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Digital Image Processing for Ultrasound Images: A Comprehensive Review

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Ultrasound (US) imaging is among common, low-cost, portable, and non-ionizing diagnostic tools used worldwide in medical environments. It is in-vivo, hence, capable of real-time image acquisition with display, and evolving medical imaging modality facing challenges (limited image quality and high inter & intra operator variability) and opportunities. Opportunities have arisen because of growth in computational power integrated with US devices and recently Covid-19 pandemic as symptoms also appear on US image. To make US devices smart, researchers need to integrate image processing techniques. This study aims to provide a comprehensive review of state-of-the-art studies used for abnormalities detection from US images, future opportunities of machine learning models to improve workflow and US-based diagnosis, and research directions in connection with the US. Several acute and chronic disorders present in the bladder, kidneys, liver, pancreas, heart, lungs, uterus, etc. are well diagnosed using US images. The detection of disorders from these organs at their early stage can improve survival rates to great extent.

Keywords: *Ultrasound Images Processing, Machine learning, Computer-aided diagnostics*

1.0 Introduction

Mainly, there are two methods executed to diagnose different physical disorders, one is an invasive method (biopsy) and the second is noninvasive (blood & imaging-based tests). In a biopsy, affected tissues are resected. There are many limitations including the risk of complications and the ability to sample only a small portion of infected cells. Biopsy may also be subject to undesired or impossible in patients and is considered impractical for successive follow-up. Moreover, a biopsy may have a sampling error due to heterogeneity present in tissues. However, it is still considered the "gold standard" method. Fibrosisent reference standard for diagnosis of hepatic fibrosis is liver biopsy. Nevertheless, this invasive procedure is being replaced with non-invasive methods. Blood tests are quick, painless, relatively inexpensive, and the most widely available noninvasive methods. Imaging tests include ultrasound, magnetic resonance electrography (MRE), magnetic resonance imaging (MRI), computed tomography (CT), X-Rays, etc. (Asghar, Gilanie, Saddique, & Habib, 2017; Attique et al., 2012; Gilanie, Attique, Naweed, Ahmed, & Ikram, 2013; Gilanie, Bajwa, Waraich, & Anwar, 2021; Gilanie, Bajwa, Waraich, Asghar, et al., 2021; Gilanie, Bajwa, Waraich, & Habib, 2019a, 2019b; Gilanie et al., 2018; Gilanie, Nasir, Bajwa, & Ullah, 2021; Ullah, Gilanie, Attique, Hamza, & Ikram, 2012).

Ultrasound or ultrasonography is an imaging method of the first choice because it is inexpensive, versatile, noninvasive, and widely available. It is based on non-ionizing radiation, so it does not have the same risks as X-Rays or other types of imaging systems that use ionizing radiation. It is among important medical imaging modalities used to help practitioners in evaluating symptoms including infection, pain, swelling, etc. Some of its protocols include abdominal ultrasound to visualize abdominal tissues and organs, bone sonometry to assess bone fragility, 3) Doppler fetal heart rate monitors to listen to the heartbeat, 4) Doppler ultrasound to visualize blood flow through blood vessels, organs, or other structures, ultrasound-guided biopsies to collect a sample of tissue, ultrasound-guided needle placement (in blood vessels or other tissues of interest.

An ultrasound can effectively be used to study abdominal structures, stomach pain & bloating, pelvic organs, joints, internal organs & blood vessels, anesthesiology, appendicitis, fetus position & development, enlarged spleen (due to disease or infection), congestive heart failure, angiology (vascular), gastroenterology/colorectal surgery, emergency medicine, gynecology & obstetrics, otolaryngology (head & neck), hemodynamics (blood circulation), neonatology, tendons, ophthalmology (eyes), muscles, penis & scrotum, urinary tract, appendicitis, musculoskeletal, etc. It is also favorably used allied with female's health issues including fibroid uterus, polycystic ovary syndrome, endometriosis, cancers of the ovary, ovarian cyst, uterus, confirm fetal viability, date the pregnancy, determine the location of fetus, check the location of the placenta concerning the cervix, intrauterine vs. ectopic, check for major physical abnormalities, check for the number of fetuses (multiple pregnancies), assess fetal growth-for evidence of intrauterine growth restriction, determine the sex of the baby check for fetal movement and heartbeat, sequelae of viral hepatitis detection, tracking DVT in patients with severe COVID-19, chronic renal failure detection, analysis of lungs, breast, kidney, heart, liver, abdominal structures for detection and assessment of various disorders and grows and size of anatomical structure, etc.

The size, appearance, and shape of an organ help to diagnose a health condition. The organs usually examined include the bladder, kidneys, liver, pancreas, heart, lungs, uterus, etc. for their assessment of different disorders in their early stage. Because cute diseases if not treated can lead to chronic ones. For instance, if one is infected with chronic hepatitis C, it may silently hurt the body. Hepatitis C virus, not just the liver, may affect many organs, tissues, and systems. Most frequent sequelae include high blood sugar, blood & vessel problem, joint & muscle pain, heart problems, kidney disease, mental health issue, osteosclerosis, nerve problem, skin problem, liver cancer, liver cirrhosis, and liver failure.

In medical environments, each moment terabytes of data are generated through medical scanners. Manual interpretation and availability of the radiologist are not possible in less developed areas. If automated systems using artificial intelligence are developed and deployed in these medical environments are cost-effective, accurate, and the definitive system would be the proposed one. Figure 1 shows machine-learning techniques used for computer-aided diagnostics.

This paper is organized as follows, section 2 contains literature reviewed, section 03 presents Problems, challenges, and issues, while machine-learning methods to process US images is the structured in section 4. Conclusions and future directions are part of section 5, while section 6 has references.

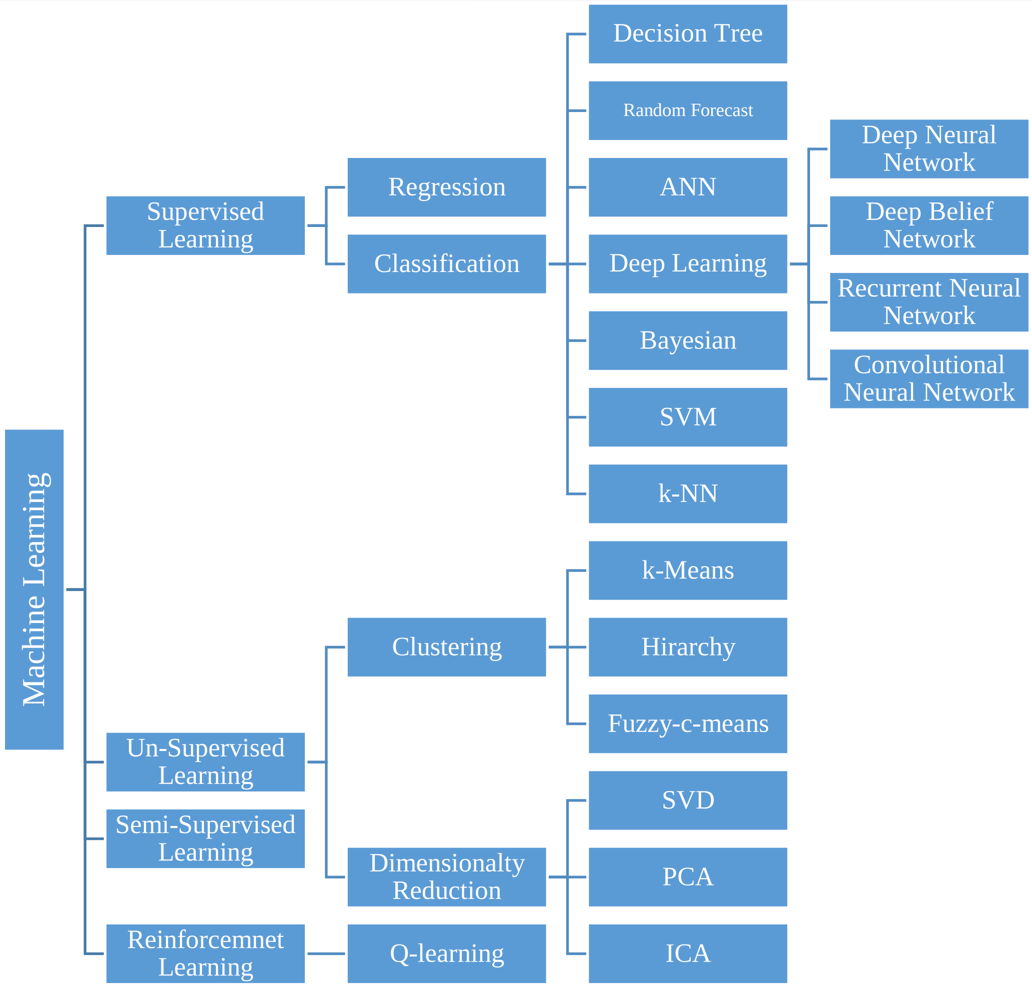

Figure 1: Machine-learning techniques used for computer aided diagnostics

2.0 Literature Review

The researchers (Cheng & Malhi, 2017) proposed a method to process and classify abdominal ultrasound images using CNN. 11 categorized images of 256 × 256 resolution have been used for training and testing of their method. The classification results are calibrated with the findings of radiologists. The proposed model achieved 77.3% and 77.9% training accuracy on CaffeNet and VGGNet respectively, while overall, test accuracy remained 71.7%. Another study (Meng et al., 2017) proposed a liver fibrosis classification method from ultrasound images through transfer learning using VGGNet. Dataset consisting of 279 total regions of interest (normal=79, early-stage fibrosis=89, and late-stage fibrosis=111) was collected from Shanghai Jiaotong University Number Six People's Hospital.). The study (Mokrane et al., 2020) introduced a Radiomics AI signature for a finding of hepatocellular carcinoma (HCC) in cirrhotic patients with uncertain liver knobs. They broke down 178 cirrhotic patients from 27 establishments, with biopsy demonstrated liver knobs. Patients were arbitrarily doled out to a disclosure accomplice (142 patients (pts.)) and an approval partner (36 pts.). Every liver knob was sectioned on each period of triphasic CT filters, and 13,920 quantitative imaging highlights (12 arrangements of 1160 highlights each mirroring the aggregate at one single stage or its change between two stages) were separated. Utilizing AI methods, the mark was prepared and adjusted (disclosure associate) and approved (approval companion) to order liver knobs as HCC versus non-HCC. In the article (Wang et al., 2020) diagnosing central liver injuries by unpracticed radiologists has been introduced. They gathered pictures and clinical information from 258 patients in danger of hepatocellular carcinoma. Two prepared unpracticed radiologists and 2 experienced radiologists surveyed all CEUS cuts. The outcome shows κ estimation of 0.774 shows that the CEUS LI-RADS calculation brought about generous consistency between the unpracticed radiologists. For the determination of hepatocellular carcinoma, the affectability, explicitness, positive prescient worth, and negative prescient worth were improved fundamentally in unpracticed radiologists utilizing the CEUS LI-RADS contrasted with customary techniques. The demonstrative exactness of the accomplished radiologists was practically equivalent to that of CEUS LI-RADS classifications allocated by the unpracticed radiologists.

The researcher suggested (Polat, Mehr, & Cetin, 2017) support vector algorithm to diagnose chronic renal failure disease with wrapper and greedy search engine. After experiments wrapper is the best classifier with the best search engines. The result shows a 98.5% filtered method with high accuracy in the chronic kidney disease test compared to other selected methods. In a study conducted by (Z. Liu et al., 2021), prostate cancer has been diagnosed from ultrasound images using the transfer learning method with the combination of S-Mask R-CNN and inception-v3. Region of interest align algorithm has been used to position feature points. A binary mask has been generated through the convolutional process to extract prostate regions from the background. Dataset has been collected from the First Affiliated Hospital of JiNan University and the Third Affiliated Hospital of Sun Yatsen University. A total of 702 images (422 images as a training set, while 140 images each as validation and testing set) have been used for experiments. The maximum Performance of the reported model in terms of precision is 0.83. In a study conducted by (Yap et al., 2020), breast regions of interest (ROI) detection & lesions localization from US images using deep learning has been proposed. The authors used Faster-RCNN and Inception-ResNet-v2 –network as a transfer learning tool to propose a 3–channel based artificial RGB method. In another study (Moon et al., 2020), a 3-D CNN model is proposed to detect breast cancer from US images. 165 cases are used for training purposes, while 81 cases are used for evaluation purposes. Overall, the tumor detection rate as per sensitivity is 95.3%. The review of the state-of-the-art methods for abnormalities detection and classification from US images is present in Table 1.

Table 1: State of the art

Sr. No.	Author Name, Year	The Proposed Methodology	Dataset Used	Classification of	Evaluation Measures Achieved
1.	(Hassan, Elmogy, & Sallam, 2017)	Deep Learning	110 US images collected from the Egyptian Liver Research Institute and the Sherbin Central Hospital, Dakahlia Governorate, Egypt	Liver Cyst, Hem, HCC and Normal	Accuracy=97.2%
2.	(Xue et al., 2020)	Deep convolutional neural network	466 patients (401 chronic hepatitis B and 65 without fibrosis)	Liver fibrosis grading	
3.	(Schmauch et al., 2019)	Deep learning	367 individual livers ultrasound images locally collected	Homogeneous Liver, Liver Angioma, Liver Metastasis, HCC, Liver Cyst, FNH (Focal Nodular Hyperplasia)	ROC-AUC=0.935
4.	(Sharma & Juglan, 2018)	SMO, IBK, ADABOOST, BF-TREE	90 ultrasound liver images collected from Delta Diagnostic	Fatty liver and Normal liver	Accuracy=95.55% Sensitivity=97.77 %

			Centre Patiala, India		
5.	(Krithiga & Lakshmi, 2020)	active contour-based segmentation, Shift variant bi-orthogonal wavelet decomposition, GLRLM, random forest-based learning	180 images collected from SRM Medical College Hospital and Research Centre Chennai, India	Normal, Fatty, Hepatitis, Cyst, Metastasis, Cirrhosis and Haemangioma	Accuracy=97.8%
6.	(Krishnamurthy, Radhakrishnan, & Kattuva, 2020)	contour technique, wavelet-texture features	The dataset of 596 ultrasound images collected from Sonoscan Ultrasonic Scan Centre, Coimbatore	Abscess Cirrhosis, Cyst, Echinococcosis, Hemangioma, Hepatocellular Carcinoma, Hepatitis, Fatty Liver, Metastasis, Hepatomegaly	Accuracy=91%
7.	(Meng et al., 2017)	Deep neural networks	279 total ultrasound images (79 healthy liver, 890 early-stage liver fibrosis and 111 late-stage liver fibrosis)	Liver fibrosis	-
8.	(Xu, Chang, Su, & Phu, 2019)	Support vector machine	79 US images (44 cases of HCC and 35 cases of liver abscess)	Liver	Accuracy=88.88%

			collected from Medical University Hospital in Taipei		
9.	(Bharti, Mittal, & Ananthasivan, 2018)	Ensemble Model k-NN SVM Rotation Forest	189 liver ultrasound images (50 chronic liver,48 normal liver, 41 HCC cirrhosis 50 cirrhosis)	Cirrhosis, Normal liver, HCC Chronic Liver,	Accuracy=96.6%
10.	(Amin et al., 2019)	Wavelet packet transform	Datasets-I 164 US images. Datasets-II 1200 images. Datasets-III 57 images	Liver	Datasets-I Accuracy=98.8% Sensitivity=97.8% , specificity=100% Datasets-II Accuracy=85.74% , sensitivity=84.4% , specificity=88.5% Datasets-III Accuracy=92.5%, Sensitivity=93.0% , Specificity=91.0%
11.	(Byra et al., 2018)	Deep convolutional neural network, SVM	550 B-mode images acquired from the Department of Internal Medicine, Hypertension and Vascular	Liver	Accuracy=0.963

			Diseases, Medical University of Warsaw, Poland		
12.	(Owjimehr, Danyali, Helfroush, & Shakibafard, 2017)	Hierarchical classification algorithm SVM	129 US images (47 steatosis,28 normal, 12 cirrhosis, 42 fibrosis)	Liver	Accuracy=94.91%
13.	(Krishnan & Radhakrishnan, 2017)	GLRLM, GLCM, Segmentation-based fractal texture analysis, Active contour segmentation, Wavelet transform	364 US images	Liver	Accuracy=91%
14.	(X. Liu, Song, Wang, Zhao, & Chen, 2017)	SVM, CNN	Dataset consist of 91 patients in which 44 normal and 47 have diseases	Liver	-
15.	(Yao et al., 2018)	SVM	177 patients with focal liver lesions	Liver	-
16.	(Tan et al., 2020)	Deep learning techniques	39 healthy and 61 hypoplastic left heart syndrome patients	Congenital Heart disease	F1-score=0.87 ROC-AUC=0.93
17.	(Song et al., 2020)	Deep learning Active contour	1727 images (1427 healthy and 300 unhealthy)	Heart	-

			collected through multi-center, China		
18.	(Jafari et al., 2019)	Deep learning	The dataset includes 427 patients' data	Heart	Dice score=92%
19.	(Kuru, Ansell, Jones, De Goede, & Leather, 2019)	Smartphone ML Techniques	Locally developed dataset	Bladder	Sensitivity=0.89 Specificity=0.93
20.	(Matsumoto et al., 2019)	Deep learning	Locally developed dataset of 81 patients	Bladder	Sensitivity=88.5% Specificity=100%
21.	(Yang et al., 2020)	Deep learning	1200 cystoscopic cancer images of 224 patients having bladder cancer and 1150 images from 221 patients with no bladder cancer collected from Urology Department of the Renmin Hospital, Wuhan University, China	Bladder tumors	Accuracy=96.9%
22.	(Kuwahara et al., 2019)	Deep learning	3,970 images were collected from 50 patients	Pancreas	Accuracy=94.0%.

23.	(Jeong et al., 2020)	Convolutional neural network	6,056 cropped polyp images (3,200 non-neoplastic polyps and 1,971 neoplastic polyps)	Gallbladder	
24.	(Negrao de Figueiredo, Mueller-Peltzer, Armbruster, Rübenthaler, & Clevert, 2019)	Pathology study	37 patients having gallbladder diseases	Gallbladder	Specificity=100% Sensitivity=100%
25.	(T. Chen et al., 2020)	principal components analysis and AdaBoost	224 patients of gallbladder polyp postoperatively	Gallbladder	Accuracy=95%
26.	(Zangana & Mohammad, 2017)	kNN+SVM+LDA	200 patients	Heart+ Gallbladder	-
27.	(Ma, Sun, Liu, & Jing, 2020)	SVM, Multi-layer perception with back propagation algorithm	Locally Developed datasets	Kidney	Accuracy=98%
28.	(Kuo et al., 2019)	CNN	4,505 kidney ultrasound images collected from China Medical University Hospital	Kidney	Accuracy=85.6%
29.	(C.-J. Chen et al., 2020)	SVM	798 kidney images	Kidney	Accuracy=90%

			collected from Keelung Chang Gung Memorial Hospital, Taiwan		
30.	(Yin et al., 2020)	Deep CNN Network	289 US images collected from locally developed datasets	Kidney	Accuracy=90%
31.	(Athavale et al., 2020)	CNN	6,135 ultrasound images, locally developed datasets	Kidney	Accuracy=90%
32.	(Sudharson & Kokil, 2020)	DNN	4940 images collected from the Department of Radiology, Chettinad Health City Hospital, Chennai	Kidney	Accuracy=96.54%
33.	(Nieuwenhuis et al., 2018)	Pathology study	436 ultrasound images	Uterus	Accuracy=90.67%
34.	(Suomi et al., 2019)	HIFU with support vector classification	89 Ultrasound images collected from Turku University Hospital, Finland	Uterus	Accuracy=80%

35.	(Ning, Zhang, Zhang, Wang, & Liao, 2020)	Deep convolutional neural network	758 US Images Collected from gynae-ultrasound. departments at the Karolinska University Hospital	Uterus	Sensitivity=96.0% Specificity=89.3%
36.	(Chen et al., 2019)	CNN-SVM	164 ultrasound Images collected from China Medical University Hospital	Lungs	Accuracy=87.0%
37.	(J Born et al.)	CNN	Dataset assembled through online 1103 images	Lungs	Accuracy=89%
38.	(Jannis Born, Wiedemann, et al., 2020)	CNN	Dataset collected from internet	Lungs	Sensitivity=93% Specificity=87%
39.	(Jannis Born, Brändle, et al., 2020)	Deep CNN	1103 datasets collected from online resources	Lungs	Accuracy=92%
40.	(P. Chen et al., 2020)	Deep learning model	332 ultrasound images collected from locally developed dataset	Lungs	Accuracy=95%

3.0 Problems, challenges, and issues

US images sometimes come with poor detection accuracy, decreased signal to noise ratio, speckle noise, preselection of an ROI for image analysis, time consumption while interpretation, lower image quality, inconsistency among human experts, high misdetection rate, higher inter/intra operator variability, control etc.

4.0 Machine-learning methods to process Ultrasound images

On the platform of machine learning, several methods are used to process ultrasound images for auto decision making. A few of these methods assisting computer-aided diagnostics are shown in Figure 2. As per the literature reviewed, Deep Learning (Deep Convolutional Networks), Convolutional Neural Networks (CNN), and Support Vector Machines (SVMs) proved themselves to be helpful for Ultrasound image processing. Deep Learning (DL) techniques are the most widely and successful techniques and became promising predictive technology with near human-level accuracy.

CNN among DL techniques is a popular one, winning various image processing-based challenges. Various CNN architectures including GoogleNet, Alexnet, InceptionV3, DenseNet121, Restnet18, etc. have shown their applicability in the literature. Although CNN is a layered architecture, however, it also requires following some important hyper-parameters.

Learning Rate: Learning rate is the most important hyperparameter. It is a hyper-parameter that controls how much the model changes each time the model weights are changed in response to the expected error. It is represented by η. It defines how quickly a network updates its parameters. A low learning rate slows down the learning process but converges smoothly. A larger learning rate speeds up the learning but may not converge. Usually, a decaying learning rate is preferred. The optimal learning ranges from 0.1 to exponentially lower values: 0.01, 0.001, etc.

Momentum: Momentum is the direction of the next step with the knowledge of the previous steps. A typical choice of momentum is between 0.5 to 0.9.

Number of epochs: An epoch is one learning cycle where the model sees the whole training dataset. It specifies how many times the learning algorithm can go through the entire training dataset. It can vary according to the available datasets.

Batch size: Mini batch size is the number of subsamples given to the network after which parameter update happens. A good default value for batch size could be 32. It can vary from range 32, 64, 128, 256, and so on.

SVM on the other hand also remained successful in terms of memory efficiency for the classification of several disorders embodied through ultrasound scanners. It uses a hyper-plane for the classification process to separate features of data classes. It selects a location away from the features of the classes to determine a line. The distances of each class are measured according to the hyper-plane determined by the SVM method. It has come up with linear and non-linear versions. Like CNN, it also has tuning of several its apartness including choice of appropriate kernel and its parameters, choosing between hard margin /soft margin, etc. literature also revealed that in some cases, while dealing with ultrasound images, features are extracted using CNN models, and SVM is used for the classification on these extracted features (Toğaçar, Ergen, & Cömert, 2020).

5.0 Conclusions and future directions

US imaging is used significantly to diagnose health problems. The abnormalities diagnosed usually in their later stage are more likely to identify on their earl stage using US images in non-invasive and in-vivo manners. Several acute and chronic disorders present in the bladder, kidneys, liver, pancreas, heart, lungs, uterus, etc. are well diagnosed using US images. Identification of health disorders when they become chronic may decrease the survival rate of the subjects. US images sometimes come with poor detection accuracy, decreased signal-to-noise ratio, speckle noise, preselection of an ROI for image analysis, time consumption while interpretation, lower image quality, inconsistency among human experts, high misdetection rate, higher inter/intra operator variability, control, etc. Opportunities are also there, because of growth in computational power integrated with US devices and recently Covid-19 pandemic as symptoms appear on US image.

6.0 References

Amin, M. N., Rushdi, M. A., Marzaban, R. N., Yosry, A., Kim, K., & Mahmoud, A. M. (2019). Wavelet-based computationally-efficient computer-aided characterization of liver steatosis using conventional B-mode ultrasound images. *Biomedical Signal Processing and Control, 52*, 84-96.

Asghar, K., Gilanie, G., Saddique, M., & Habib, Z. (2017). Automatic enhancement of digital images using cubic Bézier curve and Fourier transformation. *Malaysian Journal of Computer Science, 30*(4), 300-310.

Athavale, A. M., Hart, P. D., Itteera, M., Patel, T., Cymbaluk, D. J., Alabka, A., . . . Rosenberg, A. (2020). DEEP LEARNING TO PREDICT DEGREE OF INTERSTITIAL FIBROSIS AND TUBULAR ATROPHY FROM KIDNEY ULTRASOUND IMAGES-AN ARTIFICIAL INTELLIGENCE APPROACH. *medRxiv*.

Attique, M., Gilanie, G., Mehmood, M. S., Naweed, M. S., Ikram, M., Kamran, J. A., & Vitkin, A. (2012). Colorization and automated segmentation of human T2 MR brain images for characterization of soft tissues. *PloS one, 7*(3), e33616.

Bharti, P., Mittal, D., & Ananthasivan, R. (2018). Preliminary study of chronic liver classification on ultrasound images using an ensemble model. *Ultrasonic Imaging, 40*(6), 357-379.

Born, J., Brändle, G., Cossio, M., Disdier, M., Goulet, J., Roulin, J., & Wiedemann, N. POCOVID-Net: Automatic detection of COVID-19 from a new lung ultrasound imaging dataset (POCUS). arXiv 2020. *arXiv preprint arXiv:2004.12084*.

Born, J., Brändle, G., Cossio, M., Disdier, M., Goulet, J., Roulin, J., & Wiedemann, N. (2020). POCOVID-Net: automatic detection of COVID-19 from a new lung ultrasound imaging dataset (POCUS). *arXiv preprint arXiv:2004.12084*.

Born, J., Wiedemann, N., Brändle, G., Buhre, C., Rieck, B., & Borgwardt, K. (2020). Accelerating COVID-19 differential diagnosis with explainable ultrasound image analysis. *arXiv preprint arXiv:2009.06116*.

Byra, M., Styczynski, G., Szmigielski, C., Kalinowski, P., Michałowski, Ł., Paluszkiewicz, R., . . . Nowicki, A. (2018). Transfer learning with deep convolutional neural network for liver steatosis assessment in ultrasound images. *International journal of computer assisted radiology and surgery, 13*(12), 1895-1903.

Chen, C.-H., Lee, Y.-W., Huang, Y.-S., Lan, W.-R., Chang, R.-F., Tu, C.-Y., . . . Liao, W.-C. (2019). Computer-aided diagnosis of endobronchial ultrasound images using convolutional neural network. *Computer Methods and Programs in Biomedicine, 177*, 175-182.

Chen, C.-J., Pai, T.-W., Hsu, H.-H., Lee, C.-H., Chen, K.-S., & Chen, Y.-C. (2020). Prediction of chronic kidney disease stages by renal ultrasound imaging. *Enterprise Information Systems, 14*(2), 178-195.

Chen, P., Chen, Y., Deng, Y., Wang, Y., He, P., Lv, X., & Yu, J. (2020). A preliminary study to quantitatively evaluate the development of maturation degree for fetal lung based on transfer learning deep model from ultrasound images. *International journal of computer assisted radiology and surgery, 15*(8), 1407-1415.

Chen, T., Tu, S., Wang, H., Liu, X., Li, F., Jin, W., . . . Wang, J. (2020). Computer-aided diagnosis of gallbladder polyps based on high resolution ultrasonography. *Computer methods and programs in biomedicine, 185*, 105118.

Cheng, P. M., & Malhi, H. S. (2017). Transfer learning with convolutional neural networks for classification of abdominal ultrasound images. *Journal of digital imaging, 30*(2), 234-243.

Gilanie, G., Attique, M., Naweed, S., Ahmed, E., & Ikram, M. (2013). Object extraction from T2 weighted brain MR image using histogram based gradient calculation. *Pattern Recognition Letters, 34*(12), 1356-1363.

Gilanie, G., Bajwa, U. I., Waraich, M. M., & Anwar, M. W. (2021). Risk-free WHO grading of astrocytoma using convolutional neural networks from MRI images. *Multimedia Tools and Applications, 80*, 4295-4306.

Gilanie, G., Bajwa, U. I., Waraich, M. M., Asghar, M., Kousar, R., Kashif, A., . . . Rafique, H. (2021). Coronavirus (COVID-19) detection from chest radiology images using convolutional neural networks. *Biomedical Signal Processing and Control, 66*, 102490.

Gilanie, G., Bajwa, U. I., Waraich, M. M., & Habib, Z. (2019a). Automated and reliable brain radiology with texture analysis of magnetic resonance imaging and cross datasets validation. *International Journal of Imaging Systems and Technology, 29*(4), 531-538.

Gilanie, G., Bajwa, U. I., Waraich, M. M., & Habib, Z. (2019b). Computer aided diagnosis of brain abnormalities using texture analysis of MRI images. *International Journal of Imaging Systems and Technology, 29*(3), 260-271.

Gilanie, G., Bajwa, U. I., Waraich, M. M., Habib, Z., Ullah, H., & Nasir, M. (2018). Classification of normal and abnormal brain MRI slices using Gabor texture and support vector machines. *Signal, Image and Video Processing, 12*, 479-487.

Gilanie, G., Nasir, N., Bajwa, U. I., & Ullah, H. (2021). RiceNet: convolutional neural networks-based model to classify Pakistani grown rice seed types. *Multimedia Systems*, 1-9.

Hassan, T. M., Elmogy, M., & Sallam, E.-S. (2017). Diagnosis of focal liver diseases based on deep learning technique for ultrasound images. *Arabian Journal for Science and Engineering, 42*(8), 3127-3140.

Jafari, M. H., Girgis, H., Van Woudenberg, N., Liao, Z., Rohling, R., Gin, K., . . . Tsang, T. (2019). Automatic biplane left ventricular ejection fraction estimation with mobile point-of-care ultrasound using multi-task learning and adversarial training. *International journal of computer assisted radiology and surgery, 14*(6), 1027-1037.

Jeong, Y., Kim, J. H., Chae, H.-D., Park, S.-J., Bae, J. S., Joo, I., & Han, J. K. (2020). Deep learning-based decision support system for the diagnosis of neoplastic gallbladder polyps on ultrasonography: preliminary results. *Scientific Reports, 10*(1), 1-10.

Krishnamurthy, R. K., Radhakrishnan, S., & Kattuva, M. A. K. (2020). Particle swarm optimization-based liver disorder ultrasound image classification using multi-level and multi-domain features. *International Journal of Imaging Systems and Technology*.

Krishnan, K. R., & Radhakrishnan, S. (2017). Hybrid approach to classification of focal and diffused liver disorders using ultrasound images with wavelets and texture features. *IET Image Processing, 11*(7), 530-538.

Krithiga, R. R., & Lakshmi, C. (2020). A novel automated classification technique for diagnosing liver disorders using wavelet and texture features on liver ultrasound images. *Multimedia Tools and Applications, 79*(5), 3761-3773.

Kuo, C.-C., Chang, C.-M., Liu, K.-T., Lin, W.-K., Chiang, H.-Y., Chung, C.-W., . . . Chen, K.-T. (2019). Automation of the kidney function prediction and classification through ultrasound-based kidney imaging using deep learning. *NPJ digital medicine, 2*(1), 1-9.

Kuru, K., Ansell, D., Jones, M., De Goede, C., & Leather, P. (2019). Feasibility study of intelligent autonomous determination of the bladder voiding need to treat bedwetting using ultrasound and smartphone ML techniques. *Medical & biological engineering & computing, 57*(5), 1079-1097.

Kuwahara, T., Hara, K., Mizuno, N., Okuno, N., Matsumoto, S., Obata, M., . . . Onishi, S. (2019). Usefulness of Deep Learning Analysis for the Diagnosis of Malignancy in Intraductal Papillary Mucinous Neoplasms of the Pancreas. *Clinical and translational gastroenterology, 10*(5).

Liu, X., Song, J. L., Wang, S. H., Zhao, J. W., & Chen, Y. Q. (2017). Learning to diagnose cirrhosis with liver capsule guided ultrasound image classification. *Sensors, 17*(1), 149.

Liu, Z., Yang, C., Huang, J., Liu, S., Zhuo, Y., & Lu, X. (2021). Deep learning framework based on integration of S-Mask R-CNN and Inception-v3 for ultrasound image-aided diagnosis of prostate cancer. *Future Generation Computer Systems, 114*, 358-367.

Ma, F., Sun, T., Liu, L., & Jing, H. (2020). Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network. *Future Generation Computer Systems, 111*, 17-26.

Matsumoto, M., Tsutaoka, T., Yabunaka, K., Handa, M., Yoshida, M., Nakagami, G., & Sanada, H. (2019). Development and evaluation of automated ultrasonographic detection of bladder diameter for estimation of bladder urine volume. *PloS one, 14*(9), e0219916.

Meng, D., Zhang, L., Cao, G., Cao, W., Zhang, G., & Hu, B. (2017). Liver fibrosis classification based on transfer learning and FCNet for ultrasound images. *IEEE Access, 5*, 5804-5810.

Mokrane, F.-Z., Lu, L., Vavasseur, A., Otal, P., Peron, J.-M., Luk, L., . . . Rousseau, H. (2020). Radiomics machine-learning signature for diagnosis of hepatocellular carcinoma in cirrhotic patients with indeterminate liver nodules. *European radiology, 30*(1), 558-570.

Moon, W. K., Huang, Y.-S., Hsu, C.-H., Chien, T.-Y. C., Chang, J. M., Lee, S. H., . . . Chang, R.-F. (2020). Computer-aided tumor detection in automated breast ultrasound using a 3-D convolutional neural network. *Computer methods and programs in biomedicine, 190*, 105360.

Negrao de Figueiredo, G., Mueller-Peltzer, K., Armbruster, M., Rübenthaler, J., & Clevert, D. (2019). Contrast-enhanced ultrasound (CEUS) for the evaluation of gallbladder diseases in comparison to cross-sectional imaging modalities and histopathological results. *Clinical hemorheology and microcirculation, 71*(2), 141-149.

Nieuwenhuis, L., Keizer, A., Stoelinga, B., Twisk, J., Hehenkamp, W., Brölmann, H., & Huirne, J. (2018). Fibroid vascularisation assessed with three-dimensional power Doppler ultrasound is a predictor for uterine fibroid growth: a prospective cohort study. *BJOG: An International Journal of Obstetrics & Gynaecology, 125*(5), 577-584.

Ning, G., Zhang, X., Zhang, Q., Wang, Z., & Liao, H. (2020). Real-time and multimodality image-guided intelligent HIFU therapy for uterine fibroid. *Theranostics, 10*(10), 4676.

Owjimehr, M., Danyali, H., Helfroush, M. S., & Shakibafard, A. (2017). Staging of fatty liver diseases based on hierarchical classification and feature fusion for back-scan–converted ultrasound images. *Ultrasonic Imaging, 39*(2), 79-95.

Polat, H., Mehr, H. D., & Cetin, A. (2017). Diagnosis of chronic kidney disease based on support vector machine by feature selection methods. *Journal of medical systems, 41*(4), 55.

Schmauch, B., Herent, P., Jehanno, P., Dehaene, O., Saillard, C., Aubé, C., . . . Jégou, S. (2019). Diagnosis of focal liver lesions from ultrasound using deep learning. *Diagnostic and interventional imaging, 100*(4), 227-233.

Sharma, V., & Juglan, K. (2018). Automated classification of fatty and normal liver ultrasound images based on mutual information feature selection. *IRBM, 39*(5), 313-323.

Song, C., Gao, T., Gong, Y., Sudirman, S., Wang, H., & Zhu, H. (2020). Fully Automatic Ultrasound Fetal Heart Image Detection and Segmentation based on Texture Analysis. *Investigacion Clinica, 61*(2), 600-608.

Sudharson, S., & Kokil, P. (2020). An ensemble of deep neural networks for kidney ultrasound image classification. *Computer Methods and Programs in Biomedicine, 197*, 105709.

Suomi, V., Komar, G., Sainio, T., Joronen, K., Perheentupa, A., & Sequeiros, R. B. (2019). Comprehensive feature selection for classifying the treatment outcome of high-intensity ultrasound therapy in uterine fibroids. *Scientific reports, 9*(1), 1-11.

Tan, J., Au, A., Meng, Q., FinesilverSmith, S., Simpson, J., Rueckert, D., . . . Kainz, B. (2020). Automated Detection of Congenital Heart Disease in Fetal Ultrasound Screening *Medical Ultrasound, and Preterm, Perinatal and Paediatric Image Analysis* (pp. 243-252): Springer.

Toğaçar, M., Ergen, B., & Cömert, Z. (2020). COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches. *Computers in biology and medicine, 121*, 103805.

Ullah, H., Gilanie, G., Attique, M., Hamza, M., & Ikram, M. (2012). M-mode swept source optical coherence tomography for quantification of salt concentration in blood: an in vitro study. *Laser Physics, 22*, 1002-1010.

Wang, J. Y., Feng, S. Y., Xu, J. W., Li, J., Chu, L., Cui, X. W., & Dietrich, C. F. (2020). Usefulness of the Contrast-Enhanced Ultrasound Liver Imaging Reporting and Data System in Diagnosing Focal Liver Lesions by Inexperienced Radiologists. *Journal of Ultrasound in Medicine*.

Xu, S. S.-D., Chang, C.-C., Su, C.-T., & Phu, P. Q. (2019). Classification of liver diseases based on ultrasound image texture features. *Applied Sciences, 9*(2), 342.

Xue, L.-Y., Jiang, Z.-Y., Fu, T.-T., Wang, Q.-M., Zhu, Y.-L., Dai, M., . . . Ding, H. (2020). Transfer learning radiomics based on multimodal ultrasound imaging for staging liver fibrosis. *European radiology*, 1-11.

Yang, R., Du, Y., Weng, X., Chen, Z., Wang, S., & Liu, X. (2020). Automatic recognition of bladder tumours using deep learning technology and its clinical application. *The International Journal of Medical Robotics and Computer Assisted Surgery*, e2194.

Yao, Z., Dong, Y., Wu, G., Zhang, Q., Yang, D., Yu, J.-H., & Wang, W.-P. (2018). Preoperative diagnosis and prediction of hepatocellular carcinoma: Radiomics analysis based on multi-modal ultrasound images. *BMC cancer, 18*(1), 1089.

Yap, M. H., Goyal, M., Osman, F., Marti, R., Denton, E., Juette, A., & Zwiggelaar, R. (2020). Breast ultrasound region of interest detection and lesion localisation. *Artificial Intelligence in Medicine, 107*, 101880.

Yin, S., Peng, Q., Li, H., Zhang, Z., You, X., Fischer, K., . . . Fan, Y. (2020). Automatic kidney segmentation in ultrasound images using subsequent boundary distance regression and pixelwise classification networks. *Medical image analysis, 60*, 101602.

Zangana, S. M., & Mohammad, D. O. (2017). Relation between Ischemic Heart Disease and gallbladder disease. *The Medical Journal of Tikrit University, 22*(1), 220-228.