The role of Artificial Intelligence (AI) learning algorithms in enhancing quantitative image analysis measurements

Introduction

Traditional ultrasound examinations rely heavily on manual quantitative measurements, requiring considerable operator expertise. Since the COVID-19 pandemic, increased demand has led to disruptions, resulting in measurement inconsistencies, especially for both qualified practitioners and trainees (Harris-Live et al , 2016). To reduce variability and improve accuracy without requiring extensive specialized training, there is a growing need to modernize the process of obtaining quantitative measurements.

Recent technological advancements, including the emergence of Artificial Intelligence (AI) and Machine Learning (ML) algorithms, have opened new possibilities in medical imaging (Najjar, 2023). These innovations offer the potential to streamline workflows, enhance accuracy, and support the extraction of key quantitative measurements such as blood flow velocity and volumetric analysis of organs (Zhou Et al, 2021) (Zhou Et al, 2022) (Samala Et al , 2024).

This study aims to explore how AI and ML can improve ultrasound-based quantitative measurements by reducing human error and enhancing efficiency across various medical fields.

Methodology

The study employed case studies focused on three primary areas of ultrasound imaging in the UK:
•Obstetric Ultrasound: AI applied to fetal anomaly detection and pregnancy monitoring.
•Cardiac Ultrasound (Echocardiography): AI used to identify heart abnormalities.
•Breast Cancer Detection: AI-enhanced ultrasound for tumour detection and differentiation between benign and malignant lesions.

Publicly available datasets were sourced for these categories, totalling 300 ultrasound scans (100 per focus area). The datasets were subjected to a metric assessment using accuracy, sensitivity, and acquisition time as key performance indicators.

To develop the AI model, Radguide created a convolutional neural network (CNN) based on the well-known ResNet architecture, which was designed to classify images, extract measurement features, and learn the spatial hierarchical features within the dataset. Radguide also considered transfer learning by using a pre-trained ImageNet model, although the training primarily focused on vascular ultrasound datasets, limiting its initial generalization.

Results

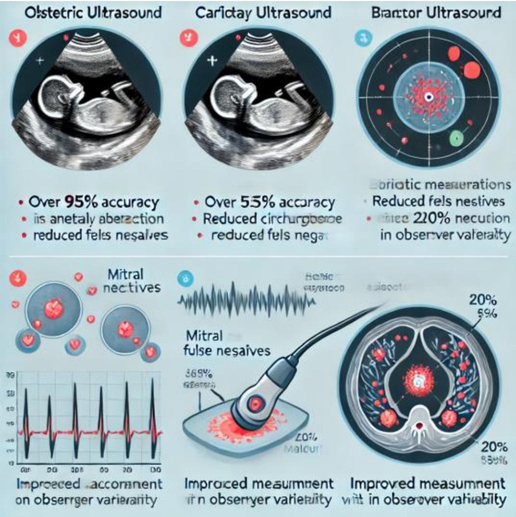

Figure 1.
QR Code – Written Results
Carictay – Cardiac Acronym
Bractor – Breast Cancer Acronym

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Findings

•Improved Diagnostic Accuracy:
AI consistently improved diagnostic accuracy across obstetrics, cardiology, and oncology. In obstetrics, AI reduced discrepancies in fetal measurements, while in echocardiography, it enhanced heart function assessments. AI's high accuracy in classifying breast tumours demonstrates its potential for early cancer detection.

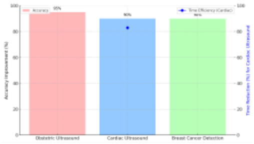

Table 1. Graph Chart

•Automation and Time Efficiency:
AI-enabled automation of tasks, such as organ segmentation and feature extraction, significantly reduced clinicians' workload. For example, AI-assisted echocardiography reduced heart chamber segmentation time from 30 minutes to under 5 minutes. In obstetric ultrasound, automated measurements facilitated faster and more standardized fetal evaluations.

•Reduction of Human Variability:
AI minimized human-induced variability, reducing inter-observer discrepancies due to varying experience levels or fatigue. This standardization is especially valuable in critical scenarios, such as detecting congenital anomalies or assessing cardiac function.

Limitations

1.Quality of Ultrasound Data:
AI model performance depends heavily on the quality of ultrasound images. Variability in image quality (due to operator skill or patient factors) may affect AI accuracy, leading to unreliable predictions.

2.Generalization Issues:
Many AI models are trained on specific ultrasound datasets and may not generalize well across different patient groups or ultrasound machines without retraining. For example, an AI model trained on fetal ultrasound data may not perform well on cardiac scans without substantial retraining.

3.Ethical and Trust Concerns:
Deep learning algorithms are often "black boxes," making their decision-making process difficult to explain. This lack of transparency may cause clinicians to hesitate in trusting AI outputs, which is crucial in medical settings.

Recommendations

1.Improved Data Standardization and Collection:
A national initiative in the UK should focus on the collection and standardization of high-quality ultrasound datasets for AI model training. Collaboration between hospitals, research institutions, and AI developers will ensure more robust algorithms and better generalization across different ultrasound systems.

2.Focus on Explainable AI (XAI):
AI models must become more transparent and explainable to build trust among clinicians. Developing explainable AI will improve clinical decision-making and increase confidence in AI-generated measurements.

3.Integration of AI in Clinical Training:
AI tools should be integrated into UK medical school curricula and hospital training programs to familiarize future clinicians with AI-enhanced ultrasound systems. This integration will ease the adoption of AI in everyday diagnostic workflows.

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