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# ROLE OF ARTIFICIAL INTELLIGENCE IN SHEAR WAVE ELASTOGRAPHY IN THE CHARACTERIZATION OF FOCAL LIVER LESIONS

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## Abstract

***Background:*** *Focal liver lesions (FLLs) encompass a wide spectrum of benign and malignant pathologies, making accurate differentiation critical for appropriate therapeutic decision-making. Shear wave elastography (SWE), a non-invasive ultrasound technique, quantitatively assesses tissue stiffness and supports the evaluation of liver lesions.*

***Objective:*** *This review explores the integration of artificial intelligence (AI) with SWE for the characterization of FLLs, emphasizing AI's ability to enhance diagnostic accuracy, reduce interobserver variability, and aid in lesion classification.*

***Methods:*** *A narrative literature review was conducted using peer-reviewed articles from PubMed, Scopus, and Web of Science databases, focusing on studies investigating the application of AI in SWE for liver imaging.*

***Results:*** *The integration of AI with SWE has demonstrated improved lesion characterization, particularly in differentiating hepatocellular carcinoma (HCC), metastases, hemangiomas, and focal nodular hyperplasia (FNH). It also enhances reproducibility and standardization across studies.*

***Conclusion:*** *AI-assisted SWE shows promise as a valuable diagnostic tool in liver imaging. However, its clinical implementation requires further validation and platform standardization through multicenter studies.*

**Keywords:** *Artificial intelligence, Elastography, Focal liver lesions, Liver imaging, Shear wave elastography*

## INTRODUCTION

Focal liver lesions (FLLs) are a widely encountered category of abdominal imaging diseases that presents a wide sphere of benign and cancerous pathologies (hemangiomas, focal nodular hyperplasia (FNH), hepatocellular carcinoma (HCC), and metastases). Proper characterization of such lesions is crucial as effective management plans including biopsy, surveillance, or surgery may be put to practice.

Inherent benefits of the traditional imaging modalities, such as the B-mode ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI), are, at some stage, limited by their affordability, availability, and sensitivity to discriminate between benign or malignant lesions of the cirrhotic livers. The non-invasive imaging tool shear wave elastography (SWE) provides additional functional information that measures the stiffness of the tissues, related to fibrosis and cellular architecture.

Despite its helpfulness, the state of SWE interpretation is capable of variability. Machine learning and deep learning algorithms (artificial intelligence, or AI) provide a viable solution, in the form of automatizing the analysis, improving image interpretation, and decreasing observer bias. AI in SWE systems could make an excellent diagnostic in both confidence and reproducibility of FLL characterization (1).

## PRINCIPLES OF SHEAR WAVE ELASTOGRAPHY

Shear wave elastography (SWE) is a fine ultrasound-based method that provides the quantitative measurement of tissue stiffness based on the velocity of shear waves' motion through liver tissue. Acoustic radiation force impulses produce these waves, which propagate perpendicularly to their source. These waves are also related to the elasticity of the tissues, with stiffer tissues being able to pass shear waves more quickly, and it is possible to approximate the mechanical properties of the lesion in kilopascals (kPa) or meters per second (m/s). This is a quantitative capability, and it gives an additional benefit to the traditional B-mode ultrasound that can only deliver qualitative and structural details.

The liver imaging SWE is divided into two main categories such as point shear wave elastography (pSWE) and two-dimensional SWE (2D-SWE). Compared to the 2D-SWE, pSWE is comparatively simple to apply but has fewer spatial details. However, 2D-SWE has a larger field of view, giving rise in real-time to elastography maps in a broader area (than tissue Doppler) that facilitate the localization and characterization of lesions. Such maps have color-coding to aid in differentiation of different types of focal liver lesions (FLLs), because they visually indicate the stiffness of tissues. Cancerous lesions, e.g., hepatocellular carcinoma (HCC) or metastases are usually stiffer than benign ones, e.g., hemangiomas or focal nodular hyperplasia (FNH).

Although SWE has several benefits, its diagnostic performance may be affected by numerous technical and biological factors. These are the depth of the lesion, the body habitus of the patient, the respiratory motion, and even the experience of the operator. Poor stiffness measurements can occur due to the variability of the angle of insonation or high-probe pressure. In addition, the stiffness area of benign and malignant lesions may overlap, particularly in the presence of cirrhosis, and therefore worsen the diagnosis. Hence, to realize high-quality and reproducible outcomes, it is important to standardize the acquisition protocols and quality control [2].

The World Federation for Ultrasound in Medicine and Biology (WFUMB) and European Federation of Societies for Ultrasound in Medicine and Biology (EFSUMB), suggest the use of certain protocols, such measurements are to be taken on the right lobe of the liver when the patient is in suspended respiration, and the pressure of the probe should be minimal when probing, where vascular structures or bile ducts are to be evaded in the area of interest. Furthermore, the development of software in SWE systems has recently provided real-time quality indicators and stability metrics so that clinicians could detect valid measurements and discard unreliable data points.

As clinical activity and technology advance, SWE has grown to be a more essential instrument in the study of non-invasive liver evaluation. It not only assists in assessing liver fibrosis, but it also plays an important role in the differential diagnosis of focal lesions in combination with grayscale ultrasound and Doppler imaging. Nevertheless, its potential is being fully utilized more frequently with the use of artificial intelligence tools (AI) that are capable of analyzing small signs of stiffness and refining the segmentation and classification of liver lesions in an objective and replicable way (3).

## ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING

In the sphere of medical imaging, the concept of artificial intelligence (AI) has been widely changing the sphere of medical imaging and adding new data-driven methods capable of simulating human cognition, like learning, interpretation, and decision-making. The use of AI in clinical radiology is on the rise as these tools are guaranteed to improve the efficiency of diagnosis, decrease variability, and facilitate complex image-based evaluations. Machine learning (ML) and deep learning (DL) mark two main categories of AI that are especially influential because of their abilities to work with big and complicated data successfully.

The key mechanisms behind machine learning models involve a classification of relationships between features chosen in medical photos and their outcomes that are related to potential diagnosis. Examples of classical algorithms applied to the task include support vector machines (SVM), decision trees, and random forests, a task that might involve differentiation between benign and malignant hepatic lesions or staging of fibrosis. These methods rely on manual selection of image features like the texture, shape, and intensity values.

Such learning, Deep learning, in particular, convolutional neural networks (CNNs), is more autonomous and end-to-end, learning complex hierarchies of features on raw imaging data. CNNs have been proven to outperform in classification, segmentation, and lesion detection duties, and at times surpass human levels when put in controlled environments. They have played a key role in the imaging of liver disease, especially detecting subtle manifestations of hepatocellular carcinoma or distinguishing between complicated lesions (3), e.g., focal nodular hyperplasia (FNH) and metastases (4).

The minimization of inter- and intra-observer variability can be named as one of the most powerful advantages of AI in imaging. Ultrasound and shear wave elastography (SWE) are modalities that have been reported to be operator dependent regarding the results obtained, whereby it might be dependent on the competence and methodology of the user. The problem is addressed through AI solutions to provide standardized analysis and a consistent interpretation, which usually increases reliability in non-specialist environments.

In addition, AI-based technology is used in radiology to automate exhausting duties associated with image segmentation, annotation, and the calculation of elastography measurements. These tools not only conserve time, but also increase throughput, so clinicians concentrate on more subtle interpretation of diagnosis. Real-time fusion of AI algorithms in liver elastography has allowed on-demand evaluation and imaging decision support on examinations.

In addition to diagnostics, AI is being worked out as prognostic modelling and risk stratification. Based on imaging characteristics combined with clinical and biochemical variables, AI can predict disease prognosis, treatment response, or risk of recurrence. These types of models are in line with the objectives of personalized medicine, whereby the data leads to interventions that produce the best outcome among patients (5).

Despite its benefits, the incorporation of AI in daily clinical practice presents several issues. These are that it requires large, well annotated datasets to train, there is a question of transparency of the algorithms (black box problem), and variability of imaging protocols that can interfere with generalizability across institutions. Furthermore, the safety and responsible use of AI systems in clinical workflow should also be considered by paying attention to ethical and regulatory issues.

Moreover, AI is gradually revolutionizing liver imaging, offering increasing accuracy, reduced subjectivity, and assisting in personalized medicine. Its use as shear wave elastography is one of the best examples of the combination of conventional imaging technologies and robust computing that will lead to more reproducible and accurate assessment of focal liver lesions (6).

## THE APPLICATION OF AI IN SWE TO LIVER IMAGING

AI may be incorporated into SWE systems in a smooth fashion as part of the embedded software that would help analyze the elastography data in real time. Possible steps involved in the workflow are lesion detection, segmentation to region-of-interest, feature extraction (e.g., texture, stiffness distribution), and classification.

The CNN-based models are able to analyze raw ultrasound and SWE data to detect the type of lesions meant using pattern learning. As an illustration, AI algorithms trained using big data managed to identify HCC with more consistency compared to humans themselves. The predictive algorithms in other models incorporate radiomics, which is an image analysis process that retrieves quantitative image characteristics (7).

In addition, the intra- and inter-observer variations can be minimized by the use of AI to standardize the measurement procedure by determining the best SWE frames. This causes increased reproducibility and clinical regard in the elastography reading (8).

## APPLICATIONS IN FOCAL LIVER LESION CHARACTERIZATION

The recent introduction of artificial intelligence (AI) into shear wave elastography (SWE) has significantly increased its clinical value both in the diagnosis of focal liver lesions (FLLs) and their staging. The conventional SWE offers quantitative values of stiffness that aid in distinguishing types of lesions in terms of elasticity of tissues. But combined with AI, these measurements are only a part of a complex diagnosis procedure of automated lesion identification, segmentation, texture analysis, and lesion classification. It also serves as a multimodal strategy to help in distinguishing between malignant and benign liver lesions in cases where the visual patterns are not enough.

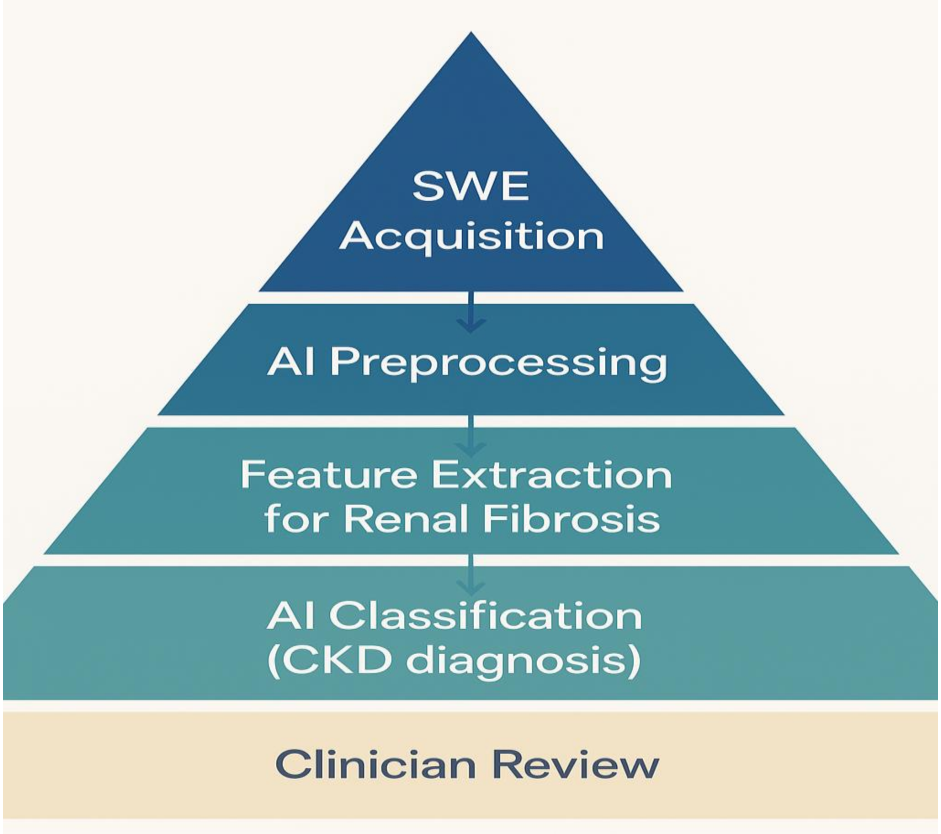

**Fig. 1.** Workflow of AI integration with SWE in liver imaging

The most frequent benign lesions of the liver are hemangiomas, which are usually soft with low stiffness values under SWE, since their pathology consists of vascular structures. Nevertheless, other lesions may cause overlaps in stiffness measurement, hence leading to problematic diagnosis, especially in a liver patient who has chronic liver disease. Specificity is enhanced through data provided by AI models learning the echotexture and stiffness distribution pattern of hemangiomas to distinguish them better than focal nodular hyperplasia (FNH) or metastases. It was revealed that the complement of AI-enhanced SWE to B-mode ultrasound features detected hemangiomas with more than 90% accuracy (9).

Another benign lesion with more varying values of stiffness and internal heterogeneity is focal nodular hyperplasia (FNH), which could be difficult to differentiate from hepatocellular carcinoma (HCC) or adenoma. AI algorithms trained on huge sets of images are capable of recognizing typical characteristics of FNH, including the central scar and radiating fibrous septa, and combining the elastography values to enhance classification. The use of radio-omics-based AI technologies that capture information about texture and shape in both SWE and conventional ultrasound demonstrated a drastic improvement in false positive rates during FNH detection.

The primary malignancy of the liver, hepatocellular carcinoma (HCC), has a high prevalence with accompanying cirrhosis; HCC manifests with greater stiffness during SWE. Nevertheless, the separation between HCC and regenerative or dysplastic nodules in diseased (cirrhotic) livers is made especially hard. This limitation is overcome by Elastography with AI, which is a technique that takes into consideration the distribution of heterogeneity of rigidity within the lesion, the lesion-to-liver rigidity ratio, and the spatiotemporal nature of it. Certain AI models have shown an area under the curve (AUC) in discriminating between early-stage HCC to benign nodules greater than 0.95, even in difficult backgrounds like cirrhotic livers.

Liver metastases. Metastatic disease to the liver is often derived from gastrointestinal, breast, or lung cancers and their stiffness profiles are extremely variable according to the primary tumor type, necrosis, and internal fibrosis. The recent AI systems make the diagnostic process more accurate when combining SWE stiffness maps with grayscale and contrast-enhanced ultrasound features. Patterns of stiffness of the peripheral rim or heterogeneous central region stiffness, suggestive of metastatic spread, can be detected by texture analysis, evaluated by deep learning classifiers. Such instruments have proven to be sensitive and specific, in contrast to distinguishing between metastases and unimportant lesions such as hemangiomas and cysts.

Another diagnostic issue is regenerative and dysplastic nodules, especially in the liver with cirrhosis. Regenerated nodules are harmless, but dysplastic nodules are precancerous to HCC. The stiffness of such nodules is usually within the intermediate range, given that a nodule may not fall within the normal or abnormal range of firmness, mandating the use of SWE-based assessment. Artificial intelligence models that incorporate longitudinal patient data, elastography trends, and multiparametric input seem promising for predicting the development of malignancy. Such changes may be identified at an early stage and motivate interventions and surveillance approaches.

Besides, multifocal lesion analysis, in which there are several nodules to examine, has long been limited by operator bias, which can complicate it, and the evaluation of all lesions at once. SWE platforms that are guided by AI have the potential to analyze several lesions simultaneously, providing standardized labeling of all lesions and prioritizing those with suspicious appearances to have further work-up or diagnosis via biopsy.

In general, AI-optimized SWE is an innovative modality of characterizing liver lesions. With the power of computation and big data, clinicians have a better chance to differentiate between an extensive overload of liver lesions, resulting in better diagnoses, more individualized approaches to the patient, and patient outcomes (10). Table I illustrates a typical AI-enhanced SWE workflow for focal liver lesion characterization.

**Table I.** Clinical value of AI-SWE across focal liver lesion types

| Lesion Type | SWE Alone | AI-SWE | Added Value by AI |
|---|---|---|---|
| Hemangioma | Low stiffness, variable | High specificity | Differentiation from FNH |
| FNH | Intermediate stiffness | Better reproducibility | Less overlap with HCC |
| HCC | High stiffness overlaps with fibrosis | Improved classification | Reduced false positives |
| Metastases | Variable | Pattern recognition | Increased lesion-specific accuracy |
| Cirrhotic nodules | Often inconclusive | High AUC with AI | Early detection of dysplastic nodules |

## DIAGNOSTIC ACCURACY AND VALIDATION STUDIES

`Several studies have demonstrated the superior performance of AI-integrated SWE over traditional SWE: Yasaka *et al.* (2018) used a CNN-based model to differentiate liver tumors and reported an AUC of 0.91 compared to 0.79 for radiologists (4). Wang *et al.* (2020) demonstrated that AI improved sensitivity and specificity in differentiating benign and malignant liver lesions using radiomic features extracted from SWE (6). Chartrand *et al.* highlighted that deep learning models could outperform human observers in several imaging tasks when trained on large and diverse datasets (5). Such studies underscore the clinical value of AI-enhanced SWE, particularly in centers with limited radiologic expertise.

## TECHNICAL CHALLENGES AND LIMITATIONS

Despite promising results, several challenges limit the widespread adoption of AI in SWE:

- Data heterogeneity: Differences in imaging protocols and equipment reduce model generalizability.
- Limited datasets: Training robust AI models requires large, annotated datasets, which are scarce in elastography.
- Interpretability: The black-box nature of deep learning limits clinician trust.
- Regulatory issues: Clinical implementation requires regulatory approval, validation, and integration into existing PACS/RIS systems (10).
- Overcoming these challenges requires standardization, multicenter collaborations, and the development of explainable AI (XAI) systems.

## FUTURE PERSPECTIVES AND CLINICAL INTEGRATION

Future directions for AI in SWE include:

- Real-time diagnostic assistance during routine abdominal ultrasound.
- Development of cloud-based platforms for collaborative model training.
- Integration with electronic medical records (EMR) for comprehensive decision support.
- AI-guided biopsy targeting based on SWE features.
- Large-scale, prospective studies are needed to validate these systems in diverse clinical populations. Interoperability and clinician training will be key to successful deployment (11).

## ROLE IN SURVEILLANCE AND FOLLOW-UP OF CHRONIC LIVER DISEASE

Chronic liver diseases, particularly cirrhosis, are associated with an increased risk of hepatocellular carcinoma (HCC). In such high-risk populations, regular surveillance is essential for early detection of malignancy. Traditionally, ultrasound and alpha-fetoprotein (AFP) levels are used for screening; however, their sensitivity for early HCC is suboptimal. The addition of SWE, particularly when augmented by AI, provides a non-invasive, quantifiable method for detecting subtle changes in liver stiffness that may precede tumor development (1, 10).

Recent studies have shown that AI-enhanced SWE systems can identify microstructural tissue alterations that are not evident on standard ultrasound imaging. For instance, subtle increases in perilesional stiffness or textural irregularity, when processed through AI algorithms, may prompt earlier detection of dysplastic nodules or small HCCs. This capability is particularly valuable in cirrhotic livers where regenerative and dysplastic nodules coexist and are difficult to distinguish based on morphology alone (11).

## TRAINING AND EDUCATION USING AI-SWE SYSTEMS

Another emerging application of AI-integrated SWE is in the training of novice radiologists, sonographers, and hepatologists. Due to the operator-dependent nature of conventional ultrasound and elastography, acquiring proficiency in image acquisition and interpretation typically requires prolonged supervised experience. AI tools offer real-time feedback and guidance during scanning, enabling trainees to recognize optimal imaging planes, apply consistent pressure, and correctly delineate lesions (12).

Simulation-based learning platforms, powered by AI, can also provide a safe environment for trainees to practice on virtual cases with known diagnoses. AI can score their performance, highlight errors, and adaptively guide the learning process. These educational benefits extend to low-resource settings, where expert supervision may be unavailable, but where SWE devices are increasingly being introduced (13).

## INTEGRATION WITH MULTI-OMICS AND PRECISION MEDICINE

The advent of precision `medicine has emphasized the importance of integrating imaging with molecular, genomic, and clinical data for tailored therapy. AI plays a crucial role in synthesizing diverse data types, and its integration with SWE opens the door to new diagnostic and prognostic tools in hepatology. For example, combining SWE stiffness maps with genomic signatures of tumors could improve prediction models for treatment response or recurrence risk (14).

In clinical research, AI can be used to correlate elastographic findings with liver biopsy results, gene expression profiles, and serum biomarkers to identify novel imaging biomarkers. These multi-modal AI frameworks can stratify patients more accurately than traditional risk models, guiding decisions such as the timing of surgery, suitability for transplantation, or likelihood of response to locoregional therapy (15).

# CONCLUSION

AI has revolutionized image interpretation and decision support across medical imaging. When integrated with SWE, it enables precise, reproducible, and automated characterization of FLLs, offering particular value in resource-limited settings. Continued innovation, validation, and clinician-AI collaboration are essential to fully harness the potential of this transformative technology.

## Authors' contribution:

SH Research & data acquisition; SS Writing initial manuscript; MNB Data analysis & editing of manuscript; ZS Conceptualization & supervision.

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