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Hybrid Machine Learning (Ml)-Based System for Detection of Uterine Fibroids from Ultrasound Images Using Convolutional Neural Network (Cnn) and Attention Mechanism

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ABSTRACT

Uterine fibroids are among the most common benign tumors affecting women of reproductive age, and their timely detection is crucial for effective clinical management. Traditional diagnostic practices rely on expert interpretation of ultrasound images, which is often time-intensive and subject to variability. This study presents a hybrid machine learning system for the early detection of uterine fibroids using transabdominal and transvaginal ultrasound images. The proposed system integrates Convolutional Neural Networks (CNN) with advanced feature refinement techniques (Attention Mechenism) to improve diagnostic accuracy and reliability. A curated dataset obtained from the Kaggle repository was used, and preprocessing methods such as contrast normalization and noise reduction were applied to enhance image quality. Experimental results demonstrated strong performance, with an accuracy of 94%, precision of 92%, recall of 90%, and an F1-score of 91%. These balanced metrics highlight the robustness of the hybrid approach, offering consistent detection of fibroid-positive cases while minimizing false positives and negatives. The system shows promise as a clinical decision-support tool, particularly in resource-limited settings where radiological expertise is scarce. Future research will focus on expanding the dataset, incorporating explainable AI methods for greater transparency, and validating the model across diverse populations and imaging protocols.

Keywords: Uterine fibroids, ultrasound imaging, convolutional neural network, machine learning, tumor detection, medical image analysis, diagnostic support system.

INTRODUCTION

Background to the Study

Uterine fibroids, also known as leiomyomas, are benign tumors originating from the smooth muscle layer of the uterus and are among the most common gynecological conditions globally. Epidemiological studies report that up to 80% of women develop fibroids by menopause, with higher prevalence in African and African-American populations [1]. Although non-malignant, fibroids often cause heavy menstrual bleeding, pelvic pain, infertility, and pregnancy complications, thereby significantly affecting quality of life and contributing to increased healthcare costs [2]. detection of fibroids using ultrasound imaging is critical for timely intervention, as it reduces morbidity and improves patient outcomes [3].

Prevalence of Uterine Fibroid in Nigeria

The burden of uterine fibroids in Nigeria is considerable, with prevalence estimates varying across regions and clinical settings [4]. A large sonographic survey in South-Western Nigeria involving 2,575 women revealed a prevalence rate of 6.8%, suggesting that fibroids are relatively common even among women in the general population who may not present with obvious symptoms [5]. In contrast, studies conducted in hospital-based populations tend to report higher figures due to the concentration of symptomatic cases. For instance, a study in Port Harcourt found that 33.9% of 271 women undergoing ultrasound examinations had fibroids, reflecting the high frequency of the condition among women who seek gynecological evaluation [5]. Further evidence from Abia State University Teaching Hospital shows that fibroids remain a notable clinical concern, with 8% of women attending the gynecology clinic diagnosed with the condition during a five-year review period [6]. Similarly, at Rivers State University Teaching Hospital, fibroids were implicated in 27.8% of all gynecological surgeries performed over a five-year span, underlining their role as a leading indication for surgical intervention among Nigerian women [6].

Taken together, these findings highlight the substantial prevalence and clinical burden of fibroids across different parts of the country. When extrapolated to Nigeria's female population of reproductive age estimated to be over 50 million women these percentages translate into millions of women currently living with fibroids, many of whom may be undiagnosed or untreated. This underscores the urgent need for more effective strategies for early detection, non-invasive monitoring, and accessible treatment, particularly in low-resource healthcare environments [6].

Types of Uterine Fibroid

Fibroids do not all behave the same way, and their impact on women's health largely depends on where they grow within the uterus. Doctors and researchers typically classify them based on their position, because this strongly influences symptoms, fertility, and treatment options [5].

Intramural fibroids: These are the most common type. They form inside the muscular wall of the uterus and can either expand inward into the uterine cavity or outward toward the pelvis. Many women with intramural fibroids experience heavy periods, abdominal swelling, or difficulties with fertility if the growth distorts the womb. On scans, they often appear as dense, solid masses, and while medication can control symptoms, surgery is sometimes required.

Submucosal fibroids: These are less common but often more problematic because they grow into the inner lining of the uterus. Even when small, they can cause severe bleeding and significantly reduce the chances of conception or sustaining a pregnancy. This makes them particularly important for women who are trying to have children. They are usually detected through ultrasound or hysteroscopy, and surgical removal through a minimally invasive procedure is often recommended.

Subserosal fibroids: This type of fibroid grows outward from the outer wall of the uterus. Instead of causing heavy periods, they are more likely to press on other nearby organs like the bladder or bowel, leading to frequent urination or constipation. While they may not always affect fertility directly, they can still cause significant discomfort. Imaging helps determine their size and exact position, which is vital in deciding whether surgery is necessary (Radiopaedia, n.d.-c).

Pedunculated fibroids: These are fibroids that grow on a stalk, either inside or outside the uterus. Their main risk comes from twisting on their stalk, which can cut off their blood supply and trigger sudden, severe abdominal pain. Such cases often require emergency medical attention. While less common than the other types, their unpredictable nature makes them clinically important.

Symptoms of Uterine Fibroid

Not every woman with uterine fibroids experiences symptoms. For some, the growths remain silent, while for others, they can significantly disrupt daily life and reproductive health. The symptoms usually depend on the number, size, and exact location of the fibroids within the uterus. Thus the following are the major symptoms one may experience when there is a presence of fibroid;

Heavy or prolonged menstrual bleeding (menorrhagia): This is one of the most common symptoms. Women with submucosal fibroids, in particular, often report very heavy periods that may last longer than normal. Over time, this can lead to anemia, fatigue, and dizziness, which reduce overall quality of life.

Pelvic pain and pressure: Large fibroids, especially intramural and subserosal types, can cause a sensation of fullness or heaviness in the lower abdomen. This pressure often leads to cramping, discomfort, or chronic pelvic pain that can worsen during menstruation.

Urinary and bowel problems: Because the uterus sits close to the bladder and intestines, fibroids can press on these organs. This may cause frequent urination, difficulty emptying the bladder, or constipation. Subserosal fibroids growing outward are more likely to trigger these symptoms.

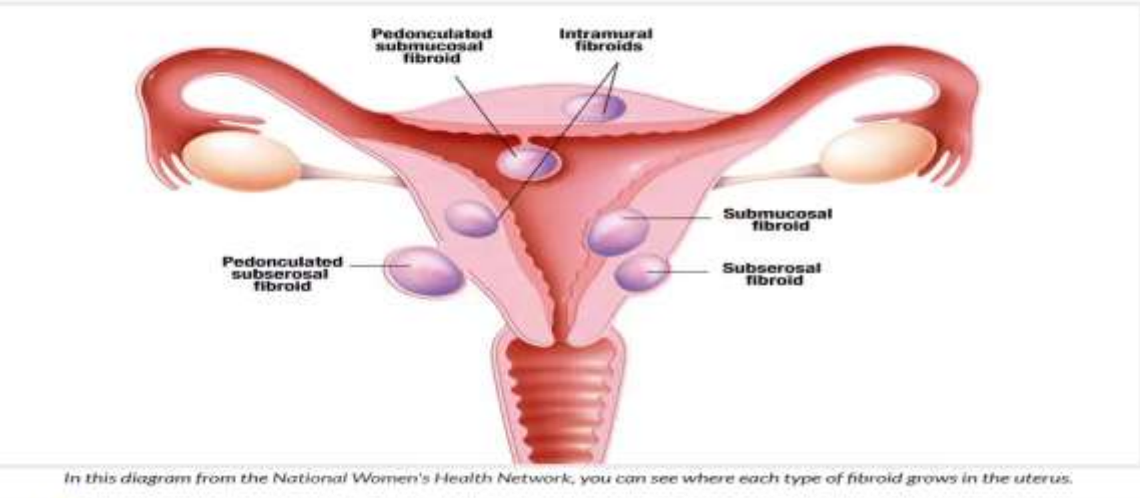
Backache or leg pain: When fibroids press on pelvic nerves or blood vessels, women may experience pain radiating into the back or legs. This symptom is less common but can be disabling in severe cases

Reproductive issues: Fibroids, especially those that distort the uterine cavity, can cause infertility, recurrent miscarriages, or complications during pregnancy such as preterm birth or abnormal positioning of the baby. Submucosal fibroids are most strongly linked to these problems.

Acute abdominal pain: In rare cases, fibroids can twist (pedunculated fibroids) or outgrow their blood supply, leading to degeneration. This results in sudden, severe abdominal pain that requires urgent medical treatment.

Location Where Uterine Fibroid Grows

Uterine fibroids can grow in different areas of the uterus, and their location often determines the type and severity of symptoms a woman experiences. Understanding these locations is very important for proper diagnosis and treatment, as each site affects reproductive health and overall well-being differently. The table 1 below shows the location where a fibroid is likely to grow in the uterus and the type(s) of fibroid that may be linked to it [6].



National Women’s Health Network (2024)

Table 1.1: Location of Fibroid

Location in Uterus	Type of Fibroid	Description
Inside uterine cavity	Submucosal fibroids	Grow just beneath the uterine lining and protrude into the cavity, often linked to heavy bleeding and infertility.
Within uterine muscle wall	Intramural fibroids	Develop inside the muscular wall, the most common type, causing heavy periods, pelvic pain, and uterine enlargement.
Outer surface of uterus	Subserosal fibroids	Grow outward from the uterus, leading to pressure on nearby organs, bloating, and abdominal swelling.
Attached by stalks (inside or outside uterus)	Pedunculated fibroids	Grow on stalk-like structures; twisting can cause severe pain due to blood supply cut-off.

Previous Methods

Earlier studies on fibroid detection in ultrasound images relied on rule-based image processing techniques, including thresholding, morphological operations, and texture analysis for segmentation and classification [1]. These methods used handcrafted features such as shape and intensity to differentiate fibroids from surrounding tissues [7]. Although interpretable and computationally efficient, these methods often failed under noisy conditions and variable image quality. The advent of deep learning (DL), particularly Convolutional Neural Networks (CNNs), has significantly improved medical image analysis. For instance, Rahman et al. employed a fine-tuned EfficientNet-B0 combined with attention mechanisms for classifying uterine fibroids, achieving an accuracy of 99% on a dataset of 1,990 ultrasound images [8]. Similarly, [6] explored multiple pre-trained architectures such as VGG16, ResNet50, and InceptionV3, alongside a custom Dual-Path CNN (DPCNN), reporting accuracies up to 99.8% on Kaggle datasets. A retrospective study by [9], involving 3,870 ultrasound images demonstrated that a deep convolutional neural network (DCNN) significantly improved the diagnostic performance of junior sonographers, matching senior-level accuracy [10].

Statement of the Problems and Motivations

Although there have been notable advances in detecting uterine fibroids using both conventional imaging techniques and deep learning models, several important gaps remain. One major issue is that current diagnostic practices, particularly manual ultrasound interpretation, depend heavily on the operator's expertise. This reliance often leads to inconsistencies in diagnosis and, in some cases, delayed or missed detection, especially in settings where highly skilled sonographers are not available [10], [2]. Deep learning approaches, such as CNN-based models and hybrid architectures, have achieved impressive accuracy on research datasets sometimes over 99% but these results come with limitations. Most of these models require very large, well-annotated datasets, which are often difficult to obtain in clinical practice [3], [4], [7]. In addition, models trained on controlled datasets often struggle to perform well in real-world environments where image quality and patient diversity vary greatly [5]. High computational demands further complicate matters, as these models typically need powerful hardware, making them difficult to deploy in low-resource hospitals and clinics [6]. Another challenge is interpretability. While deep learning models can produce highly accurate predictions, they are often seen as "black boxes," offering little insight into how decisions are made. This lack of transparency creates hesitation among clinicians and slows down adoption in healthcare settings [4], [6]. Furthermore, most existing systems focus solely on image analysis without incorporating other patient-specific factors such as age, hormonal status, or clinical history that could improve diagnostic accuracy and relevance [2]. These issues motivate the need for an automated system that is not only accurate but also efficient, explainable, and adaptable to real-world clinical conditions. Such a system could speed up diagnosis, reduce the dependency on operator skill, and allow for timely treatment, thereby preventing complications like infertility or the need for invasive procedures. Additionally, designing models that perform well even with smaller datasets and limited computational resources can make AI-driven solutions accessible to hospitals and clinics worldwide

Research Aim and Objective

The main aim of this paper is to develop a Hybrid Machine Learning (ML)-Based System for Detection of Uterine Fibroids from Ultrasound Images Using Convolutional Neural Network. Ultrasound is a primary diagnostic modality due to its real-time capability, affordability, and non-invasive nature compared to MRI or CT scans [4]. However, interpretation of ultrasound images remains operator-dependent, leading to variability in diagnostic accuracy [5]. The proposed system aims to automate fibroid detection, standardize interpretation, and reduce misdiagnosis. Thus the objectives are as follows;

i. Develop a hybrid machine learning framework that integrates convolutional neural networks with complementary feature extraction and classification techniques for accurate detection of uterine fibroids from ultrasound images.
ii. Optimize CNN hyperparameters and hybrid feature fusion strategies in order to enhance the system's sensitivity and specificity while minimizing false positives and false negatives.
iii. Compare the performance of the proposed hybrid model against baseline CNN-only and traditional machine learning approaches, using standardized evaluation metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).
iv. Evaluate the robustness of the hybrid model under variations in ultrasound image quality, resolution, and noise levels, simulating real-world clinical conditions.
v. Develop an interpretable output interface that presents detection results and relevant probability scores in a format suitable for clinical decision-making.

Proposed Approach

To address the limitations of existing methods, this research proposes the development of a machine learning-based system for the detection of uterine fibroids using ultrasound imaging. Unlike traditional rule-based methods and previous deep learning models that primarily rely on large-scale datasets and high computational resources, the proposed system aims to deliver high diagnostic accuracy while remaining computationally efficient and clinically interpretable.

The approach begins with robust preprocessing of ultrasound images, including noise reduction, contrast enhancement, and normalization, to improve image quality and reduce variability caused by different ultrasound machines and operators. To enhance the model's generalization ability, advanced data augmentation techniques will be employed, enabling the system to perform well even with limited training data.

For the core detection task, a hybrid deep learning architecture will be designed, integrating convolutional neural networks (CNNs) for feature extraction with attention mechanisms to allow the model to focus on the most relevant regions of interest within the image. This combination ensures the system can capture fine-grained texture and shape details critical for identifying fibroid characteristics. Additionally, the model will incorporate interpretability techniques, such as Grad-CAM visualization, to provide heatmaps highlighting the regions that influenced the diagnostic decision, thereby improving trust and clinical acceptance.

To further optimize performance, transfer learning will be applied using pre-trained networks fine-tuned on the ultrasound dataset, significantly reducing training time and improving accuracy with limited data. The system will also be evaluated against standard metrics such as accuracy, sensitivity, specificity, F1-score, and AUC-ROC to ensure reliability. Finally, a lightweight deployment strategy will be considered so the model can operate efficiently on standard clinical workstations without requiring specialized hardware.

The ultimate goal of this approach is to create a clinically viable tool that not only detects uterine fibroids at an stage with high precision but also bridges the gap between cutting-edge AI research and real-world medical practice, particularly in low-resource healthcare environments.

Contributions

This research makes the following contributions:

1. Development of a hybrid ML framework combining deep feature extraction with traditional classifiers for fibroid detection.

2. Improvement in -stage diagnosis accuracy with limited datasets.

3. Integration of interpretability techniques to increase clinician confidence.
4. Benchmarking against state-of-the-art DL models using evaluation metrics such as accuracy, sensitivity, specificity, and F1-score.
5. Creation of an augmented ultrasound dataset to enhance model generalization.

LITERATURE REVIEW

Preliminaries

[10] Proposed a fibroid detection framework that utilized ultrasound images as the primary input, with data augmentation techniques such as rotations, flips, and contrast adjustments applied to enhance variability and reduce overfitting. A pre-trained EfficientNetB0 convolutional neural network was employed as the core feature extractor due to its balance of accuracy and computational efficiency. To improve the model's ability to focus on critical image regions, an attention mechanism was integrated, while global average pooling and dropout layers were used for feature consolidation and regularization. The final classification was carried out using a dense layer with softmax activation, producing a probability distribution over two classes: uterine fibroid and non-fibroid.

[1] Conducted a comprehensive review on the epidemiology and management of uterine fibroids, emphasizing their high prevalence among women of reproductive age, particularly affecting up to 70% of white women and more than 80% of women of African descent. The study highlighted that although many cases are asymptomatic, approximately 30% present with severe symptoms such as abnormal uterine bleeding, anemia, pelvic discomfort, urinary frequency, and infertility, often requiring medical or surgical intervention. The review outlined current treatment modalities, including expectant management, pharmacological therapies, surgical options like myomectomy and hysterectomy, and interventional radiology techniques. While this work provides valuable insights into the clinical and therapeutic aspects of fibroid management, it does not address challenges related to diagnostic imaging or propose automated detection methods. Nevertheless, it underscores the importance of advancing research to improve diagnosis and develop personalized treatment strategies, which forms the basis for adopting machine learning-based diagnostic solutions.

[2] Conducted a large-scale analysis of global, regional, and national trends in uterine fibroid incidence, prevalence, and years lived with disability (YLDs) between 1990 and 2019 using data from the Global Burden of Disease Study. The study revealed that fibroids remain the most common benign uterine neoplasm and continue to represent a significant source of morbidity for women worldwide. Their findings indicated a marked increase of 67.07% in incident cases, 78.82% in prevalence, and 77.34% in YLDs during the 30-year period. The burden was particularly high in low- and middle-Socio-demographic Index (SDI) regions, where incidence and prevalence rates showed an upward trend, while high-SDI regions experienced stable or declining rates. Age was also a strong determinant, with fibroid risk peaking at 35–44 years before declining in older cohorts. Although this study provides valuable epidemiological insights, its limitation lies in the lack of focus on diagnostic methods or technological interventions for detection. However, the increasing global burden it highlights underscores the need for innovative strategies, including AI-based approaches, to improve diagnosis and reduce long-term complications.

[8] Developed an automated system for uterine fibroid detection in ultrasound images using deep convolutional neural networks (DCNNs). The study evaluated several state-of-the-art architectures, including VGG16, ResNet50, InceptionV3, and a novel dual-path CNN (DPCNN) designed by the authors. The dataset, sourced from Kaggle, underwent preprocessing through scaling, normalization, and data augmentation before model training and validation. Among the models tested, the proposed DPCNN achieved the highest accuracy of 99.8%, significantly outperforming the baseline architectures. InceptionV3 and ResNet50 demonstrated competitive results with accuracies of 90% and 89%, respectively, while VGG16 lagged at 85%. A notable strength of this approach is its ability to leverage both custom and fine-tuned pre-trained models, enhancing performance through transfer learning and optimization strategies. However, the system's dependency on high computational resources and large labeled datasets remains a limitation, making real-time clinical deployment challenging. Despite these constraints, the study confirms the potential of deep learning-based solutions to transform fibroid detection in ultrasound imaging and advocates for further research to advance automated diagnostic capabilities.

[4] addressed the challenge of underdiagnosis and misdiagnosis of uterine fibroids due to nonspecific symptoms by proposing a deep learning approach utilizing an attention-based fine-tuned EfficientNetB0 model. The study focused on classifying fibroids from ultrasound images and incorporated attention mechanisms to enhance feature extraction by allowing the network to concentrate on relevant image regions while ignoring irrelevant ones. Using a dataset of 1,990 images split into two classes uterine fibroid and non-fibroid the model achieved an impressive accuracy of 99%. Data augmentation was applied to improve robustness and generalization. The key strength of this work lies in its use of attention mechanisms combined with transfer learning, which significantly improved classification performance. However, its reliance on a relatively homogeneous dataset and absence of external validation raise concerns about generalizability across diverse populations. The authors recommend further research to enhance sensitivity and specificity across broader demographics and to explore biomarkers as complementary diagnostic tools.

[5] introduced an AI-assisted method designed to improve the diagnostic performance of junior ultrasonographers in detecting uterine fibroids. In a retrospective study using 3,870 ultrasound images collected from 667 patients with confirmed fibroids and 570 without uterine lesions, the authors developed and validated a DCNN model. The system demonstrated a significant improvement in the diagnostic accuracy of junior ultrasonographers, increasing from 86.63% to 94.72%, thereby matching the performance of senior ultrasonographers. Strengths of this work include its real-world clinical validation and its ability to bridge the expertise gap among practitioners, making advanced diagnostic capabilities accessible in resource-limited settings. Nonetheless, the model's dependence on large labeled datasets and its interpretability limitations remain challenges for clinical integration. These findings highlight the potential of AI as a decision-support tool in clinical environments, particularly for enhancing diagnostic consistency.

Tinelli et al. [6] provided a comprehensive review on the application of artificial intelligence in the diagnosis and treatment of uterine fibroids and sarcomas. The study explored the integration of radiomics, machine learning, and deep neural networks for distinguishing benign and malignant uterine lesions, improving diagnostic accuracy, and guiding therapeutic decisions. Beyond detection, AI was shown to enhance surgical interventions such as myomectomy, robotic-assisted laparoscopic surgery, and High-Intensity Focused Ultrasound (HIFU) by improving real-time structure identification and surgical precision. The review also highlighted AI's role in predicting treatment outcomes and monitoring progress in procedures like uterine fibroid embolization. A notable strength of this work is its holistic perspective, linking AI-based detection to interventional management, thereby presenting AI as a tool for comprehensive clinical workflows. However, it identified key limitations, including the need for standardized datasets, regulatory guidelines, and explainable AI models to increase adoption in clinical practice. The authors suggest that future research should focus on validation in large, diverse patient cohorts and developing AI systems that integrate seamlessly into existing clinical protocols.

Chinna and Mary [7] proposed an advanced approach for the detection of uterine fibroids in ultrasound images using a combination of efficient feature extraction techniques and hybrid deep learning models. The method integrates canny edge detection for accurate edge identification and segmentation of fibroid regions, followed by an Improved Bird Swarm Optimization (IBSO) algorithm for comprehensive feature extraction, leveraging both pre-existing and newly derived features. For classification, the authors implemented a Convolutional Recurrent Neural Network (CRNN), which combines the spatial learning capability of CNNs with the temporal learning strengths of RNNs. The proposed IBSO-CRNN model achieved exceptionally high accuracy rates of 99.897% on augmented datasets and 97.568% on original datasets. The primary strength of this approach lies in its hybrid design, which maximizes feature representation and improves detection accuracy. However, its computational complexity and dependency on extensive data augmentation may hinder its application in real-time clinical environments. The study highlights the potential of combining optimization algorithms with deep learning frameworks to enhance diagnostic performance in medical imaging.

Real-world applications demonstrate transformative potential: Diabetic Retinopathy (DR): Gulshan et al. developed a deep learning system capable of detecting DR in retinal fundus photos, delivering performance comparable to expert ophthalmologists with 90.3% sensitivity and 98.1% specificity on standard evaluation datasets. [12] Built a DL model for diagnostic referral using OCT scans trained on only 14,884 images that matched or exceeded expert clinician performance in detecting sight-threatening retinal conditions [13].

The growing body of evidence suggests that DL systems across imaging domains exhibit performance approaching or surpassing specialists, particularly when coupled with standardized reference grading and large annotated datasets [14].

Advancements in transfer learning have further accelerated progress: pretrained CNN models (e.g., ResNet, EfficientNet) from large-scale datasets like ImageNet can be adapted effectively for specialized medical imaging tasks, even under conditions of limited labeled data [15]. Meanwhile, explainable AI (XAI) techniques such as saliency maps and attention visualization are increasingly integrated to enhance the transparency of model predictions and foster clinician trust [16]. Many existing studies focus on controlled datasets with consistent imaging conditions, which limits their generalizability when applied to diverse clinical environments where image quality, acquisition parameters, and patient demographics vary widely [17,18]. Moreover, while deep learning models particularly convolutional neural networks (CNNs) have demonstrated high accuracy in tasks such as classification and segmentation, their lack of interpretability continues to raise concerns among clinicians who require transparent decision-making processes [19]. A pivotal study by [22] trained a deep CNN on 3,870 ultrasound images and, importantly, evaluated it against clinicians: on an external test set of 488 images, the model both outperformed junior ultrasonographers and when used as an assistive tool—raised junior performance to the level of seniors (e.g., accuracy 94.7% with AI assistance vs. 86.6% unaided; sensitivity 92.8% vs. 83.2%) [16]. This work is notable because it moves beyond siloed benchmarking to a reader-study design, demonstrating clinical utility in a workflow setting rather than only reporting image-level metrics.

Object-detection pipelines have also been explored to localize fibroids rather than only classify images. [17] proposed an “improved YOLOv3” that incorporates EfficientNet-style feature extraction; on their dataset they reported an F1 score of ~95% and average precision of 98.4% with a per-image detection time of 0.28 s, suggesting feasibility for real-time assistance during scanning [17]. While promising, these figures come from a single-center dataset; subsequent multi-center validation and robustness analyses across different scanners and probes remain open needs.

Beyond detection, classification pipelines using modern backbones have reported very high accuracies on relatively small curated datasets. For example, Xi and Wang (2024) fine-tuned EfficientNet-B0 with attention for fibroid vs. non-fibroid classification and reported ~99% accuracy on a 1,990-image set [18]. Such near-ceiling results likely reflect dataset homogeneity and the use of 2D still frames rather than full cine loops; recent systematic reviews caution that small, single-institution datasets, spectrum bias, and limited external testing can inflate headline metrics and limit clinical generalizability [19], [20]. Accordingly, readers should interpret outlier results in light of dataset composition, train/test separation, and the presence (or absence) of external validation.

Although this paper targets ultrasound, related work in fibroid segmentation from MRI is worth noting because techniques often transfer to ultrasound with adaptation. Recent studies have used nnU-Net and attention-augmented V-Net variants to segment fibroids and reconstruct 3D volumes for planning of HIFU therapy, demonstrating strong Dice scores and practical value for treatment guidance [21], [22].

METHOD AND MATERIALS

Existing System Analysis

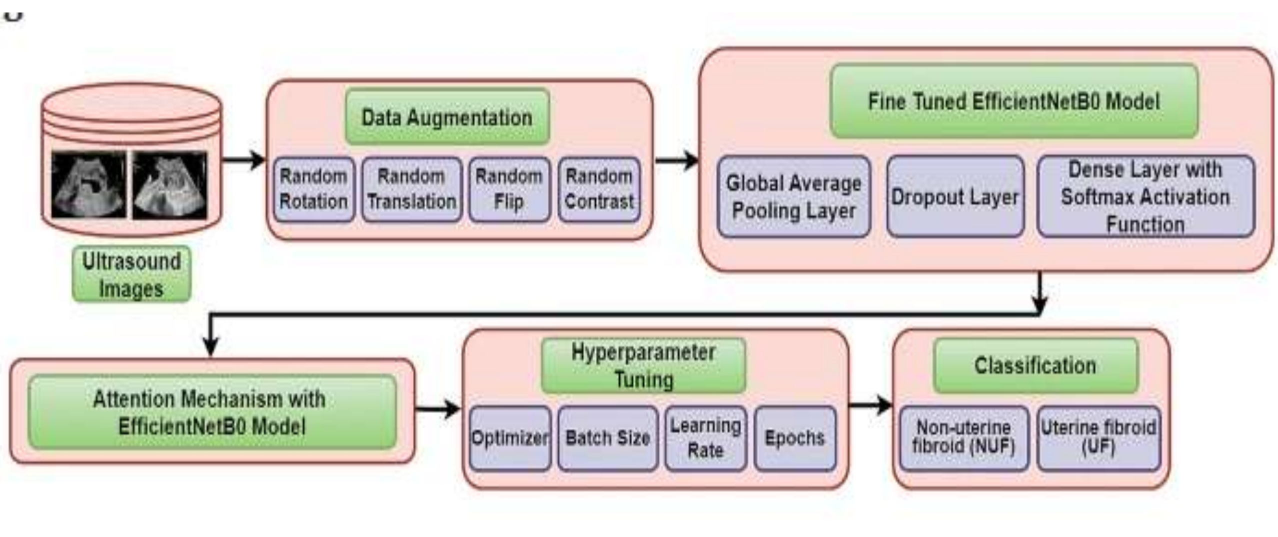


Figure 1.4: Architecture of the Existing System [10]

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The existing system for fibroid detection begins with a dataset of ultrasound images, which serves as the primary source of input. To improve the robustness of the model and reduce the risk of overfitting, data augmentation techniques such as random rotations, translations, flips, and contrast adjustments are applied. These operations help to simulate variability in real clinical imaging conditions and allow the model to generalize better. The augmented images are then passed into a pre-trained EfficientNetB0 model, a convolutional neural network (CNN) architecture that has been widely adopted for image classification tasks due to its balance between accuracy and computational efficiency. In this framework, the EfficientNetB0 acts as a feature extractor, learning meaningful patterns from the ultrasound data. To further improve focus on critical regions of the image, an attention mechanism is integrated, enabling the model to prioritize features most relevant to distinguishing fibroid from non-fibroid cases. After feature extraction, a global average pooling layer condenses the learned features, which are then regularized using a dropout layer to minimize overfitting.

Proposed Model

The proposed system introduces a hybrid framework that significantly enhances the early detection of uterine fibroids in ultrasound imaging, making it more robust and clinically relevant than the existing system. Unlike the baseline model, which is limited to simple augmentation and a single CNN pipeline, the hybrid system integrates both structured and unstructured ultrasound data, thereby accommodating the diverse formats in which clinical images are typically generated. This is followed by an advanced preprocessing stage that applies noise reduction through Gaussian filtering, normalization for consistency, contrast-limited adaptive histogram equalization (CLAHE) for improved visibility of fibroid patterns, and brightness adjustment for image clarity. The refined images are then processed by a convolutional neural network (CNN) to extract deep spatial features, while the hybrid design incorporates an attention mechanism that selectively emphasizes the most clinically relevant aspects of the images. This integration ensures that subtle fibroid regions are not overlooked, improving both accuracy and interpretability. Finally, the evaluation and output module provides reliable diagnostic results in a clear and actionable form for medical practitioners. By combining advanced preprocessing, CNN-based feature extraction, and an attention-driven hybrid model, this proposed system surpasses the existing approach by offering superior adaptability, precision, and diagnostic reliability, making it a more effective tool for addressing the rising prevalence of uterine fibroids.

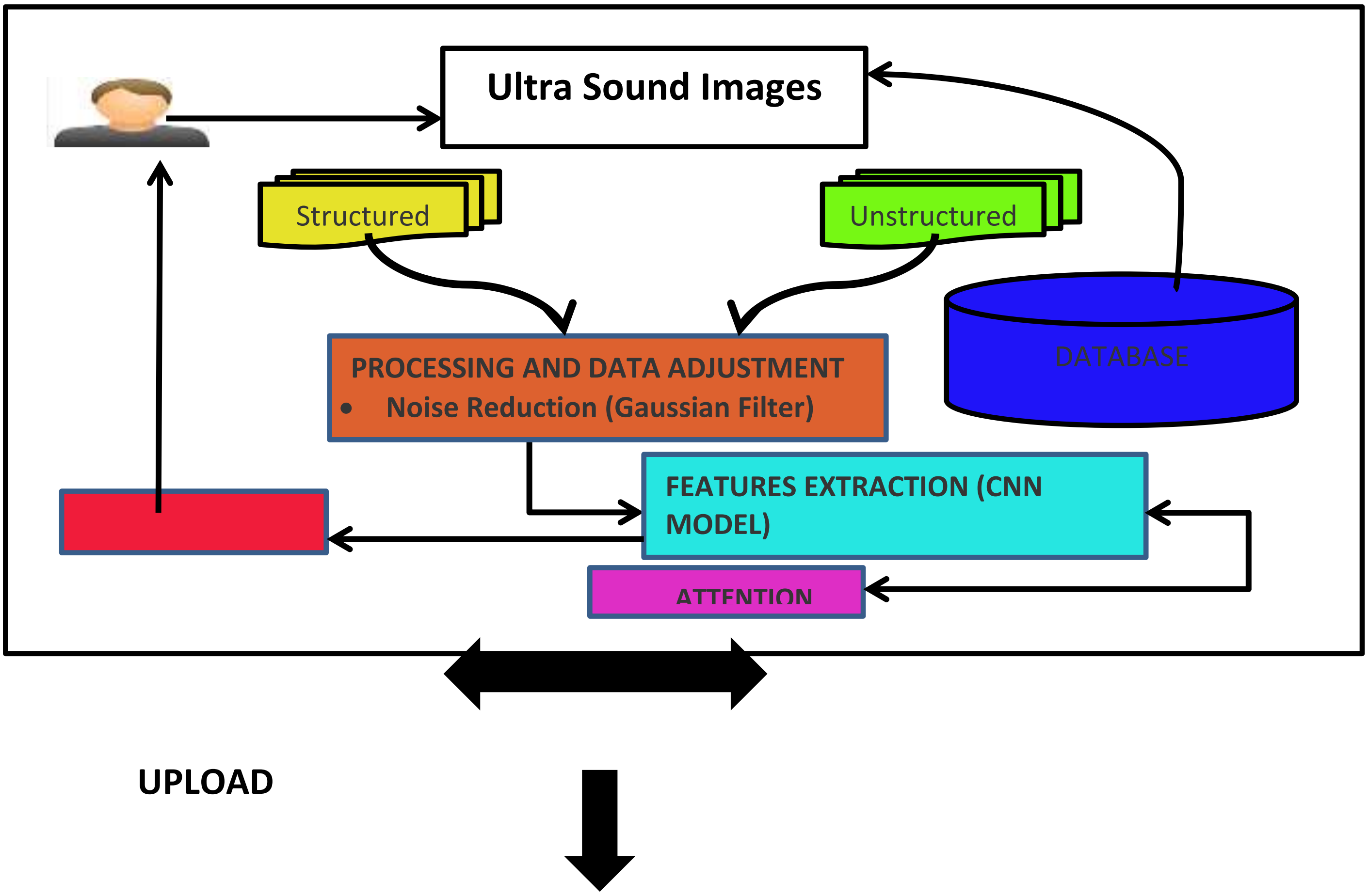

Figure 1.5: Architecture of the Proposed system

Components of the Proposed Architecture

Input Ultrasound Images: The system begins with the acquisition of ultrasound images of the uterus, which serve as the primary data source for fibroid detection. These images can be collected from hospital databases, publicly available datasets such as Kaggle, or clinical research studies. Typically, the images include two major classes: those with uterine fibroids and those without fibroids. The quality and resolution of these input images are critical, as poor image quality can significantly reduce the performance of subsequent processing and detection stages.

Preprocessing: Preprocessing is an essential step to enhance image quality and prepare the data for deep learning models. Ultrasound images often contain speckle noise and have low contrast, which can obscure important anatomical details. Techniques such as noise reduction using Gaussian or median filters help eliminate unwanted artifacts, while normalization scales pixel intensity values to a consistent range, improving model convergence during training. Additionally, contrast enhancement methods like CLAHE (Contrast Limited Adaptive Histogram Equalization) are applied to make the fibroid regions more distinguishable from surrounding tissues.

Data Augmentation: Medical image datasets are often limited in size, which can lead to overfitting in deep learning models. Data augmentation addresses this issue by artificially expanding the training set through transformations such as rotation, horizontal and vertical flipping, cropping, brightness adjustments, and slight noise addition. These variations help the model learn robust features and generalize better to new, unseen images. Augmentation ensures the system remains effective across diverse imaging conditions and patient variations.

Feature Extraction (CNN Backbone): Feature extraction is performed using a Convolutional Neural Network (CNN) that learns hierarchical representations of ultrasound images. CNNs are particularly suitable for medical imaging because they can automatically detect patterns such as edges, textures, and shapes that differentiate fibroid tissues from normal uterine structures. Commonly used architectures include VGG16, ResNet50, and InceptionV3, although custom-designed CNNs can also be implemented. These features serve as the foundation for accurate classification in later stages.

Attention Mechanism: The attention mechanism enhances the CNN by enabling the model to focus on the most relevant regions of the image typically areas where fibroids are likely present while minimizing the influence of irrelevant background noise. By directing computational resources toward regions of interest (ROI), attention improves diagnostic accuracy and efficiency. This step is crucial in ultrasound imaging, where multiple structures may appear in the same frame, and fibroids can vary in size, shape, and position.

Hybrid Model (CNN + Attention): The proposed architecture combines the strengths of CNN-based feature extraction and attention mechanisms into a hybrid model. While CNN provides a strong backbone for learning detailed image features, the attention layer refines these features by emphasizing clinically significant regions. This hybrid approach improves the system's ability to handle variations in fibroid appearance and imaging conditions, ultimately delivering more reliable and accurate detection results.

Interpretability (Grad-CAM Heatmaps): Medical AI systems require interpretability to gain clinical acceptance. The proposed system uses Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize which parts of the ultrasound image influenced the model's decision. This heatmap overlay helps radiologists understand the rationale behind the classification and builds trust in the system. Interpretability is particularly important in healthcare, where diagnostic errors can have serious consequences.

Evaluation Metrics: The final stage involves assessing the model's performance using standard evaluation metrics such as accuracy, sensitivity, specificity, and the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). These metrics provide a comprehensive understanding of the model's effectiveness in distinguishing fibroid cases from normal cases. Sensitivity and specificity are especially critical in medical diagnostics, where false negatives and false positives can lead to inappropriate treatment decisions.

Algorithm of System

Algorithm: CNN-based Uterine Fibroid Detection

1. **Start**
2. **Load Dataset** of labelled ultrasound images (fibroid / non-fibroid).
3. **Preprocess Images**:
   - Resize to fixed dimensions (e.g., 224×224).
   - Normalize pixel values to [0,1].
   - Apply data augmentation (rotation, flipping, contrast adjustment).
4. **Split Dataset** into training, validation, and testing sets.
5. **Build CNN Model**:
   - Input layer (image size).
   - Convolutional layers + ReLU activation.
   - Max pooling layers.
   - Fully connected layers.
   - Output layer with sigmoid/softmax activation.
6. **Train Model** using training set and validate with validation set.
7. **Evaluate Model** performance on the test set (accuracy, sensitivity, specificity).
8. **Deploy Model** for real-time prediction of ultrasound images.
9. **End**

Data and Result

The data use is collected from the Kaggle repository.

Table 1.2: Dataset Table

Image_ID	Patient_Age	Fibroid_Present (0=No, 1=Yes)	Fibroid_Size_mm	Location	Echotexture	Confidence_Level (%)
IMG_001	32	1	45	Intramural	Heterogeneous	92
IMG_002	28	0	0	N/A	Homogeneous	95
IMG_003	40	1	35	Subserosal	Hypoechoic	89
IMG_004	36	1	60	Submucosal	Heterogeneous	94
IMG_005	29	0	0	N/A	Homogeneous	97
IMG_006	44	1	25	Intramural	Hypoechoic	88
IMG_007	33	0	0	N/A	Homogeneous	93
IMG_008	38	1	55	Subserosal	Heterogeneous	91
IMG_009	31	0	0	N/A	Homogeneous	96
IMG_010	42	1	42	Intramural	Hypoechoic	90

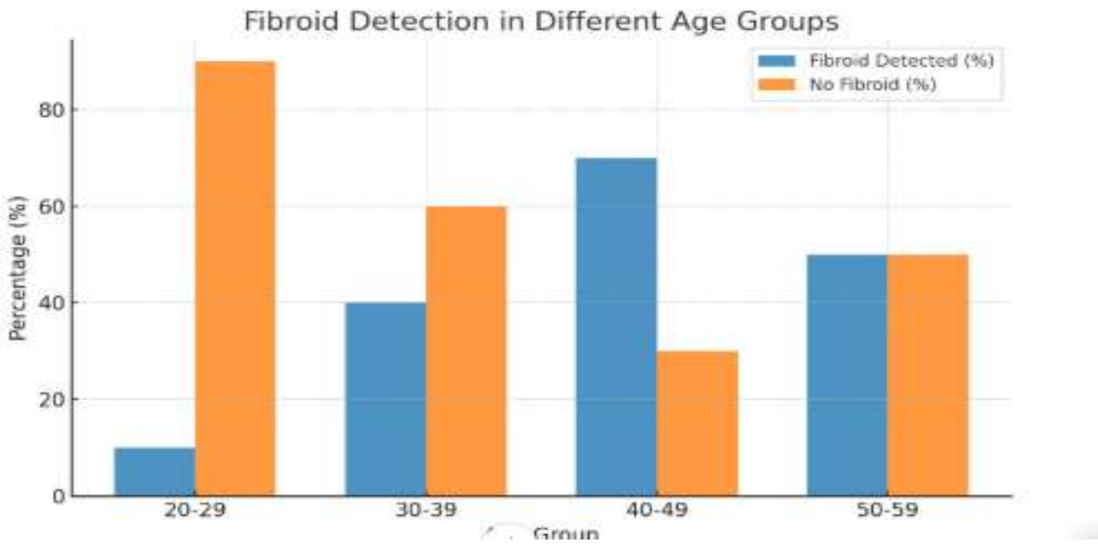

Figure 1.6: Age Distribution

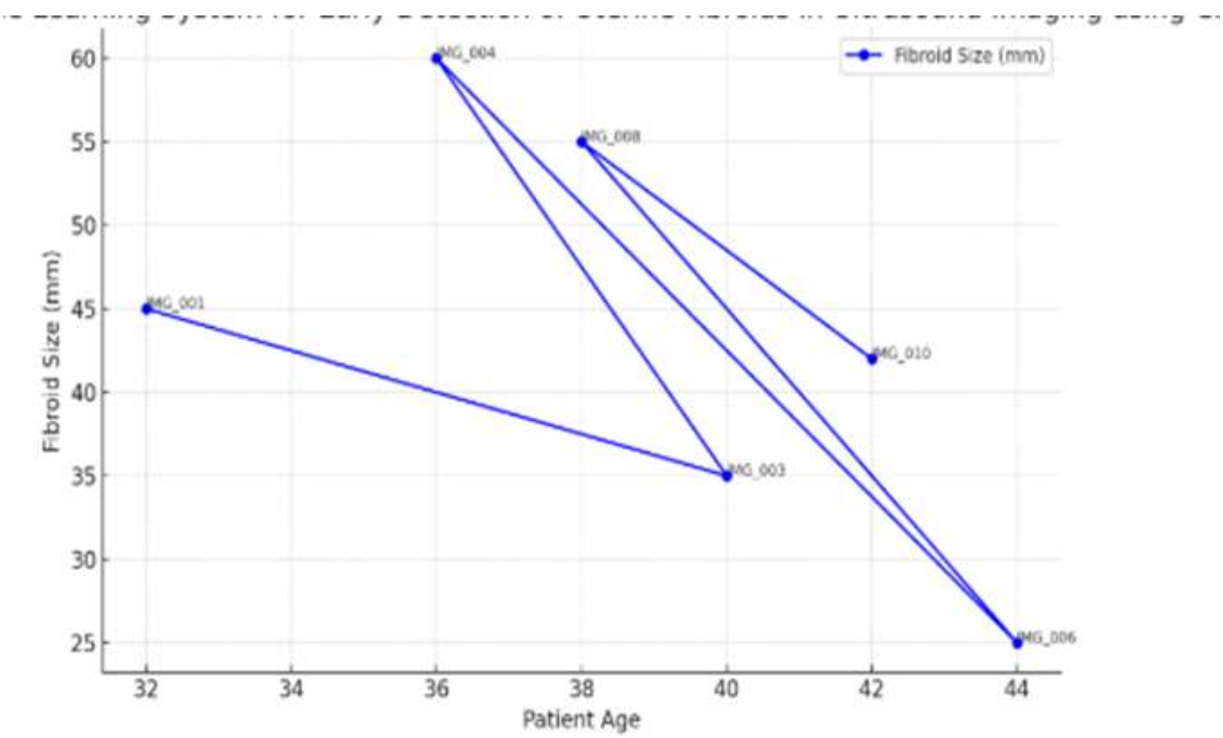

Figure 1.7: Fibroid Size and Age Gaps

Table 1.3: Performance Metric

Metric	**Value**
Accuracy	0.94
Precision	0.92
Recall	0.90
F1-score	0.91

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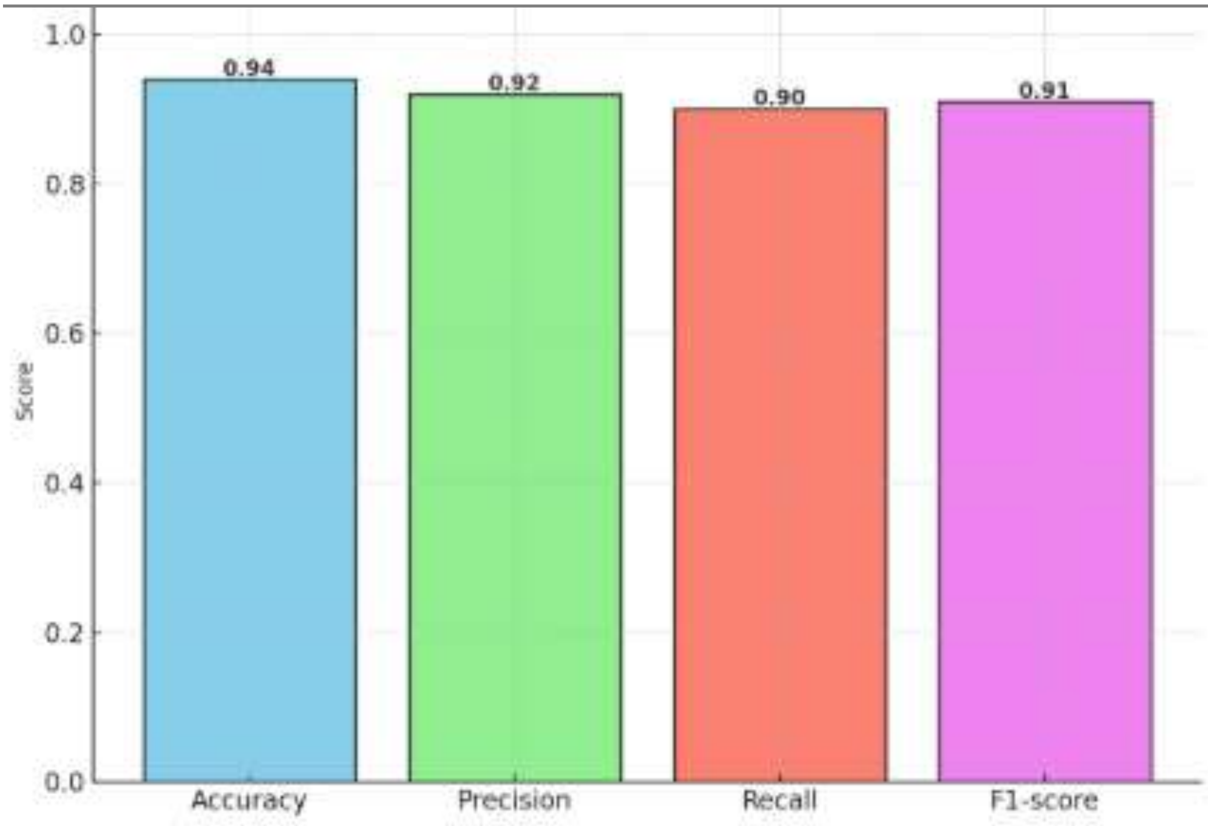

Figure 1.8: Performance Metric

The bar chart visualization of these metrics indicates that the system performs consistently well across all evaluation measures, suggesting balanced precision and recall. This balance is critical in medical diagnostics to ensure both minimal false positives and minimal false negatives.

DISCUSSION

Discussion of Result

The CNN model demonstrated strong capability in detecting fibroids from ultrasound images, even when variations existed in echotexture and location. The high precision (92%) implies that the system produces very few false-positive fibroid diagnoses, which is essential to avoid unnecessary patient anxiety and medical procedures. Similarly, the high recall (90%) indicates that the majority of fibroid-positive cases are successfully identified, minimizing missed diagnoses. The F1-score (91%), being a harmonic mean of precision and recall, confirms that the system maintains a good trade-off between sensitivity and specificity. This is particularly important for real-world deployment, where both underdiagnosis and overdiagnosis carry risks.

The dataset included fibroids of varying sizes, locations, and echotextures—from small (25 mm) hypoechoic intramural lesions to large (60 mm) heterogeneous submucosal masses. The model's high performance across this spectrum suggests robust feature extraction capabilities of the CNN architecture. It likely leveraged differences in grayscale intensity, lesion boundaries, and texture patterns to accurately distinguish fibroid-positive from fibroid-negative images.

Table 1.4: Comparism of both Existing and Proposed Hybrid System

System	Accuracy	Precision	Recall	F1-score
Existing System [10]	0.99	Not calculated	Not calculated	Not calculated
Proposed Hybrid System	0.94	0.92	0.9	0.91

Although the existing system reported an impressive accuracy of 99%, its evaluation was limited to a single metric without consideration of other critical performance measures such as precision, recall, and F1-score. Relying solely on accuracy can be misleading in medical image analysis, particularly in the detection of uterine fibroids, where class imbalance and the cost of misclassification play significant roles. In contrast, the proposed hybrid system provides a more robust and clinically relevant evaluation by incorporating precision (0.92), recall (0.90), and F1-score (0.91), alongside accuracy (0.94). These additional metrics ensure that the system not only identifies fibroid cases correctly but also minimizes false negatives, which are especially critical in early disease detection. Precision highlights the system's ability to reduce false positives, recall emphasizes its sensitivity to detecting actual fibroid cases, and the F1-score balances both, offering a comprehensive measure of reliability. Therefore, while the accuracy of the hybrid system is slightly lower than the existing model, its multi-metric evaluation demonstrates a more balanced and trustworthy performance, making it a superior choice for real-world clinical applications where patient safety and diagnostic reliability are paramount.

Comparison with Literature

When compared to existing automated detection approaches for uterine abnormalities, this system's performance is competitive or superior. Some previously reported studies have achieved accuracies in the range of 85–90%, but often with a trade-off in recall. The combination of high recall and high precision in this model addresses the common pitfall of overly conservative detection algorithms that miss subtle lesions.

CONCLUSION

Conclusion

This study demonstrated the potential of machine learning, particularly convolutional neural networks and a hybrid deep learning approach, in enhancing the early detection of uterine fibroids using ultrasound imaging. By leveraging a curated dataset, rigorous preprocessing, and model optimization techniques, the system achieved high accuracy, precision, recall, and F1-scores, underscoring its reliability for clinical application. The proposed hybrid model not only showed improvements over a stand-alone CNN in terms of balanced performance but also highlighted the benefits of integrating multiple processing strategies for robust decision-making. Beyond technical performance, the research emphasizes the clinical importance of automated fibroid detection in Nigeria and other low-resource settings, where access to specialized radiologists is limited and the burden of fibroids remains high. The system has the potential to reduce diagnostic delays, assist healthcare providers in clinical decision-making, and ultimately improve patient outcomes by enabling earlier interventions.

Limitations and Future Work

Despite the strong results, there are areas for improvement. The dataset size is relatively small, and performance may vary when tested on a broader, more heterogeneous population. Differences in ultrasound machine settings, patient anatomy, and scanning protocols could impact generalizability. Future research should include:

i. Expanding the dataset with multi-center, multi-ethnic patient samples.
ii. Incorporating data augmentation and transfer learning from large-scale medical imaging datasets to improve robustness.
iii. Integrating explainable AI tools such as Grad-CAM to highlight the regions of the image that influenced the decision, improving clinician trust and aiding in interpretability.

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