectively). Compared with embryologists' performance, the model achieved a mean average precision of 0.741 and an average recall of 0.376[75].

TABLE 1 Comparison of different AI techniques in reproductive medicine.

AI technique	Purpose	Key features	Challenges	Conclusions
Supervised ML[42]	Identify Klinefelter Syndrome in patients with NOA and evaluate against expert clinical evaluation.	Uses patient data (e.g., karyotype, hormones) for training, showing high sensitivity and specificity.	Requires a comprehensive dataset and rigorous training validation to maintain high accuracy across diverse patient profiles.	Enhances detection rates for Klinefelter syndrome in complex cases, benefiting less experienced clinicians.
Random forest model[43]	Predicts which patients with varicocele are likely to benefit from treatment using pre-operative data.	Leverages clinical and hormonal data to accurately predict postoperative improvements in sperm concentration (AUC = 0.72).	Has limited external validation and relies on preoperative data quality, leading to potential variability in success across clinics.	Offers individualized outcome predictions to offer preoperative counseling for patients undergoing varicocele repair.
Radiomics[45]	Extracts information from medical imaging to aid in oncological management and clinical decision-making.	Analyzes imaging features for applications in tumor segmentation and oncological survival prediction.	Requires data preprocessing and feature selection to reduce overfitting; multidisciplinary expertise is crucial.	Improves precision medicine in oncological patients by enabling imaging-based decisions ameliorating patient outcomes.
CNN[47]	Explores how a CNN model can automate feature extraction in radiology to enhance imaging diagnostic accuracy.	Utilizes the CNN model for feature learning and reducing manual extraction, while improving diagnostic accuracy.	Manages small datasets and overfitting risk; requires robust validation to ensure proper generalizability.	Radiologist performance is enhanced by automating complex imaging tasks; offers improved patient care.
RNN[48]	Leverags sequential data processing using RNN for predictive modeling.	Analyzing six different RNN architectures models and their modeling applications e.g., image-to-text translation.	Complex computational resources are required.	Facilitates predictive modeling for sequential data, applicable to language processing and time-series analysis.
Computer-aided sperm analysis of human sperm[62]	Developing an ML model classifying human sperm motility for enhanced reproductive evaluation.	Leverages a support vector machine framework to classify sperm motility patterns, achieving high accuracy and reproducibility.	Addresses complexities in classification and validation against existing methods.	Provides a reliable, high-throughput tool for assessing sperm motility, potentially aiding in infertility diagnostics.
ANN[61]	Utilization of ANNs in predicting sperm retrieval in patients with NOA.	Develops a nomogram to predict sperm retrieval.	Moderate ROC value (0.6).	The use of preoperative factors in aiding clinicians predict SSR.
Gradient-boosted trees and random forest[63]	Predictive model to predict sperm retrieval in NOA.	Employs ensemble ML models including decision trees and logistic regression.	Model complexity.	AI-based model facilitating prediction of SSR.

Abbreviations: AI, artificial intelligence; ANN, artificial neural network; AUC, area under the curve; CNN, convolutional neural network; ML, machine learning; NOA, nonobstructive azoospermia; RNN, recurrent neural network; ROC, receiver operating characteristic; SSR, surgical sperm retrieval.

Recently, a two-phase proof of concept study was published showcasing a CNN model that was trained using approximately 10 000 sperm images from 8 azoospermic patients to detect sperm within samples. Furthermore, a side-by-side comparison between two azoospermic sample cohorts ($n = 4$), examined by the AI versus an embryologist and another side-by-side testing by embryologist with and without AI support ($n = 4$) was performed. Results from this study demonstrated in the first stage that compared to the embryologist, the time taken by AI to detect the sperm in the sample was $0.02 \pm 0.30 \times 10^{-5}$ s versus 36.10 ± 1.18 s ($p < 0.0001$) with significantly improved recall of $91.95 \pm 0.81\%$ versus $86.52 \pm 1.34\%$ ($p < 0.001$). Results further showed that out of 2660 sperm, the AI identified, in less than 1000th of the time, 1997 sperm compared to only 1937 sperm that were identified by the embryologist.

The way the software operates is by creating a bounding box around the sperm that appears while panning through the slide, reflecting a real-time identification of the sperm (Figure 5). Furthermore, time taken per droplet in the searching process was significantly less for the AI-assisted embryologist (98.90 ± 3.19 s vs. 168.7 ± 7.84 s, $p < 0.0001$) with 1396 sperm being found compared to 1274 sperm found without AI assistance[13].

The robustness of a model is further strengthened by expanding the capability of detection in unconventional conditions, by adjusting for image augmentation, which involves subjecting the same training-set images to various circumstances, for example, rotation, color variation, image flipping, or changes in focus so as to train the model to identify the desired object even if the circumstances around are changed[75,76]. Furthermore, another team of researchers have successfully developed an ML model that is trained using bright-field microscopy to identify rare sperm in both, semen and micro-TESE tissue samples. This model was developed using a CNN algorithm trained and validated using 35 761 and 7663 image patches, respectively. The model was then tested with 7663 and 7985 image patches, containing numerous and rare sperm samples, respectively.

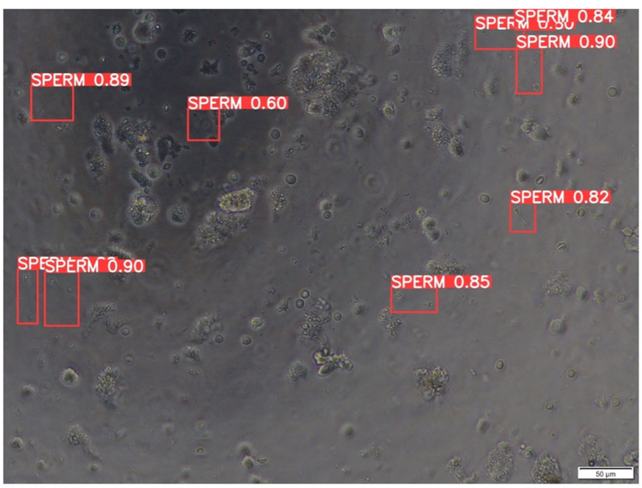

FIGURE 5 Microscopic image demonstrating the real-time sperm identification process using sperm search software. Image used with permission from Steven A. Vasilescu (2024) NeoGenix Biosciences Pty Ltd, Sydney, New South Wales, Australia.

Moreover, for sperm-only samples, the algorithm achieved a positive predictive value, sensitivity and F1-score at ×10 magnification of 91%, 95.8% and 93.3%, respectively. However, for the sperm-abundant micro-TESE samples, it achieved 84%, 72.2%, and 77.9%, respectively, and for sperm-rare micro-TESE samples, it achieved 84.4%, 86.1%, and 85.2%, respectively[11].

7 | CHALLENGES OF AI IN SSR

Despite the innovative measures offered by AI in the realm of SSR, there remain some challenges that would be faced by fertility specialists, urologists, and researchers. This hurdle resides in the specimen variability, which is highly complex requiring extensive training of the model to adapt to the different specimen composition and complex cellular environment[11–13].

8 | ETHICAL CONSIDERATIONS

Comprehending the magnitude of the ethical landscape towards the rising application of AI in reproductive medicine is paramount. Informed consents about the whereabouts of the therapeutic plan should clearly be outlined, with adequate transparency allowing for patient contribution in the decision-making process. The significance of the matter resides in the involvement of the offsprings, which is produced following the selection process of an AI-based model. In such a context, with the lack of studies to measure future outcomes, creates a challenge toward evaluating the impact of AI sperm selection, on the potential offspring's health[38].

Furthermore, as numerous factors interplay in the management process of patients when AI is involved, knowing upon which the reasonability should fall is crucial. However, concern regarding the universal adoption of this technology is based on the essence of individual variability[77]. Additionally, addressing the associated financial burden to this expensive utility is paramount to ensure universal applicability across the medical landscape[78].

9 | FUTURE DIRECTIONS

AI has shown promising innovative measures in managing male infertility, especially in improving SSR for NOA patients. It is expected that as these AI-driven techniques advance further, their role in increasing the SSR precision

TABLE 2 Summary of key outcomes.

Aspect	Key findings
Computational tools	Using different ML models including CNN[14], artificial neural networks[57,58,60,62], recurrent neural networks[48], random forest, and gradient-boosted trees[63] for predictive modeling, etc.
Utility in male reproductive medicine	AI models are being integrated in various applications, including semen analysis (automated motility[62] and morphology[58] evaluation), prediction of sperm presence in NOA patients, and SSR outcomes[61].
Image processing techniques	ML models are being developed using CNNs and other deep learning algorithms to identify rare sperm in complex testicular tissues, resulting in improved detection accuracy and speed in SSR procedures[12,13].
Challenges	Data variability in conjunction with limited sample sizes and the need for complex computational demands pose obstacles to widespread implementation[11–13].
Future directions	Need for more comprehensive datasets, with more diversity in the examined samples, and further validation studies are needed to allow generalizability.

Abbreviations: CNN, convolutional neural networks; ML, machine learning; NOA, nonobstructive azoospermia; SSR, surgical sperm retrieval.

will subsequently evolve with further improvements in the SSR-related precision by refining algorithms to further adapt with the complexity and diversity of testicular specimens. This refinement is expected to reduce both false positives and false negatives, ultimately leading to more accurate results. The expected improvement in AI-based models will possibly include expanding and diversifying datasets to better train models, making them become integral in the decision-support process[63]. This may involve integrating sperm ultrastructural data with functional information, such as fertilization capabilities, to provide predictive outcomes based on these parameters, thereby indicating which sperm are most likely to yield the best results in ART[10,79] (Table 2).

10 | CONCLUSION

In conclusion, NOA remains a challenging medical disorder, not only requiring an experienced medical team, but also requires an efficient and technologically advanced laboratory. The capability of identifying rare sperm within the complex testicular specimens is paramount in enabling azoospermic patients to father their biological offspring. AI has emerged as a disruptive force transforming contemporary medical practices, evolving as a revolutionary tool using its computational algorithms to perform robust image processing and object identification. This functionality has recently been implemented in identifying rare sperm in testicular micro-TESE suspensions, increasing the rate of sperm recovery and hence, the chances of males previously rendered infertile to achieve biological parenthood.

AUTHOR CONTRIBUTIONS

Hussein Kandil is solely responsible for all aspects of this article, including conception, data analysis, interpretation, and manuscript preparation.

CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

ETHICS STATEMENT

The author has nothing to report.

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