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A REVIEW ON UTERINE FIBROID DETECTION, PREDICTION AND PREVENTION USING DATA SCIENCE TECHNIQUES

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ABSTRACT:
Uterine fibroids are the most common benign tumors in women at reproductive age, the Uterine fibroids which nevertheless remain a clinically challenging diagnosis to detect, predict and treat. This review combines the use of machine learning, deep learning, radiomics and hybrid models to the diagnostics of fibroid. Methods are subdivided into classical classifiers like SVM and decision trees or advanced methods like YOLOv7, DenseUNet and 3D DA-VNet. The combination of imaging (MRI, ultrasound) and patient reported information and omics-based features has permitted better segmentation, classification and prediction of outcome. An accuracy of over 90% has always been obtained with the appearance of models with accuracy greater than 0.87, as far as the Dice accuracy metric is concerned and a result value stronger than 0.90 as far as the AUC accuracy metric is concerned. The multimodal fusion and protection-oriented modeling are still problematic despite the improvements. This review points out the salient gaps and future directions like explainable AI, integration of health through mobile devices and real-time support in surgery. The results aim at educating the proper formulation of proactive, individualized fibroid treatment.

KEYWORDS: Clinical decision support, Deep Learning,Machine Learning, Prediction Model, Radiomics.

INTRODUCTION:

Uterine fibroids (leiomyomas) occur in 20 to 70 percent of women up to the age of 50 years and may lead to such symptoms as heavy bleeding, pelvic pain and infertility. Conventional diagnosis routes include imaging and clinical assessment, yet with the latest developments in artificial intelligence (AI) fibroid studies have been altered[1]. The work that was reviewed was devoted to the data-driven methods of fibroid detection, prediction, and protection. The classical machine learning models that were used included decision tree and support vector machine to classify fibroids and with the emergence of deep learning network architectures like YOLOv5[29], DenseUNet[30] and MBF-CDNN[24] have demonstrated an impressive performance in the segmentation and real time identification of fibroid. The research done with Radiomics extracted thousands of features out of MRI scans to predict the outcome of treatment[23], and the NLP-driven models were utilized to triage the symptoms[2,22]. The latest attempts also incorporate the investigation of hybrid forms between CNNs and optimization algorithms[37], instance segmentation methodology as applied to FIGO classification[35] and mobile health data as applied to the correlation of lifestyle with it[18]. Although these results are promising, there are still issues of generalizability, interpretability, and multimodal integration. This review has tried to outline the present environment, indicate performance standards, as well as provide future directions of customized fibroid care.

CLINICAL AND BIOLOGICAL BACKGROUND UTERINE FIBROIDS:

Uterine fibroids or leiomyomas, are benign tumours of uterine smooth muscle affecting up to 70% of the women by age 50. Hormonal influences - particularly estrogen, progesterone and genetic inclination and environmental stimuli influence their development[30]. The size, quantity and location of fibroids are frequently defined and categorized as submucosal, intramural and subserosal type as per the FIGO system[5]. Fibroids clinically may result in heavy menstrual bleeding, pelvic pains, urinary symptoms and infertility. The two (fibroids and malignant uterine sarcomas) should be distinguished because a misdiagnosis can be associated with the incorrect choice of treatment. Separating fibroids and sarcomas using radiomics based models has been done using MRI images and deep learning classifiers[5,20]. ANN and Mass Spectrometry models have both attempted to model cervical and ovarian hippocampal cancers, indicating the similarity between imaging and biomarker phenotype[13,20,26]. Such factors as fibroblast growth factor, transforming growth factor-beta, and extracellular matrix remodeling control the biology of fibroid growth. Recent studies have embraced some biomarkers like FSH, LH and lipid profiles as predictive models of fibroid growth and response to treatment[16,34]. It is suggested that multi-omics reviews could be important to implement the combination of genomics, proteomics and metabolomics providing greater information about the pathogenesis of fibroids and approaches to personalized care[3].

DATA TYPES IN UTERINE FIBROIDS RESEARCH:

In the Uterine fibroid research, there are a wide variety of data types that each contribute to their detection, segmentation, prediction and prevention in their own way.

Medical Imaging Data Medical imaging data, especially with regard to the detection and segmentation processes are by far the most abundant type of data in fibroid research.

MRI Data: includes T2-weighted imaging (T2WI), contrast-enhanced T1-weighted imaging (CE-T1WI) and ADC maps. They are applicable in radiomics feature extraction and volumetric segmentation, and treatment outcome prediction [5,10,23,25,27,31,34,38].

Ultrasound Data: Grayscale, Doppler and elastography images are utilized in classification models, EfficientNet[6], MBF-CDNN[24] and IBSO-CRNN [37].

Laparoscopic Frames: YOLOv5/YOLOv7 real-time detection models are used which use annotated video frames of surgical operations to localize fibroid during intra-operation[29].

Risk Modelling and Classification Structured clinical data: It Includes demographic characteristics (age, BMI), symptom-profiles (bleeding, pain) and biomarkers (FSH, LH, lipid profiles, NLR)[1,4,16,34]. In Treatment parameters are HIFU energy, ablation volume, Funaki types are used in regression and ensemble model[10,21,25].

Radiomics Features: Radiomics The conversion of imaging data into quantitative features. In Features feature (entropy, contrast), shape feature (sphericity, compactness) and intensity feature (signals ratios, histogram bins). Obtained with the assistance of the tools like PyRadiomics and applied in the LightGBM, SHAP, PCA-LDA models to predict the results[23,27].

Textual and NLP Data: Text data can be triaged and auto-reported on symptoms. TF-IDF algorithm and Naive Bayes algorithm are used in processing Patient-reported symptoms to classify a disease[2,22]. The CNN-BiGRU architectures are used to generate image captions and it assists in automatic reporting of ultrasound images[39]. Medications records are mined to obtain efficacy and safety of treatment[17].

Mobile Health and Lifestyle Data: Mobile platform-based real-world data is assisting the process of prevention modeling. Covering diet diaries, pain scale, menstrual cycle and quality of life scales[18]. Computed on clustering algorithms (DBSCAN, UMAP), as well as temporal symptoms modeling using LSTM.

Omics Data: Omics information is regarding biological richness and personalization. Genomics, proteomics and metabolomics are synthesized sequentially to understand the pathogenesis and the hormonal balance of fibroid[3]. Omics integration despite being utilized sparingly offers personal diagnostics and treatment design.

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DATA SCIENCE METHODS APPLIED FOR UTERINE FIBROID STUDY:

Machine Learning (ML): Machine learning can be described as the algorithms that learn patterns from the data to make a prediction or take a decision without being expressly programmed. These models typically require manual feature engineering, meaning that the researchers select and preprocess the input variables. Examples in Fibroid Research In Support Vector Machines (SVM): Fibroid classification by clinical features Age, BMI and hormone levels[1,4,15]. Random Forests (RF) and Decision Trees (DT): To predict the treatment outcomes and rank the importance of features[7,21,34] Gradient Boosting Machines (GBM): Ensemble Model used to predict HIFU success [23].

Deep Learning (DL): A subset of ML, Deep learning is based on Neural networks which are multi-layered and can automatically learn features from raw data - notably good for images, text and complex signals. DL models consume a lot of data and processing power but are very good at tasks such as segmentation and real-time detection. Examples in Fibroid Research Convolutional Neural Networks CNN In ultrasound and MRI-based fibroid detection: Used for ultrasound and MRI based fibroid detection[6,24,28]. YOLOv5/YOLOv7: Real-time object detection for laparoscopic video frames[29]. DenseUNet, DA-VNet Improved Segmentation Models for Fibroid Boundary Delineation [31,38].

Hybrid Models: These are a combination of the ML and DL or using optimization algorithms for improved performance and interpretability. Examples: In MBF-CDNN: Fuzzy logic and CNN for ultrasound classification[24]. In IBSO-CRNN: Improved bird swarm optimization based recurrent networks for elastography based detection[37].

Transfer Learning: Transfer learning is when we use pretrained models (e.g., VGG16, Inception-V4) - trained on a large dataset - and fine-tune them to fibroid specific tasks. This is especially helpful in cases where there is a limited amount of data. Examples: The Inception-V4 + SVM: Applied for Classification of MRI with limited number of samples[36]. VGG16: Application in fibroids detection in TCGA-UCEC DICOM images [32].

Radiomics/ Feature Engineering: Radiomics is the process of extracting quantitative features from the medical images which is used by the ML models. Feature Engineering is the process of selecting and transforming variables to try and improve the performance of the model. Examples: In LightGBM + SHAP: Used to predict the results of HIFU based on radiomic features[23]. PCA-LDA: Applied for growth risk modelling of fibroids[27]. Radiomics enables stratifying the risk of malignancy and predicting growth[30,34.]

Natural Language Processing (NLP): NLP techniques for analyzing textual data e.g. patient reported symptoms or image captioning on medical images. Examples: In TF-IDF + Naive Bayes: Used for the classification of diseases on the basis of symptoms[2,22]. The CNN-BiGRU: Descriptive ultrasound image captioning[39].

REAL TIME DETECTION METHODS FOR THE UTERINE FIBROID STUDIES:

Real-time detection has become a revolutionary application of deep learning in the research of uterine fibroids, especially in surgical and diagnostic processes. Among such reviewed papers, a number of research studies implemented high-speed object detection models capable of fibroid identification in live imaging streams - in particular for laparoscopic video frames and ultrasound data.

The most prominent techniques are based on YOLO (You Only Look Once) architecture like YOLOv3, YOLOv5 and YOLOv7. These models are optimized for speed and precision, which makes them ideal for intraoperative guidance. For example, in[29]benchmarked YOLOv4-v7 and found that YOLOv7 beats others with F1 scores greater than 97% and frame rate greater than 100 FPS. This enables surgeons to be able to identify fibroids in real-time for minimally invasive procedures. Other models such as CenterNet and SSD were also tested and versions of YOLO were always able to offer better performance. In [5]applied yolo_v3 for fibroid vs. sarcoma differentiation of MRI with fast inference and clinical utility. Meanwhile, [11]applied a DCNN to help junior sonographers take real-time ultrasound to improve the accuracy of the diagnosis.

Hybrid models such as IBSO-CRNN[37] employed optimization algorithms and CNNs to perform near-instant classification in elastography-based imaging. In addition, in[39]CNN-BiGRU has been introduced for real-time captioning of ultrasound images to assist the automated reporting and education of the patient. Despite these advances, there are continuing challenges in the quality of the annotation, generalisability across institutions and clinical validation. Future studies should involve aiming at lightweight deployment, better regulation, and integration with surgical robotics and mobile platforms.

Table1: Real-time Detection Approaches

Model used	Application	Performance
YOLOv3	Fibroid vs. sarcoma classification (MRI)	Fast inference, high precision[5]
DCNN	Ultrasound Interpretation support	Elevated junior accuracy[11]
YOLOv4-v7, SSD, CenterNet	Laparoscopic fibroid localization	YOLOv7:F1>97%, FPS>100[29]
IBSO-CRNN	Ultrasound elastography classification	99.89% accuracy, fast processing [37]
CNN-BiGRU	Real-time ultrasound captioning	BLEU-4: 0.55, ROUGE-L:0.78[39]

PREDICTION AND PREVENTION MODEL OF UTERINE FIBROID STUDIES:

Prediction Models

Prediction models for uterine fibroids are mostly developed to predict the results of treatment, growth of fibroids and the risk of recurrence. These models integrate structured clinical information of the patient, imaging features and radiomics to develop individual risk scores and decision support tools.

Treatment Outcome Prediction: In[10,21,23]models were developed based on MRI-derived features (e.g. ADC values, Ktrans, subcutaneous fat thickness) and clinical parameters to predict HIFU and embolization success. Techniques included LightGBM, logistic regression and SHAP increased interpretability.

Growth and Recurrence Modeling: In [27]a model-based radiomics hazard model to estimate risk of growth of fibroids was introduced which combined PCA-LDA and survival analysis. In [34]regression curves have been used to visualize the prognosis post treatment that can help planning follow up.

Risk Stratification: The classical ML algorithms such as SVM, RF, ensemble classifiers were applied to classify the patients based on the fibroid size, location and hormonal profile[1,4,15]. These models had AUC as high as 0.90, and R squared values greater than 0.85.

Prevention Models:Prevention-oriented modelling is an area where there is still room for improvement but is making inroads with mobile health and lifestyle analytics.

Lifestyle-Based Prediction: In [18]used Mobile health data (such as diet logs, pain scores, and menstrual tracking) to group the patients into phenotypes using the DBSCAN and LSTM. This way, early intervention and individually tailored lifestyle recommendations are encouraged.

Medication Mining: In [17]treatment records from 328 studies were processed to identify low risk medications such as mifepristone using the association rule mining and comparative safety profiling.

Symptom-Based Screening: In [2,22]they used NLP technique (TF-IDF + Naive Bayes) to classify gynecological conditions using the reported symptoms from the patient, thus allowing to perform an early triage and preventive care.

Review of Data Science Approaches in Uterine Fibroid Research: Trends and Perspective:

Uterine fibroids affect up to 70% of women by age 50, and the diagnostic and therapeutic pathways are fragmented. The combination of data science that includes machine learning (ML), deep learning (DL), radiomics and natural language processing (NLP) has enabled new opportunities in precision diagnostics, predictive modeling and real-time surgical support. This is a review combination of insights derived from peer-reviewed studies to map current trends and future directions of fibroid research using Artificial Intelligence (AI).

Key Trends in the Application of Data Science: Transition from Classical ML to Deep Learning Early studies were based on SVM, Random Forest and Logistic Regression, for fibroid classification and risk stratification [1,4,15]. Recently, work favoured to CNN, VGG16, and a combination of CNN and classifier such as MBF-CDNN[24] and IBSO-CRNN[37] with classification accuracy up to 99.89% are favoured.

Radiomics-Driven Prediction Models: Radiomics features obtained from MRI and ultrasound such as entropy, compactness and ADC values are incorporated in LightGBM and SHAP enhanced models to predict HIFU success and fibroid growth[23,27]. In[34] introduced regression-based prognostic curves with R2 = 0.851 for post treatment monitoring.

Real-Time Detection for Surgical Support: YOLOv5 and YOLOv7 models[29] displayed F1 scores of more than 97% and frame rates of more than 100 FPS in fibroid localization in laparoscopic vision. These models are made optimally for edge deployment and intraoperativeguidance.

Multimodal and Hybrid Integration: While most of the models are based on imaging and clinical information, [3]incorporated multi-omics fusion and [18]applied mobile health data for lifestyle-based phenotyping. However, actual multimodal integration is still very uncommon, indicating an opportunity for future research.

NLP and Automated Reporting: Models based on text [TF-IDF + Naive Bayes[2,22]] are in favour of symptoms triage. In [39] proposed CNN-BiGRU to perform real-time captioning of ultrasound images, where the BLEU-4 score and ROUGE-L score are 0.55 and 0.78, respectively.

Perspectives and Future Directions

Explainable AI: Tools like SHAP [23]and PCA-LDA[27] are increasingly used to visualize the feature importance to improve the clinical trust.

Longitudinal Modeling: Time-series approaches (e.g. LSTM[18]), underutilized, but vital in monitoring fibroid progression and recurrence.

Prevention-Oriented Analytics: In [17]the team mined medication records from 328 studies to identify the low-risk treatments and in[18], the team employed clustering to correlate the lifestylefactors with symptom severity.

Clinical Translation: Despite good performance measures, there have been few models that have been validated in the real world. In [11]discussed DCNN assisted ultrasound interpretation for junior sonographers, but further deployment is required.

Open Collaboration: Standardized data sets and federated data learning frameworks are essential for reproducibility and cross-institutional benchmarking - which does not yet exist in the vast majority of studies.

PERFORMANCE EVALUATIONS AND TYPES OF MODELS IN UTERINE FIBROID RESEARCH:

Data science models in uterine fibroid research are created for the following types of tasks: classification, segmentation, prediction and real-time detection. Across the papers, several different types of machine learning (ML), deep learning (DL), hybrid and ensemble models were evaluated using strict performance metrics.

Table2: Model Types and Their Applications

Model Category	Techniques Used	Primary Application
Classical ML	SVM, RF, DT, KNN, Naive Bayes	Classification, risk stratification
Deep Learning	CNN, VGG16, Inception-V4, DPCNN, EfficientNet	Detection, segmentation, captioning
Segmentation Models	UNet, DenseUNet, DA-VNet, Mask-RCNN, PointRend	Fibroid boundary delineation
Ensemble Models	Voting, GBM, AdaBoost	Outcome prediction, classification
Hybrid Models	MBF-CDNN, IBSO-CRNN	Feature optimization, ultrasound classification
NLP Models	TF-IDF + Naive Bayes, CNN-BiGRU	Symptom screening, automated reporting
Real-Time Detection	YOLOv3–v7, SSD, CenterNet	Surgical guidance, live fibroid localization
Radiomics + ML	LightGBM, PCA-LDA, SHAP	Treatment outcome prediction

Table3: Performance Metrics Across Model Types

Model Task	Metric Used	Top Performance Reported
Classification	Accuracy	99.89% (IBSO-CRNN)[37]
	F1 Score	>97% (YOLOv7)[29]
	U-Kappa	0.402 (Inception-V4 + SVM)[36]
Segmentation	Dice Similarity Coefficient	0.878 (DA-VNet)[38]
	Hausdorff Distance	11.18 mm (DA-VNet)[38]
Prediction	AUC	0.90 (LightGBM + SHAP)[23]
	R^2 (Regression Fit)	0.851 (MRI-based prognostic model)[34]
	Hazard Ratio	0.33 (Radiomics growth model)[27]
NLP & Captioning	BLEU-4 Score	0.55 (CNN-BiGRU)[39]

CHALLENGES AND LIMITATIONS IN CURRENT RESEARCH:

Despite the increasing interest in promoting AI-oriented strategies for the uterine fibroid treatment, current research reveals a number of ongoing limitations from a methodological, clinical, and ethical perspective.

Data Fragmentation and Limited Multimodal Integration: Most of the studies are based on single modality input such as clinical, imaging or genomic data without unifying them into a single model. This limits the depth of diagnosis and generality. For example, although in [1]the structured clinical features are used, the fusion of radiomics or omics is missing, which limits the robustness of the prediction.

Model Overfitting and Lack of External Validation: There are several machine learning models for which the accuracy is very high (for example, for the Gradient Boosting algorithm: 77% in[1]), but are not validated usually on a different dataset. This raises the issue of reproducibility and practicality.

Underrepresentation of Protection-Oriented Frameworks: A significant body of research exists in the detection and prediction of cybersecurity threats, and there is little attention to proactive or preventive care. Few models contain wearable information, longitudinal tracking, or early risk alerts - critical for real-time intervention.

Ethical and Societal Barriers: Privacy issues surrounding reproductive health data make sharing difficult and so does modeling together. Moreover, cultural taboos and socioeconomic disparities cause underreporting of symptoms with skewing of datasets and making models less fair - highlighted in[2].

Limited Explainability and Clinical Translation: Complex models such as deep neural networks are often not interpretable, and therefore it can be hard to implement them in a clinical workflow. Clinicians need clear decision pathways, and these pathways are not typically discussed in current studies.

Absence of Longitudinal and Temporal Modeling: Most models are static in nature - they do not take into account the progression of fibroids over time and/or treatment outcomes. Without time series data, predictive systems are reactive but not adaptive.

RESEARCH GAP AND METHODOLOGY TO BE USED IN UTERINE FIBROID:

Disintegrated Modalities and Lack of Integration: Most studies examine separate modalities, ultrasound In[1,5,6,24,28,33,37], MRI In [9,25,31,32,34,38,40], structured clinical data in [2,4,7,15,19] or omics in[3,20] without incorporating them into a unified diagnostic or predictive framework. This is limiting holistic understanding and multi-modal support in decision making.

Limited Longitudinal Modeling / Growth Prediction: Fibroid progression over time is not modeled in a few studies. In [16]uses regression to predict growth; In [27] introduces a radiomics-based risk score (AUC 0.80); In [30]uses Deep Set Networks to predict shrinkage post-UFE. However, longitudinal multi-modal models are still rare.
Underutilization of Treatment Response/ Medication Data: Medication history and treatment outcomes based on NPVR are explored in[17,21]. In [34]uses features of MRI to predict prognosis post-HIFU. In [40]models NPVR >=80% using logistic regression. Yet, there have been few studies linking imaging and treatment trajectories in the real-world, or risk of recurrence.
Patient-Reported and Mobile Health Data: Sparse Consumption in[18,22] show how the use of mobile apps can reduce diagnostic delay in endometriosis. In [30]models symptom specific outcomes post-UFE. However, fibroids studies do not often include patient-reported outcomes or mobile health data so that fibroids can be tracked in real time.
Segmentation and Feature Extraction Issues: Ultrasound segmentation is hard because of the speckle noise and low contrast. In [5]benchmarks despeckling filters; In [33]SRAD and Lee filters most effective in[35]is where multiclass instance segmentation is introduced; In [38]3D DA-VNet with attention gates is proposed. Yet, there is a lack of generalizability across devices and populations.
Explainable AI and Clinical Interpretability: In [23]applies SHAP to LightGBM on feature importance. In [25]uses interpretable regression. In [34]uses Boruta for feature selection using MRI. However, most deep learning models[6,24,28,36,37] are not transparent, which limits clinical trust and adoption.
Limited Application of Radiomics and Multi-Omics: In[3]including proteomics and genomics; In [20]using mass spectrometry + ML for the detection of ovarian cancer. In [27]does use PCA-LDA to radiomics scoring. These approaches are promising and are underutilized in fibroid-specific pipelines.
Captioning & models of language in medical imaging: In [39]introduces CNN-BiGRU for Uterine ultrasound captioning achieving BLEU-4 score of 0.55 and ROUge-L score of 0.78. This is a new direction but there are not many studies on NLP for fibroid images interpretation and reporting generation.
Lack of Real time Models/Edge aware Models: In [12]we are using YOLOv3 for the case of fibroids real-time detection. Laparoscopic uterus localization[29] benchmarks YOLOv4/5/7. Canny edge detection for ultrasound segmentation[37]. However, edge-aware and real time models are still not so common in fibroid clinical workflows.

FUTURE DIRECTIONS OF THE UTERINE FIBROID RESEARCH:

Multimodal Data Fusion for Precision Diagnostics Combine data from imaging data (MRI, ultrasound), clinical history, genomics and proteomics to create comprehensive, diagnostic models. It employs radio genomic mapping which matches the morphology of fibroids with its molecular signature. It applies federated learning to protect the privacy of the patients while training on different data sets.
Real-Time Monitoring and Predictive Modeling: Develop wearable-integrated systems for monitoring symptoms (i.e. bleeding, episodes of pain). It used time series models (Lstm, Gru etc) in order to predict fibroid growth or response to treatment. Personalize care pathways and patient-reported outcomes with NLP.
Explainable AI for Clinical Translation: At present, explainable AI models may be seen as black box models and models that are explainable (e.g. SHAP, LIME) may be used to build trust amongst clinicians. Construct tools to aid in decision making, which are clear visual presentations of risk factors and decision-making regarding treatments.
Protection-Oriented Frameworks: Go beyond detection and prediction when it comes to protection. It develops artificial intelligence systems to identify the early risk factors (e.g. hormonal imbalance, lifestyle factors) which would lead to fibroids. Explore preventive interventions Digital therapeutics and behavioural nudge
Hybrid and Ensemble Modeling: Ensemble Classifier Using CNN and Radiomics and Clinical Features to Robustly Classify Fibroids. It uses the use of ensemble methods (e.g. stacking of XGBoost, Random Forest, SVM) in order to increase generalisability across populations.
Biomarker Discovery through Multi-Omics: Use transcriptomics, metabolomics and methylomics to define fibroid specific biomarkers. It takes advantage of unsupervised clustering to stratify subtypes of fibroids and tailor treatment.
Digital Health Platforms and Telemedicine: Implement the mobile application for remote diagnosis and treatment tracking and patient education. Integrate AI-powered chatbots for triage of symptoms and follow-up support
Socio-Cultural and Ethical Integration: Beating the underreporting of cases due to stigma because of culturally sensitive AI interfaces. Do the datasets and tools for fibroids care provide equitable access to fibroid care. (e.g. multilingual).

DISCUSSION:

Despite all these advancements, there are a number of limitations. Many models are based on single modality data, have no outside validation and are not amenable to interpretation, impeding clinical uptake. Protection-oriented frameworks are still lacking and the monitoring of real-time using wearables or longitudinal tracking is rarely realised. Moreover, cultural taboos and limits for data privacy prohibit symptom reporting and outcome of joint research, particularly in low-resource settings.

CONCLUSION:

The exhaustive analysis of studies shows a dynamically changing scenario in the research field of uterine fibroids by the various uses of artificial intelligence, machine learning (ML) and multi-omics technologies, which are revolutionizing the paradigms of diagnosis and treatment. Itshows the effectiveness of classification algorithms - Decision Tree, Random Forest, XGBoost and Gradient Boosting - in creating decision support tools for fibroid treatment and the accuracy is up to 77%. Similarly,underline the application of Natural Language Processing (NLP), and Naive Bayes classifiers in gynecological disease prediction based on symptoms, which are also of utmost accessibility and user-centric.To consequently close these gaps, future studies will need to focus on multimodal fusion (integration of imaging, clinical and omics data) to improve the precision of diagnosis. Explainable AI frameworks lie at the heart of addressing the levels of trust between the result of algorithms and clinical decision-making. Emerging technologies such as federated learning, wearable integration and patient-reported outcome modelling are prospective leads to achieve proactive and personalised care.Ultimately, this review underscores the transformative potential of hybrid artificial intelligence systems in the management of uterine fibroids. By adopting integrative, transparent, and patient-centric methods, researchers and clinicians can strive to create a future of equitable, preventive, and precision reproductive healthcare.

ETHICAL CLEARANCE STATEMENT:

It is a review article that is founded on the already existing studies. No patient information or human animal experimenting was done so that there was no ethical clearance that was needed.

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