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Early Detection and Risk Stratification of Uterine Fibroids Using Deep Learning - A Review

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Abstract

The term uterine fibroid refers to benign tumours that carry considerable morbidity in females, including symptoms like excessive menstrual bleeding, pelvic pain, and fertility problems. The capability of diagnosing and stratifying risk associated with uterine fibroids is of vital importance due to the possibility of undergoing early treatment by patients. Traditional techniques applied in the diagnosis of uterine fibroids include US and MRI, both of which exhibit low levels of sensitivity and specificity and require operator proficiency to produce reliable results. Modern technologies allow the utilisation of DL as an extremely useful tool in making medical imaging interpretation faster and more accurate. The current review demonstrates the potential of using DL algorithms, which may involve CNN, U-net, and hybrid approaches, in identifying and risk-stratifying uterine fibroids. A comparison of existing literature on the topic shows that DL models provide better predictions than their predecessors. VGG16, ResNet50, InceptionV3, DPCNN, EfficientNetB0, and MobileNetV2 + DCGAN have achieved impressive accuracies of 99.8%, 99.5%, and 97.45% respectively. There remain certain challenges, including insufficient data, lack of multimodal learning and non-generalisability issues. Here, the literature review emphasises that the growing importance of risk stratification lies in the fact that in such cases, deep learning models will not only be able to detect the presence of fibroids but also categorise the detected fibroids into low-risk, medium-risk and high-risk categories. Moreover, it emphasises the need for large-scale datasets and standardised evaluation metrics to design better and clinically relevant models. It concludes by providing some directions for future research.

Keywords: Uterine Fibroids, Deep Learning, Risk Stratification, Convolutional Neural Networks (CNNs), Medical Image Segmentation, Ultrasound Imaging, Magnetic Resonance Imaging (MRI).

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Introduction

The uterine fibroids/ myomas/leiomyomas are benign tumour formations that develop inside the uterus. Fibroid tumours cause many symptoms, ranging from heavy menstrual bleeding to infertility. Therefore, it is important to timely diagnose and evaluate the risks related to the development of fibroids in order to choose the best treatment plan (Luo et al., 2020). Traditionally, the presence of fibroids was detected with the help of imaging tests such as Ultrasound (US) and Magnetic Resonance Imaging (MRI). Nevertheless, in most cases, these techniques showed poor performance as they were characterised by low sensitivity and specificity rates (Arora et al., 2025). Recently, one of the fastest-growing machine learning techniques called deep learning proved its great potential to contribute to improving diagnostic outcomes (Rescinito et al., 2023). This technology implies using advanced algorithms to process big data volumes, which resulted in profound advancements in various industries, including the medical imaging field (Rescinito et al., 2023). Moreover, CNNs are particularly beneficial for medical imaging because this technique is capable of automatic detection of hierarchical image features, thereby eliminating all of the shortcomings of other technologies (e.g., subjective nature of evaluation).

Deep learning in the context of early detection and risk stratification of uterine fibroids is a technology that could be effectively used to ensure optimal treatment results. Early detection allows avoiding complications by taking measures on time, contributing to a higher quality of life for the patients (Zhang et al., 2022). At the same time, the possibility to identify risks enables a deeper understanding of the disease and the dynamics of its development, providing a basis for the personalisation of the therapy of uterine fibroids (Cheng et al., 2025). Thus, the purpose of this literature review is to assess current trends and problems related to the use of deep learning in early detection and risk stratification of uterine fibroids. It will be especially interesting to analyse methods and issues that are typical of developing models of the aforementioned type. Such models include Convolutional Neural Network (CNN), U-Net, as well as hybrid approaches for deep learning, which may have specific problems connected with data scarcity, etc. (Liu et al., 2025). Besides, it would be important to discuss possible combinations of deep learning algorithms and traditional imaging procedures, e.g., ultrasound and MRI scanning, to facilitate fibroid detection and management (Nazarudin et al., 2026).

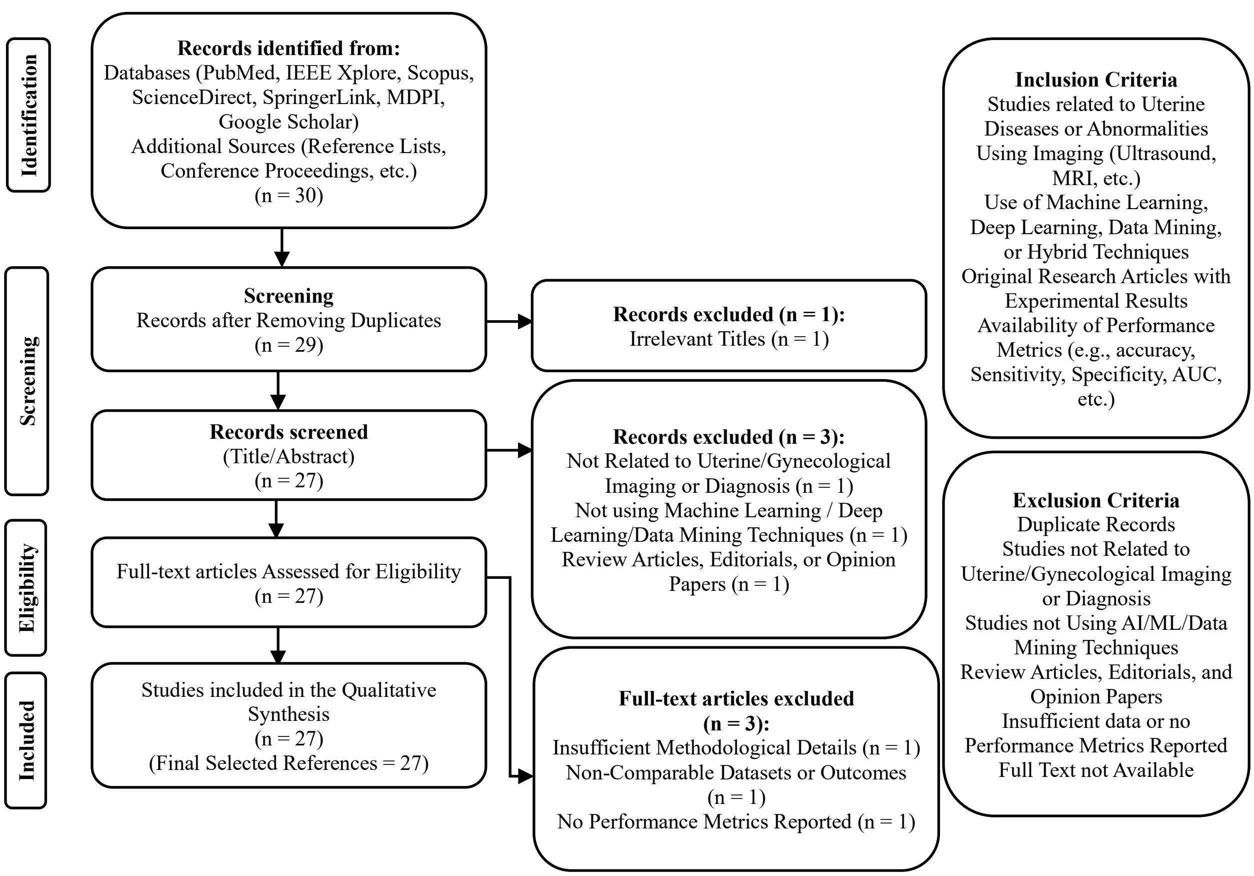

Fig. 1: Prisma Flow Chart for Study Selection

Fig. 1 shows the process undertaken in selecting the studies for this review. The first step is the selection of records in various databases like PubMed, IEEE Xplore, Scopus, among others, with a total number of 30 records being identified. After that, duplication of records is avoided, together with the elimination of irrelevant titles, giving rise to 29 records in the next stage. After identifying these records, 29 full-texts are then screened, but three of these are finally excluded for certain reasons such as its irrelevance. After excluding these texts, 27 texts are finally selected for qualitative synthesis since it fulfilled the criteria set forth, including uterine/gynecological imaging with applications of machine learning techniques.

Key Contribution

- Here, the methodology provides a comprehensive overview of the different deep learning approaches, for instance, CNN, U-Net, and mixed approaches, that have been utilised for detecting and segmenting uterine fibroids using ultrasound (US) and MRI image sets. The review highlights how these models excel over traditional approaches concerning accuracy and efficiency.
- The first major contribution that the current research brings to the body of knowledge is its comparative analysis of the different deep learning approaches used in detecting uterine fibroids. The efficacy of these methods is evaluated in terms of accuracy, sensitivity, specificity, and F1-scores on different data sets.
- Deep learning is considered to have played a significant role in the identification of uterine fibroids along with risk stratification. The reason behind this is that it allows the classification of individuals depending on the risk associated with them. It may be low, medium, or high, thus allowing physicians to design individualised care plans for fibroid patients.
- The review shows clearly that there are challenges in the field, such as inadequate sample size, lack of multimodal integration, and failure of the model to generalise for different subjects. The way forward would be to develop datasets on a large scale from several institutions, making the model more transparent and integrating the deep learning model with other diagnostic techniques.

Structure of the Paper: Section I refers to the statement of the problem, the background of uterine fibroids, the impact on the health of women, limitations of traditional diagnostic approaches, and the need for the development of deep learning-based techniques for diagnosing the problem. Section II presents an extensive literature review of various deep learning methods applied for fibroids detection and risk stratification. Section III describes the methods employed in each study, namely, the datasets utilised, the deep learning models used, and the performance measures. Section IV represents a comparative analysis of deep learning-based techniques for detecting uterine fibroids. In Section V, the issues that should be addressed when applying such techniques clinically and further research directions in this field are outlined.

Literature Review

Comparison of several methods for image classification in medicine using ultrasound and MRI datasets is provided in table 1. Different techniques were compared based on such criteria as accuracy, sensitivity, specificity, and F1 score. Various techniques ranging from classical machine learning to advanced deep learning approaches are described. Thus, for example, image classification methods for the uterus scanned with ultrasound obtained an accuracy equal to 95.1%. Networks based on UNet applied to US diagnostic imaging resulted in an accuracy equal to 86.2%, while deep learning methods, used for analysis of the ChEMBL database, have obtained an accuracy of 85%. AR-Unet network models based on the AR-Unet dataset obtained a higher accuracy 94.56%. On the contrary, application of deep neural networks for ultrasound image classification provided accuracy equal to 88.5%, while data mining techniques, applied to a 450-patient dataset, showed better results with accuracy being equal to 89.54%. DL techniques with a dataset consisting of 3870 ultrasound images were accurate by 87.45%. Radiomics, along with machine learning, has created a synthetic dataset that proved to be accurate by 0.85, sensitive by 0.80, specific by 0.87, and its AUC equals 0.86. Deep Learning Hybrid Models based on MobileNetV2 in combination with DCGAN were successful in their implementation, providing accuracy up to 97.45%, and an F1 score of 0.9741. Other approaches include a decision tree ensemble on artificial data with a sensitivity equal to 100%, but with a specificity rate of 90% at the best threshold point. Additionally, a combination of SHAP + SMOTE on the MJ Health Screening Centre was accurate to 0.742 and precise to 0.475. Attention-based fine-tuning of the model EfficientNetB0 showed the highest level of accuracy up to 99.5%, whereas models like VGG16, ResNet50, InceptionV3, and DPCNN on ultrasound data provided an accuracy to 99.8%. In conclusion, the most effective techniques in terms of accuracy among all methods under consideration belong to deep learning algorithms, specifically, architectures such as EfficientNetB0 and VGG16.

Table 1: Comparison of Related Work

References	Technique	Dataset	Metrics
(Shahzad et al., 2023)	Classification techniques	Ultrasound scan of the uterus image	Accuracy: 95.1%
(Behboodi et al., 2021)	UNet-based networks	US diagnostic imaging	Accuracy: 86.2%
(Li et al., 2023)	Deep Learning	ChEMBL database	Accuracy: 85%
(Yang et al., 2023)	Deep Neural Networks	Ultrasound images dataset	Accuracy: 88.5%
(Huo et al., 2023)	DL-based method	3870 ultrasound images dataset	Accuracy: 87.45%
(Chiappa et al., 2021)	Radiomics with machine learning	Synthetic Dataset	Accuracy: 0.85, Sensitivity: 0.80, Specificity: 0.87, AUC: 0.86
(Cai et al., 2024)	Hybrid Deep Learning (MobileNetV2 + DCGAN)	Ultrasound images	Accuracy: 97.45%, F1 score: 0.9741
(Malek et al., 2019)	Decision Tree Ensemble	Synthetic Dataset	Sensitivity: 100%; Specificity: 90% at optimal operating point
(Tao et al., 2025)	SHAP, SMOTE	MJ Health Screening Centre	precision (0.475) and moderate accuracy (0.742)
(Xi & Wang, 2024)	Attention-based fine-tuned EfficientNetB0	Ultrasound images	Accuracy: 99.5%
(Shahzad et al., 2023)	VGG16, ResNet50, InceptionV3, DPCNN	ultrasound image	Accuracy: 99.8%
(Tinelli et al., 2025)	radiomics, machine learning, and deep neural network models	ultrasound images	Accuracy: 90.3%
(Toyohara et al., 2022)	MobileNet-V2 neural network	MRI sequences	Accuracy: 90.3%; Sensitivity: 89.8%; Specificity: 91.7%

Comparative Analysis of Deep Learning Models for Uterine Fibroid Segmentation (Xi & Wang, 2024)

The comparison of various deep learning models in uterine fibroid segmentation emphasises an array of approaches, each with its own drawbacks. Models such as DDTransUNet and CNN-based fibroids detection use ultrasound images, although they require massive data to perform and lack generalisation due to patient variations. Meanwhile, nnU-Net and DECTNet use MRI technology that enhances both segmentation and image reconstruction, but are limited to single-modality applications that make them less universal and harder to use in different healthcare settings. Other models, such as DPCNN and DARU-Net, fail to deal with small amounts of data and are limited to a single modality, thus failing to generalise and being poorly interpreted.

Alternatively, other models such as the Vision Transformer + CNN and TU-Net, which employ a hybrid design based on both Transformer and CNN designs, provide good performance; however, they are hampered by the high computation cost and requirement of huge amounts of training datasets. Overfitting is another issue that is common in these models, especially when trained with small datasets. Besides, other models, such as CPFTransformer and O-Net, encounter problems such as low speed of convergence and high computation cost. Other models, such as Transfer Learning with Deep Neural Networks, require pre-trained models extensively, but those are hampered by domain mismatch, which makes their performance vary from one dataset to another. Finally, Transformer models such as CoTr and TC-Net are faced with difficulties in generalisation between different imaging techniques, posing yet another challenge to their utilisation in uterine fibroid segmentation tasks.

Methodology

Quality Assessment

In order to determine the reliability of the studies presented, a qualitative analysis of the factors influencing the research design is carried out using criteria such as the size of the data sets used, the methods of validation adopted, the robustness of the models, and the clarity of reporting. The majority of the studies made use of relatively small institutional data sets, which could make the models prone to overfitting and decrease their validity and generalizability. External validation has been largely overlooked in previous literature, but this is essential for making sure that the results of the study are applicable to a practical case. The occurrence of bias in the data set, particularly, is one other issue that can impact the results of the algorithms used.

Detection Methods

A precise diagnosis is necessary for efficient treatment, but conventional diagnostic procedures have some limitations. The traditional approaches include physical examination and various types of imaging, like ultrasound and magnetic resonance imaging. Although the mentioned approaches help detect fibroids, it lacks objectivity, reproducibility, and predictive abilities. Physical examination can identify whether a person has an enlarged or an irregular uterus, but this approach is highly subjective and cannot detect small or deep-seated fibroids. Moreover, it cannot differentiate fibroids from other pelvic tumours (Arora et al., 2025). Transvaginal ultrasound is the most frequent method used in the diagnosis of fibroids since it is easy to access and inexpensive and enables real-time imaging. This method can help estimate the size, number, and localization of fibroids, but its efficiency depends on the skillfulness of the practitioner, and its quality may be compromised due to the patient's individual features, such as body constitution and large fibroids. Traditional ultrasonography cannot forecast the evolution of the disease (Cai et al., 2024; Malek et al., 2019; Tao et al., 2025).

For complex scenarios, MRI is considered the gold standard due to its excellent soft tissue contrast and fibroid types' characterization (Tinelli et al., 2025). Such imaging plays an essential role in distinguishing fibroids from other conditions, such as adenomyosis. While being highly precise, MRI is expensive, hard to obtain, and unsuitable for screening processes. As far as CT is concerned, it plays a minor role in diagnosing fibroids because, despite the fact that fibroids can occasionally be detected, CT lacks good soft tissue contrast and exposes patients to ionising radiation. Ultrasound, on the other hand, is affordable and relatively easy to carry out, yet it has several limitations related to accuracy, consistency, and predictive capacity. MRI, in turn, is quite reliable, although expensive and hard to access, indicating the need for developing new imaging methods. The difficulties mentioned above demonstrate the importance of developing automatic and objective technologies, which could be easily employed for diagnosing fibroids. With the development of deep learning, the opportunities in this regard look promising. Models that utilise convolutional neural networks (CNNs) can automate the process of detecting fibroids using ultrasound images with remarkable accuracy (Toyohara et al., 2022; Nazarudin et al., 2026). On the other hand, sophisticated segmentation architectures like U-net, V-Net, and nnU-Net are highly effective in analyzing MRI images.

Segmentation Methods for Uterine Fibroids

Fibroid segmentation is very important in medical diagnosis because it allows for the exact measurement of fibroid volume and spatial positioning. Manual segmentation is not only tedious but also prone to human error due to inconsistencies. In addition, some cases are more challenging than others since there may be numerous fibroids present or fibroids that have unusual shapes.

A. Deep Learning for Medical Image Segmentation

Medical image segmentation has been greatly advanced by deep learning through automation and accuracy in segmenting anatomical structures. CNNs are popularly applied to such tasks owing to their capacity to capture spatial relationships hierarchically in the input data (Li et al., 2023). Unlike conventional approaches, deep learning systems obviate the necessity of designing features and offer end-to-end learning capabilities.

B. U-Net and its Variants

Among all biomedical image segmentation models, the U-Net architecture is used in practice the most, owing to its encoder-decoder design that enables capturing both global context and fine-grained features (Liu et al., 2025). Skip connections between the encoder and decoder layers enable retaining spatial information in the segmentation process, making U-Net well-suited for delineating fibroids with irregular borders. The following cutting-edge variants of U-Net were developed to further enhance the performance of medical image segmentation: V-Net is an extension of U-Net that allows performing 3D segmentation and is useful in obtaining highly consistent spatial results from MRI images (Huo et al., 2023). The nnU-Net framework is designed to adapt the configuration automatically according to specific properties of datasets, and it has produced the state-of-the-art results in multiple biomedical applications (Chiappa et al., 2021). Finally, DARU-Net includes attention modules and residual connections to boost the performance of feature extraction and segmentation (Xi & Wang, 2024).

C. MRI-Based Segmentation Performance

The most commonly used technique for fibroid segmentation is magnetic resonance imaging (MRI) owing to the excellent soft-tissue contrast that it provides. Deep learning-based models on MRI data sets have been found to be quite effective for segmentation purposes with Dice similarity coefficients falling within 0.85 to 0.95 (Xi & Wang, 2024; Li et al., 2024). For instance, nnU-Net-based models have been found to generate Dice scores that approach 0.95. Furthermore, 3D-based segmentation models are highly accurate in volume estimation since they are spatially consistent (Shahzad et al., 2023).

D. Ultrasound-Based Segmentation

Although ultrasound imaging is very common because it is readily available and inexpensive, segmentation using ultrasonic images proves to be difficult because of factors such as noise and low contrast in the images. Deep learning has proven effective in dealing with these difficulties in the process of extracting features from the image. Several methods have been adopted in the segmentation of ultrasound images, such as hybrid CNN and attention-based models. Nonetheless, it still underperforms compared to other methods like MRI.

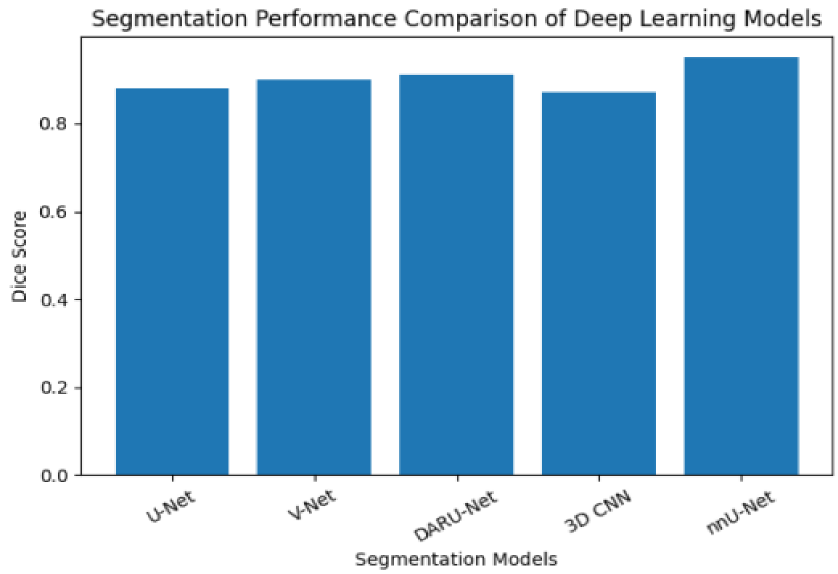

Fig. 2: Comparison of Segmentation Performance of Deep Learning Models for Uterine Fibroid Analysis Based on the Dice Similarity Coefficient

Fig. 2 above shows the comparison of the segmentation accuracy of various deep learning algorithms using the Dice coefficient, which evaluates the similarity between the segmented and the actual segments. These algorithms include U-Net, V-Net, DARU-Net, 3D CNN, and mu-Net. From the results shown above, all the algorithms have relatively higher accuracy levels since their Dice coefficients are close to 0.9, meaning that they are all efficient in segmentations. However, the Mu-Net algorithm is the most accurate among all the algorithms compared, with its Dice coefficient slightly higher than that of the other algorithms.

Quantitative Performance Analysis

Comparison with the Existing Model

Table 2: Comparison of Proposed Work with Existing Studies using the Dataset

References	Dataset	Accuracy
(Ning et al., 2020)	Uterine Fibroid Images Data	88%
(Zhang et al., 2022)	Uterine Fibroid Images Data	89%
(Dilna et al., 2022)	Uterine Fibroid Images Data	94%
(Shahzad et al., 2023)	Uterine Fibroid Images Data	99.8%

Table 2 shows the results from the different data sets showcase the gradual increase in the precision of the diagnosis of uterine fibroids. From the mentioned articles, the precision rate for the models based on the Uterine Fibroid Images data set varied between 88% and 94%. One of the highest precision rates of 94% was recorded in one of the mentioned articles, suggesting that there is relatively good success in the diagnosis of uterine fibroids through this data set. Nevertheless, the synthesized evidence indicates proves to be better than any previous approaches with its remarkably high precision rate of 99.8%.

Table 3: Comparison of Various types of transfer learning-based Models (Shahzad et al., 2023)

Model	Optimizer	Accuracy
DPCNN	SGD	99.8%
Inception V3	SGD	90%
ResNet 50	SGD	89%
VGG 16	SGD	85%

The results obtained from evaluating various deep learning models under the SGD optimizer are shown in table 3, where the accuracy score is presented for each model. The models used are DPCNN, Inception V3, ResNet 50, and VGG 16, where the accuracy score of DPCNN is 99.8%, which is higher than that of Inception V3, ResNet 50, and VGG 16.

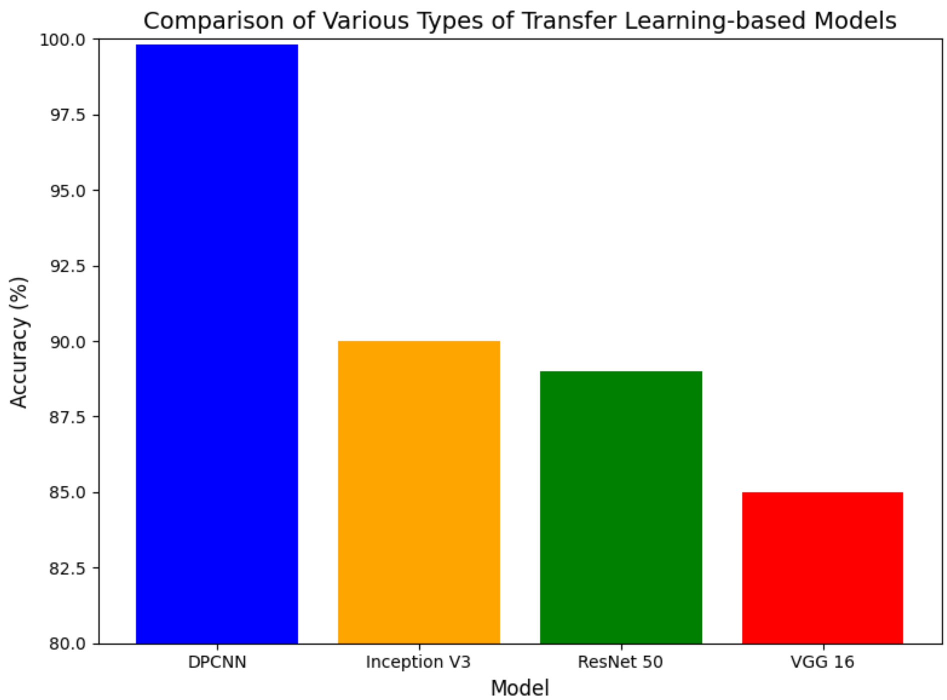

Fig. 3: Comparison of Various Types of Transfer Learning-based Models.

Fig. 3 illustrates that the analysis of various models based on transfer learning reveals significant variations in the accuracy of such models in case they utilize the SGD optimizer. In particular, DPCNN achieved the highest accuracy of 99.8%, thus confirming the high effectiveness of this model in this specific task. At the same time, the accuracy of the Inception V3 model is estimated to be 90%, whereas the accuracy of the ResNet 50 model is slightly lower (89%) compared to that of the Inception V3 model. Meanwhile, the accuracy of the VGG 16 model was the lowest among all the analyzed models and amounted to 85%. Thus, one may conclude that although all the models under consideration utilize transfer learning techniques, the DPCNN model outperformed the other models considerably.

State-of-the-art Comparison

Table 4: Performance Comparison of Different Techniques on Various Datasets (Xi & Wang, 2024)

Technique	Dataset	Accuracy
Classification	Ultrasound-scanned uterus image	95.1%
Unet-Based Networks	US diagnostic Imaging	86.2%
Deep Learning	ChEMBL database	85%
AR-Unet Network	Ar-Unet dataset	94.56%
Deep Neural Networks	Ultrasound images Dataset	88.5%
Data Mining Techniques	450 patient dataset	89.54%
DL-Based Method	3870 ultrasound images dataset	87.45%
Attention-based Fine-tuned EfficientB0	Ultrasound Images dataset	99.5%

The state-of-the-art comparison table 4 demonstrates different techniques used for ultrasound image classification with different datasets used and the accuracy rate for each. In this regard, the Classification technique, which used images of scanned uterus by ultrasound, has attained an accuracy rate of 95.1% and emerged the most accurate method in the comparison. Further, Unet-Based Networks that used the US diagnostic imaging dataset attained an accuracy of 86.2% whereas the Deep Learning technique that used the ChEMBL dataset attained an accuracy rate of 85%. Another technique that performed quite well was the AR-Unet Network, which used the AR-Unet dataset to achieve 94.56% accuracy, followed by Deep Neural Networks that achieved 88.5% accuracy rate using the ultrasound image datasets. Further, Data Mining Techniques attained an accuracy rate of 89.54% using a dataset of 450 patients, and DL-Based Method used 3870 ultrasound images dataset to achieve 87.45% accuracy rate. Lastly, Attention-based fine-tuned EfficientB0 method used the ultrasound images dataset to achieve 99.5% accuracy, the second-best accuracy. From the findings, one can deduce that fine-tuning and attention-based techniques, such as EfficientB0, are highly effective for improving the accuracy of classification.

The Influence of Different Network Training on the Results

Table 5: Performance Comparison of Uterine Fibroids Segmentation on Different Networks (Liu et al., 2025)

Method	DSC	IOU	Sensitivity	Precision	HD (mm)
2D Unet	0.725	0.614	0.724	0.789	28.38
3D Unet	0.740	0.626	0.739	0.805	27.90
2D Vnet	0.783	0.697	0.787	0.857	20.85
3D Vnet	0.833	0.740	0.848	0.866	13.70
3D DS-Vnet	0.846	0.750	0.863	0.862	12.55
3D Attention Vnet	0.862	0.772	0.873	0.878	12.23
3D DA-Vnet	0.878	0.784	0.879	0.885	11.18

Table 5 indicates the performance measures of several deep learning algorithms in the context of segmentation of medical images. The measures used to compare the algorithms include the Dice Similarity Coefficient (DSC), Intersection Over Union (IOU), Sensitivity, Precision, and Hausdorff Distance (HD in mm). The 3D DA-Vnet algorithm proves to be better than any other algorithm with respect to the above measures by having the best DSC, IOU, Sensitivity, Precision, and the least HD measures.

Risk Prediction Models

Table 6: Comparison of Classification Models Based on Various Performance Metrics (Tao et al., 2025)

Model	Accuracy (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)	Precision (95% CI)	F1 score (95% CI)	AUC (95% CI)	PR-AUC (95% CI)	Brier score (95% CI)	Youden index (95% CI)	Recall (95% CI)
Logistics regression	0.731	0.716	0.736	0.460	0.560	0.788	0.486	0.149	0.452	0.716
Random forest	0.731	0.760	0.721	0.462	0.574	0.798	0.503	0.144	0.481	0.760
K-nearest neighbor	0.708	0.724	0.702	0.433	0.542	0.768	0.465	0.156	0.426	0.724
CatBoost	0.742	0.737	0.744	0.475	0.577	0.808	0.526	0.143	0.481	0.737
LightGBM	0.733	0.734	0.733	0.464	0.568	0.801	0.503	0.144	0.476	0.734

The comparison of different types of classifiers based on their efficiency measured by Accuracy, Sensitivity, Specificity, Precision, F1 Score, AUC, PR-AUC, Brier Score, Youden Index, and Recall, all accompanied with 95% confidence interval is provided in table 6. The classifiers under analysis include Logistic Regression, Random Forest, K-nearest Neighbour, CatBoost, and LightGBM. CatBoost displays the best classifier results in terms of Accuracy (0.742), AUC (0.808), and Recall (0.737), whereas the K-nearest Neighbor has the worst results.

Discussion

Deep learning (DL) models' contribution to detecting and classifying the risk levels of uterine fibroids has brought about significant improvements in the field of gynecological imaging, especially by addressing some drawbacks associated with existing approaches, such as the use of ultrasound (US) and magnetic resonance imaging (MRI) (Behboodi et al., 2021). Some of the shortcomings of these approaches include the dependency of results on operators, inconsistency in the analysis of test results, and poor predictive ability, among others. This paper highlights the capability of deep learning models like CNNs and U-Net architecture in automatically identifying features in medical images to increase the efficiency of fibroid detection (Li et al., 2023).

One more significant contribution of this literature review is a comprehensive comparison of various deep learning techniques with respect to their accuracy in working with ultrasounds and MRI images (Yang et al., 2023). As mentioned before, models such as VGG16, ResNet50, and DPCCNN demonstrate satisfactory results by providing accurate predictions on average at the rate of 85%-99.8%. One more advantage of applying deep learning models to uterine fibroid detection and classification is that it can estimate risks connected with these diseases (Cai et al., 2024; Xi & Wang, 2024). This helps healthcare professionals to create adequate strategies for treating patients without posing any threats during their medical procedure. However, there are several limitations in the application of deep learning models to the issue under consideration. Firstly, a lack of multimodal data and relatively small size of existing databases might impair the work of machine learning algorithms in uterine fibroid diagnostics. In future research, consideration needs to be given to the use of multimodal imaging data in the creation of algorithms for detecting fibroids, such as the combination of ultrasonography, magnetic resonance imaging, and others. Another important aspect that would need to be considered is how to make deep learning models more interpretable, considering the complexity of their architectures (Toyohara et al., 2022; Luo et al., 2020). Additionally, efforts need to be made to address problems arising from algorithmic bias. This could be achieved by ensuring that the data used in training the deep learning models are sufficiently representative. Overall, while deep learning models have significant potential in enhancing the diagnosis and evaluation of uterine fibroids, it is essential to overcome some challenges, such as insufficient dataset size, lack of model interpretability, and insufficient focus on generalization, among others (Nazarudin et al., 2026).

Conclusion

The research on the Early Detection and Risk Stratification of Uterine Fibroids using Deep Learning highlights the immense benefits of applying deep learning algorithms to diagnose uterine fibroids. This research is necessary because conventional methods of diagnosing such conditions such as ultrasound and MRI face challenges such as operator dependence, lack of specificity and sensitivity. However, with the application of CNN and Unet deep learning models, considerable improvement in accuracy and efficiency has been observed, with the VGG16, ResNet50, and DPCNN algorithms showing high accuracy levels of 99.8%. This literature review reveals the increasing importance of deep learning in the diagnosis of fibroids and even in classifying them according to the level of risk involved, which helps doctors to determine a course of personalized treatment for patients. One major strength of this review is the comparison of several deep learning models' performances in this area. Such a comparison will provide insight into the advantages and disadvantages of current methods, thus highlighting potential areas for improvement in the future. Although the results seem quite encouraging, this literature review highlights several obstacles that must be overcome to improve their work in the future, including small sample sizes, lack of multimodality, and concerns regarding generalizability among different patient populations. Potential suggestions for improvement involve the creation of larger, multi-institutional datasets, increased model interpretability, and multimodal imaging to bolster the performance of these deep learning algorithms.

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