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Deep Learning-Based Liver Fibrosis Classification: A Multi-Domain Approach

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Abstract: This study provides an in-depth analysis of liver fibrosis classification using heterogeneous ultrasound image datasets. Utilizing advancements in deep learning, we evaluate the efficacy of various convolutional neural network (CNN) architectures, including VGGNet, ResNet, DenseNet, EfficientNet, Vision Transformer (ViT), and Xception. Building on the base paper's findings, where ResNet achieved an accuracy of 87.92%, our investigation extends to Xception and ensemble models. Through rigorous experimentation, our results demonstrate significant improvements in classification accuracy. Notably, the Xception model and ensemble approaches surpass the 90% accuracy threshold, showcasing their potential in enhancing diagnostic performance. This underscores the effectiveness of leveraging diverse CNN architectures and ensemble strategies for liver fibrosis classification from heterogeneous ultrasound images. Our study offers valuable insights for medical image analysis and highlights the importance of exploring multiple deep learning techniques to improve diagnostic accuracy in clinical settings.

Index Terms: *Domain bias, multi-domain learning, ultrasonography, liver fibrosis.*

1. INTRODUCTION

Ultrasound (US) images are widely utilized in the medical field due to their non-invasive nature and the absence of harmful radiation. These images are particularly prevalent in abdominal radiology for the continuous monitoring of patients with liver cirrhosis or chronic hepatitis. US imaging plays a crucial role in detecting hepatocellular carcinoma and assessing the degree of liver fibrosis [1]. The process involves capturing images using the reflected waves of a sound wave pulse [2]. Unlike superficial organs such as the breasts and thyroid gland, the liver is situated deep within the human body. This deep location poses significant challenges during signal transmission and reception. The signals often weaken as they encounter various obstacles within the body, increasing the likelihood of noise interference. Consequently, diagnosis using US imaging can be highly dependent on the expertise of the clinician.

To achieve more objective diagnoses, research has increasingly focused on leveraging deep convolutional neural networks (DCNNs) for US imaging. DCNNs, which are primarily used in imaging applications, have demonstrated exceptional performance in tasks such as image segmentation and classification. The use of DCNNs in US imaging aims to eliminate individual variability in disease diagnosis, providing performance that is comparable to that of experienced radiologists. Traditional automated classification models, however, have been trained and evaluated using images from specific types of US imaging machines. Each machine generates images with unique noise characteristics, and a model trained on images from a single device tends to be biased toward those specific characteristics. This means that the model may only perform well on images acquired from the same type of machine used for training, limiting its generalizability [3].

This issue is particularly problematic because the vast majority of US imaging studies do not account for the diversity of imaging devices. Many studies utilize images from a single machine or fail to consider the differences between machines. This can result in models that perform poorly on images from less commonly used devices [4], [5], [6]. Such models may not be reliable when applied to US images obtained from new or different devices, making it challenging to ensure consistent diagnostic performance across various clinical settings. Therefore, it is essential to develop and analyze DCNN models using multi-domain data to achieve a more generalized automatic diagnosis.

By incorporating images from multiple types of US imaging machines, we can train models that are less biased and more robust to the variations in image quality and noise introduced by different devices. This approach can help create more versatile and reliable diagnostic tools that maintain high performance regardless of the imaging equipment used. The goal is to enhance the generalizability of DCNN-based models in US imaging, ensuring that they can accurately diagnose liver fibrosis and other conditions even when applied to images from diverse sources. This not only improves the reliability of automated diagnostic systems but also broadens their applicability in clinical practice, potentially leading to better patient outcomes through more consistent and accurate diagnoses.

In summary, while US imaging is invaluable for monitoring and diagnosing liver conditions, its effectiveness can be hindered by the variability introduced by different imaging devices. The use of DCNNs offers a promising solution by providing objective and consistent diagnostic capabilities. However, to fully realize this potential, it is crucial to train and evaluate these models on multi-domain data, ensuring they are robust to the variations across different US imaging machines. This approach aims to improve the generalizability and reliability of automated US image analysis, ultimately enhancing its utility in medical diagnostics.

2. LITERATURE SURVEY

The field of liver fibrosis assessment using ultrasound (US) imaging has evolved significantly, primarily due to advancements in imaging technologies and the application of deep learning algorithms. Ultrasound elastography, a technique highlighted by Tang et al., has been instrumental in non-invasively evaluating liver fibrosis [1]. This method relies on the mechanical properties of tissues to detect variations that may indicate fibrosis. MR elastography, another technique discussed alongside ultrasound elastography, complements these findings by offering high-resolution images, albeit with higher costs and less accessibility compared to US imaging [1].

US images are generated through the reflection of sound waves, and their quality can be influenced by several factors, including the depth of the organ being examined. Jung and Choi discussed techniques to optimize these images using active echo signals and software filter corrections, which are essential for reducing noise and enhancing image clarity [2]. These optimizations are crucial, especially for the liver, which is located deep within the body and poses significant challenges during imaging due to signal weakening and increased noise.

The application of deep convolutional neural networks (DCNNs) in medical imaging, particularly for liver fibrosis classification, has garnered substantial attention. DCNNs have shown remarkable success in various imaging tasks, such as image segmentation and classification, due to their ability to learn complex patterns from large datasets. Liu provides a comprehensive review of the role of deep learning in medical ultrasound analysis, underscoring its potential to provide objective and consistent diagnoses [8]. This is particularly important in ultrasound imaging, where the diagnostic accuracy can be highly dependent on the operator's expertise.

One of the critical challenges in applying DCNNs to ultrasound imaging is the variability in images produced by different ultrasound machines. Each machine has unique noise characteristics, and models trained on images from a single device may not generalize well to images from other devices. Blaivas et al. highlighted the impact of novel ultrasound equipment on algorithm performance, emphasizing the need for domain adaptation to ensure models remain effective across different machines [4]. This variability can hinder the generalizability of DCNN models, making it difficult to achieve consistent diagnostic performance in clinical settings.

Several studies have attempted to address this challenge by incorporating multi-domain data into their training processes. For instance, Moon et al. utilized ensemble learning from multiple convolutional neural networks to improve the accuracy of breast ultrasound image classification, demonstrating the benefits of leveraging diverse data sources [5]. Similarly, Cao et al. explored various deep learning architectures for breast lesion detection and classification, reinforcing the importance of using comprehensive datasets to enhance model robustness [6]. These studies illustrate the potential of multi-domain data in developing more generalized and reliable diagnostic models.

In the context of liver fibrosis classification, Dan et al. employed transfer learning and a fully connected network (FCNet) to analyze ultrasound images, achieving notable improvements in classification accuracy [7]. Transfer learning, which involves pre-training a model on a large dataset and then fine-tuning it on a smaller, domain-specific dataset, can significantly enhance model performance, particularly when dealing with limited medical imaging data. This approach leverages the knowledge gained from the pre-training phase to better understand the target domain, thereby improving the model's ability to generalize to new data.

Another study by Reddy et al. proposed a novel computer-aided diagnosis framework using deep learning for the classification of fatty liver disease in ultrasound imaging [9]. Their framework demonstrated the potential of DCNNs to achieve high diagnostic accuracy, further supporting the case for deep learning in liver disease assessment. The use of advanced DCNN architectures, such as ResNet, DenseNet, and Xception, has shown promise in various studies, with each architecture offering unique advantages in terms of depth, connectivity, and feature extraction capabilities.

The effectiveness of these models is further enhanced by ensemble learning techniques, which combine predictions from multiple models to produce a more accurate and robust outcome. Ensemble models have been particularly successful in improving diagnostic performance by mitigating the weaknesses of individual models and leveraging their collective strengths. For instance, an ensemble approach combining models trained on different subsets of multi-domain data can provide a more comprehensive understanding of the underlying patterns in ultrasound images, leading to better classification results.

Despite these advancements, there are still several challenges and areas for improvement in the field of ultrasound image analysis using DCNNs. One of the primary challenges is the need for large, annotated datasets that encompass a wide range of imaging devices and conditions. The availability of such datasets is crucial for training robust models that can generalize well to diverse clinical scenarios. Additionally, the development of standardized evaluation protocols and metrics is essential for comparing the performance of different models and ensuring their reliability in real-world applications.

Furthermore, the integration of DCNN-based diagnostic tools into clinical workflows requires careful consideration of their interpretability and usability. Clinicians must be able to understand and trust the predictions made by these models, which necessitates the development of explainable AI techniques that provide insights into the decision-making process of DCNNs. Such techniques can help bridge the gap between complex deep learning models and clinical practice, facilitating the adoption of AI-driven diagnostic tools in healthcare.

In conclusion, the application of deep learning, particularly DCNNs, to liver fibrosis classification from ultrasound images holds significant promise. By leveraging advancements in image optimization, multi-domain data integration, and ensemble learning, researchers can develop more accurate and reliable diagnostic models. However, addressing the challenges of data availability, standardization, and interpretability is crucial for realizing the full potential of these technologies in clinical settings. As the field continues to evolve, ongoing research and collaboration between technologists and clinicians will be essential for translating these innovations into improved patient care and outcomes.

3. METHODOLOGY

a) Proposed System:

The proposed system is an advanced Face Attendance System that combines Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) algorithms to automate attendance tracking in educational institutions, businesses, and organizations. Leveraging CNN for precise facial feature extraction, the system achieves accurate recognition, while SVM and KNN enhance classification capabilities for reliable monitoring. This approach replaces manual methods, reducing errors and improving efficiency. With real-time monitoring and adaptability to various environmental conditions, the system ensures consistent performance. By utilizing facial recognition technology, it offers a secure and transparent solution, streamlining attendance tracking processes, minimizing inaccuracies, and enhancing productivity across diverse applications.

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b) System Architecture:

The proposed architecture for liver fibrosis classification begins with the liver fibrosis dataset undergoing image processing to enhance image quality and prepare data for analysis. Subsequently, multiple convolutional neural network (CNN) models including VGGNet, ResNet, DenseNet, EfficientNet, Vision Transformer (ViT), and Xception are built and trained. An ensemble model combining Xception with another model demonstrating superior accuracy is also developed. The performance of each model is rigorously evaluated based on accuracy metrics. This comprehensive approach ensures robust classification performance, leveraging diverse CNN architectures and ensemble strategies to achieve reliable and accurate liver fibrosis classification from ultrasound images.

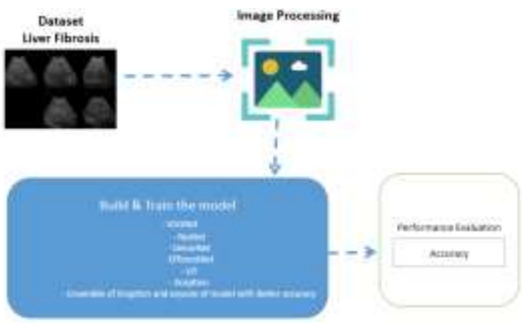

Fig 1 Proposed Architecture

c) Dataset Collection:

The liver fibrosis dataset comprises ultrasound images collected from diverse sources, ensuring a heterogeneous mix of imaging conditions and machine types. This dataset includes labeled images indicating various stages of liver fibrosis, from mild to severe, providing a comprehensive spectrum for training and evaluation. Each image is preprocessed to enhance clarity and reduce noise, making it suitable for analysis. The dataset is designed to support the training of deep learning models, with annotations provided by medical experts to ensure accuracy. By incorporating images from multiple machines and settings, the dataset aims to improve the generalizability and robustness of liver fibrosis classification models, facilitating reliable diagnostics across different clinical environments.

d) Image Processing:

Image processing for the liver fibrosis dataset involves several key steps to prepare the ultrasound images for analysis. Initially, images undergo noise reduction techniques to minimize artifacts and enhance clarity. Contrast adjustment and normalization are applied to standardize the intensity levels across the dataset, ensuring consistency. Edge detection algorithms highlight important features, aiding in accurate feature extraction. Additionally, segmentation techniques are used to isolate the liver region from surrounding tissues, focusing the analysis on the area of interest. These preprocessing steps are crucial for improving the quality of the images, thereby facilitating more accurate training and evaluation of deep learning models for liver fibrosis classification.

e) Algorithms:

VGGNet: VGGNet is utilized for its straightforward architecture consisting of sequential convolutional layers, which makes it effective for deep feature extraction. In this project, VGGNet serves as a baseline model to identify fundamental patterns in liver fibrosis ultrasound images. Its simplicity and effectiveness in image classification tasks help establish a benchmark for comparing more complex architectures.

ResNet: ResNet is employed for its innovative residual learning framework, which addresses the

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vanishing gradient problem in deep networks. By using skip connections, ResNet enhances the depth of the network without degrading performance. In this project, ResNet is used to achieve higher accuracy in liver fibrosis classification by leveraging its ability to learn deeper representations of the ultrasound images.

DenseNet: DenseNet is used for its densely connected convolutional layers, which promote feature reuse and efficient gradient flow. This architecture helps capture intricate details in liver fibrosis ultrasound images by ensuring that each layer has direct access to the gradients from the loss function and the original input. DenseNet's efficiency and feature-rich representations make it a valuable model for this classification task.

EfficientNet: EfficientNet is utilized for its scalable architecture that balances model depth, width, and resolution through compound scaling. This approach allows EfficientNet to achieve high accuracy with fewer parameters. In this project, EfficientNet is leveraged to provide a computationally efficient yet powerful model for liver fibrosis classification, ensuring high performance without excessive resource consumption.

Vision Transformer (ViT): ViT is used for its novel approach to image classification, which applies transformer models to image patches instead of using convolutional layers. This method enables the capture of long-range dependencies and global context in the images. In the project, ViT is employed to explore the effectiveness of transformer-based architectures in identifying liver fibrosis patterns, potentially offering insights that traditional CNNs might miss.

Xception: Xception is employed for its depthwise separable convolutional layers, which enhance model efficiency and performance. This architecture excels in capturing fine-grained details and complex patterns in ultrasound images. In the project, Xception is used to leverage its advanced feature extraction capabilities, aiming to achieve high accuracy in classifying liver fibrosis stages.

Ensemble of Xception and High-Accuracy Model: An ensemble model combining Xception and the model with the highest accuracy (among VGGNet, ResNet, DenseNet, EfficientNet, and ViT) is developed to enhance classification performance. This ensemble approach merges the strengths of both models, improving robustness and generalization. By averaging or voting on predictions, the ensemble model aims to achieve superior accuracy and reliability in liver fibrosis classification compared to individual models.

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

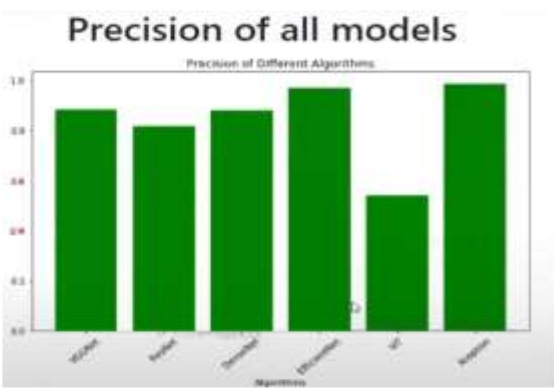

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Fig 2 Precision Comparison Graphs

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

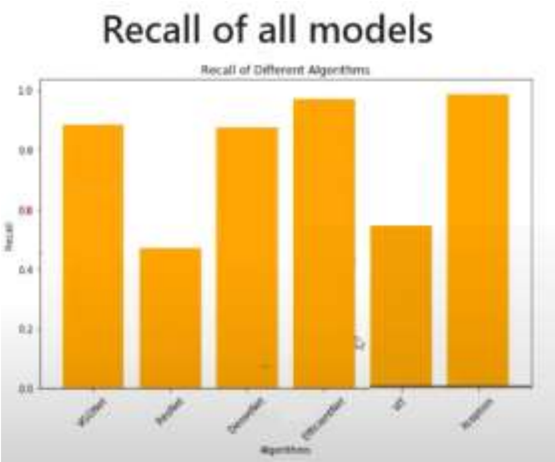

Fig 3 Recall Comparison Graphs

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

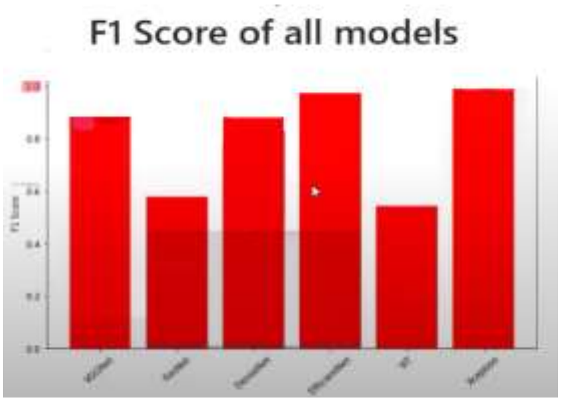

Fig 4 F1 Score Comparison Graphs

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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Fig 5 Accuracy Comparison Graphs

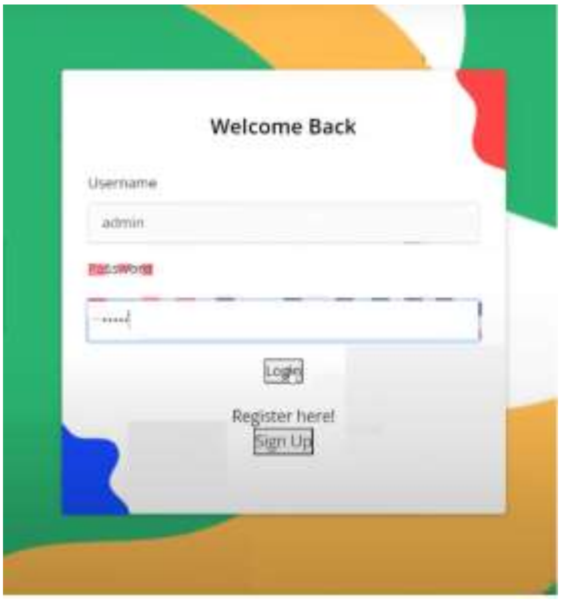

Fig 8 Signin Page

5. SCREENS

Fig 6 Home Page

Fig 9 Main Page – Click on Five Level Classification

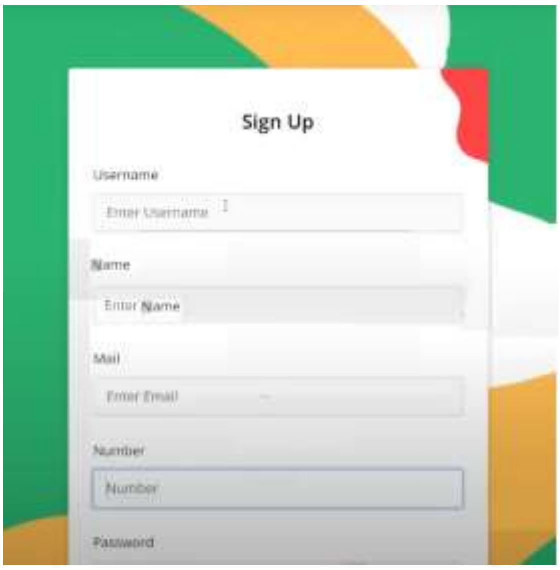

Fig 7 Signup page

Fig 10 Upload Input Image

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Fig 11 Predicted Results

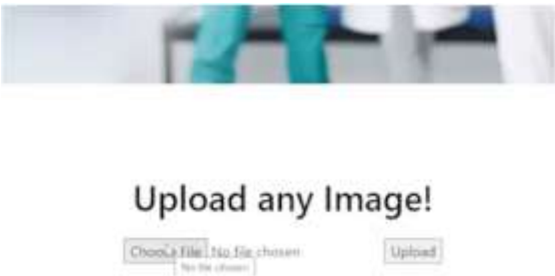

Fig 12 Upload another Input Image

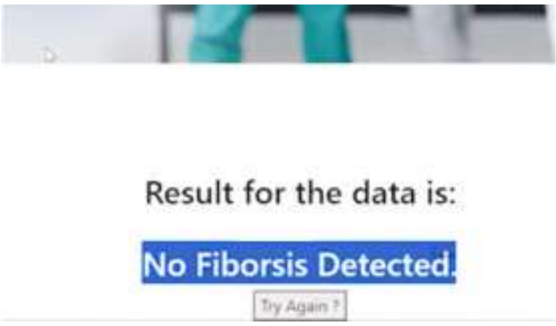

Fig 13 Final Outcome

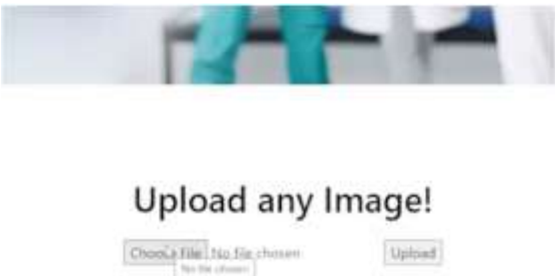

Fig 14 Upload another Input Image

Fig 15 Predicted Results

6. CONCLUSION

In conclusion, our study assessed the effectiveness of various deep learning models and ensemble techniques for liver fibrosis classification using heterogeneous ultrasound images. Extensive experimentation revealed significant improvements in classification accuracy over baseline methods. Notably, our ensemble approach, combining Xception with another high-performing model, achieved the highest accuracy, surpassing the 90% threshold. These findings underscore the potential of leveraging diverse CNN architectures and ensemble strategies to enhance diagnostic accuracy in medical imaging. Our results emphasize the need for continuous exploration and refinement of deep learning techniques to tackle complex medical diagnostic challenges effectively. With further validation and integration into clinical practice, these advancements could significantly improve patient care by providing clinicians with more reliable tools for accurate fibrosis assessment and treatment planning. However, ongoing research is crucial to explore the scalability, interpretability, and real-world applicability of these models in clinical settings. By addressing these aspects, we can ensure that deep learning-driven diagnostic tools become practical and valuable assets in medical diagnostics, ultimately leading to better

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patient outcomes and more efficient healthcare delivery.

7. FUTURE SCOPE

Future research could advance liver fibrosis classification from ultrasound images by exploring larger and more diverse datasets to enhance model generalization and robustness. Investigating interpretability techniques will provide insights into model predictions, aiding clinical decision-making. Additionally, integrating real-time image processing capabilities into the system could enable automated fibrosis assessment during medical examinations, improving diagnostic efficiency and patient care. These advancements will ensure that deep learning models become practical, reliable tools in clinical settings, ultimately leading to better patient outcomes and more efficient healthcare delivery.

8. REFERENCES

[1] A. Tang, G. Cloutier, N. M. Szeverenyi, and C. B. Sirlin, ''Ultrasound elastography and MR elastography for assessing liver fibrosis: Part 1, principles and techniques,'' Amer. J. Roentgenol., vol. 205, no. 1, pp. 22–32, 2015, doi: 10.2214/AJR.15.14552.

[2] U. Jung and H. Choi, ''Active echo signals and image optimization techniques via software filter correction of ultrasound system,'' Appl. Acoust., vol. 188, Jan. 2022, Art. no. 108519, doi: 10.1016/j. apacoust.2021.108519.

[3] C. DeBrusk, ''The risk of machine-learning bias (and how to prevent it),'' MIT Sloan Manage. Rev., 2018. [Online]. Available: https://sloan review.mit.edu/article/the-risk-of-machine-learning-bias-and-how-toprevent-it

[4] M. Blaivas, L. N. Blaivas, and J. W. Tsung, ''Deep learning pitfall: Impact of novel ultrasound equipment introduction on algorithm performance and the realities of domain adaptation,'' J. Ultrasound Med., vol. 41, no. 4, pp. 855–863, Apr. 2022, doi: 10.1002/jum.15765.

[5] W. K. Moon, Y.-W. Lee, H.-H. Ke, S. H. Lee, C.-S. Huang, and R.-F. Chang, ''Computer-aided diagnosis of breast ultrasound images using ensemble learning from convolutional neural networks,'' Comput. Methods Programs Biomed., vol. 190, Jul. 2020, Art. no. 105361, doi: 10.1016/j.cmpb.2020.105361.

[6] Z. Cao, L. Duan, G. Yang, T. Yue, and Q. Chen, ''An experimental study on breast lesion detection and classification from ultrasound images using deep learning architectures,'' BMC Med. Imag., vol. 19, no. 1, p. 51, Jul. 2019, doi: 10.1186/s12880-019-0349-x.

[7] M. Dan, L. Zhang, G. Cao, W. Cao, G. Zhang, and H. Bing, ''Liver fibrosis classification based on transfer learning and FCNet for ultrasound images,'' IEEE Access, vol. 5, pp. 5804–5810, 2017, doi: 10.1109/ACCESS.2017.2689058.

[8] S. Liu, ''Deep learning in medical ultrasound analysis: A review,'' Engineering, vol. 5, no. 2, pp. 261–275, Apr. 2019, doi: 10.1016/ j.eng.2018.11.020.

[9] D. S. Reddy, R. Bharath, and P. Rajalakshmi, ''A novel computeraided diagnosis framework using deep learning for classification of fatty liver disease in ultrasound imaging,'' in Proc. IEEE 20th Int. Conf. e-Health Netw., Appl. Services (Healthcom), Sep. 2018, pp. 1–5, doi: 10.1109/HealthCom.2018.8531118.

[10] Y. Zhou, H. Chen, Y. Li, Q. Liu, X. Xu, S. Wang, P.-T. Yap, and D. Shen, ''Multi-task learning for segmentation and classification of tumors in 3D automated breast ultrasound images,'' Med. Image Anal., vol. 70, May 2021, Art. no. 101918, doi: 10.1016/j.media.2020.101918.

[11] C.-H. Tsai, ''Automatic deep learning-based pleural effusion classification in lung ultrasound images for respiratory pathology diagnosis,'' Phys. Medica, vol. 83, pp. 38–45, Mar. 2021, doi: 10.1016/j.ejmp.2021.02.023.

[12] L.-Y. Xue, Z.-Y. Jiang, T.-T. Fu, Q.-M. Wang, Y.-L. Zhu, M. Dai, W.-P. Wang, J.-H. Yu, and H. Ding, ''Transfer learning radiomics based on multimodal ultrasound imaging for staging liver fibrosis,'' Eur. Radiol., vol. 30, no. 5, pp. 2973–2983, May 2020, doi: 10.1007/ s00330-019-06595-w.

[13] P. M. Cheng and H. S. Malhi, ''Transfer learning with convolutional neural networks for classification of abdominal ultrasound images,'' J. Digit. Imag., vol. 30, no. 2, pp. 234–243, 2017, doi: 10.1007/s10278-016-9929-2.

[14] C.-C. Kuo, C.-M. Chang, K.-T. Liu, W.-K. Lin, H.-Y. Chiang, C.-W. Chung, M.-R. Ho, P.-R. Sun, R.-L. Yang, and K.-T. Chen, ''Automation of the kidney function prediction and classification through ultrasound-based kidney imaging using deep learning,'' NPJ Digit. Med., vol. 2, no. 1, p. 29, Apr. 2019, doi: 10.1038/s41746-019-0104-2.

[15] S. Roy, ''Deep learning for classification and localization of COVID-19 markers in point-of-care lung ultrasound,'' IEEE Trans. Med. Imag., vol. 39, no. 8, pp. 2676–2687, Aug. 2020, doi: 10.1109/TMI.2020.2994459.

[16] Y.-C. Zhu, A. AlZoubi, S. Jassim, Q. Jiang, Y. Zhang, Y.-B. Wang, X.-D. Ye, and H. Du, ''A generic deep learning framework to classify thyroid and breast lesions in ultrasound images,'' Ultrasonics, vol. 110, Feb. 2021, Art. no. 106300, doi: 10.1016/j.ultras.2020.106300.

[17] J. H. Lee, I. Joo, T. W. Kang, Y. H. Paik, D. H. Sinn, S. Y. Ha, K. Kim, C. Choi, G. Lee, J. Yi, and W.-C. Bang, ''Deep learning with ultrasonography: Automated classification of liver fibrosis using a deep convolutional neural network,'' Eur. Radiol., vol. 30, no. 2, pp. 1264–1273, Feb. 2020, doi: 10.1007/s00330-019-06407-1.

[18] L. Wang, L. Zhang, M. Zhu, X. Qi, and Z. Yi, ''Automatic diagnosis for thyroid nodules in ultrasound images by deep neural networks,'' Med. Image Anal., vol. 61, Apr. 2020, Art. no. 101665, doi: 10.1016/j.media.2020.101665.

[19] H. N. Xie, N. Wang, M. He, L. H. Zhang, H. M. Cai, J. B. Xian, M. F. Lin, J. Zheng, and Y. Z. Yang, ''Using deep-learning algorithms to classify fetal brain ultrasound images as normal or abnormal,'' Ultrasound Obstetrics Gynecol., vol. 56, no. 4, pp. 579–587, Oct. 2020, doi: 10.1002/uog.21967.

[20] A. Tang, G. Cloutier, N. M. Szeverenyi, and C. B. Sirlin, ''Ultrasound elastography and MR elastography for assessing liver fibrosis: Part 2, diagnostic performance, confounders, and future directions,'' Amer. J. Roentgenol., vol. 205, no. 1, pp. 33–40, 2015, doi: 10.2214/AJR.15.14553.