QUANTIFICATION AND SEGMENTATION OF BREAST CANCER DIAGNOSIS: EFFICIENT HARDWARE ACCELERATOR APPROACH

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To my parents, wife and kids for giving me love, supports and encouragement.

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ABSTRACT

The mammography image eccentric area is the breast density percentage measurement. The technical challenge of quantification in radiology leads to misinterpretation in screening. Data feedback from society, institutional, and industry shows that quantification and segmentation frameworks have rapidly become the primary methodologies for structuring and interpreting mammogram digital images. Segmentation clustering algorithms have setbacks on overlapping clusters, proportion, and multidimensional scaling to map and leverage the data. In combination, mammogram quantification creates a long-standing focus area. The algorithm proposed must reduce complexity and target data points distributed in iterative, and boost cluster centroid merged into a single updating process to evade the large storage requirement. The mammogram database's initial test segment is critical for evaluating performance and determining the Area Under the Curve (AUC) to alias with medical policy. In addition, a new image clustering algorithm anticipates the need for large-scale serial and parallel processing. There is no solution on the market, and it is necessary to implement communication protocols between devices. Exploiting and targeting utilization hardware tasks will further extend the prospect of improvement in the cluster. Benchmarking their resources and performance is required. Finally, the medical imperatives cluster was objectively validated using qualitative and quantitative inspection. The proposed method should overcome the technical challenges that radiologists face.

ABSTRAK

Kawasan eksentrik imej mamografi ialah ukuran peratusan ketumpatan payudara. Cabaran teknikal kuantifikasi dalam radiologi membawa kepada salah tafsir dalam saringan. Maklum balas data daripada komuniti, institusi dan industri menunjukkan bahawa rangka kerja kuantifikasi dan segmentasi telah menjadi kaedah utama untuk membina dan mentafsir mamogram digital. Segmen kluster algoritma mempunyai kemunduran dalam kluster bertindih, perkadaran dan penskalaan berbilang dimensi untuk memetakan dan memanfaatkan data. Digabungkan, kuantifikasi mammogram menciptaan kawasan tumpuan fokus yang berterusan. Algoritma yang dicadangkan mesti mengurangkan kerumitan dan pengedaran berulang titik data sasaran, dan menambah baik kluster pusat pengelompokan ke dalam proses kemas kini untuk mengelakkan keperluan storan yang besar. Segmen ujian awal pangkalan data mamografi adalah penting untuk menilai prestasi dan menentukan kawasan di bawah lengkung *(AUC)* mengikut dasar perubatan. Di samping itu, algoritma kluster imej baharu menjangkakan keperluan untuk pemprosesan bersiri dan selari berskala besar. Tiada penyelesaian di pasaran dan adalah perlu untuk melaksanakan protokol komunikasi antara peranti. Mengeksploitasi dan meletakkan penempatan tugas perkakasan akan mengembangkan lagi prospek penambahbaikan kluster. Sumber dan prestasinya perlu ditanda aras. Akhir sekali, pemeriksaan kualitatif dan kuantitatif digunakan untuk mengesahkan kluster imperatif perubatan secara objektif. Kaedah yang dicadangkan perlu mengatasi cabaran teknikal yang dihadapi oleh pakar radiologi.

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LIST OF SYMBOLS AND ABBREVIATIONS

c	–	The number of clusters
F	–	Denotes the distribution function
$f_x(x;\theta)$	–	Probability density function
I_i	–	The index set
J	–	A clustering objective
L	–	Iteration counter
m	–	Index of fuzziness
S_{ij}	–	Extra weighted
w_j	–	A weight
x_j	–	The vector in m-dimensional Euclidean
X	–	Data set
x	–	Data set
z	–	Complete metric space
z_i	–	A cluster center
β	–	A coefficient
μ_i	–	The membership functions
$\hat{\theta}$	–	Weighted mean
γ^*	–	Gross error sensitivity
2-D	–	Two-Dimensional
PFCM	–	Proficient Fuzzy C-Means
3-D	–	Three-Dimensional
AHB	–	Advance High-Performance Bus
AI	–	Artificial Intelligence
ALU	–	Arithmetic-Logic Unit
ANSI	–	American National Standards Institute
AMBA	–	Advanced Microcontroller Bus Architecture

ASIC	–	Application-Specific Integrated Circuit
AUC	–	Area Under the Curve
BI-RADS	–	Breast Imaging Reporting and Data System
BM	–	Bus Macros
BRAM	–	Block RAM
CAD	–	Computer-Aided Detection
CAGR	–	Compound Annual Growth Rate
CC	–	Craniocaudal
CREST		Collaborative Research in Engineering, Science and Technology Centre
CNN		Convolutional Neural Network
CPU	–	Central Processing Unit
CT	–	Computed Tomography
CUDA	–	Compute Unified Device Architecture
DCIS	–	Ductal Carcinoma In Situ
DDR	–	Double Data Rate
DDSM	–	Digital Database for Screening Mammography
DEL	–	Detector Element
DFF	–	D-Type Flip-Flops
DICOM	–	Digital Imaging and Communications in Medicine
DMA	–	Direct memory access
DP	–	Dual-Port
DPR	–	Dynamic Partial Reconfiguration
DSP	–	Digital Signal Processors
IC	–	Integrated Circuit
EBI	–	External Bus Interface
EM	–	Expectation Maximization
EPROM	–	Electrically programmable read-only memory
FCM	–	Fuzzy C-Means
FSM	–	Finite State Machine
FIFO	–	First In, First Out

FIPT	–	FPGA Image Processing Toolkit
FIR		Finite Impulse Response
FN	–	False Negatives
FP	–	False Positives
FPGAs	–	Field-Programmable Gate Arrays
FPL	–	Field-Programmable Logic
Gbps	–	Gigabits per Second
GE	–	General
GFLOPs	–	GigaFlop
GOA		Grasshopper Optimization Algorithm
GPP	–	General Purpose Processors
GPU	–	Graphics Processing Unit
GUI	–	Graphical User Interface
HDL	–	Hardware Description Language
HPC	–	High-Performance Computing
HPRC	–	High-Performance Reconfigurable Computing
HW	–	Hardware
I/O	–	Input / Output
IC	–	Influence Curve
ICAP	–	Internal Configuration Access Port
IDE	–	Integrated Development Environment
IEEE	–	Electrical and Electronics Engineers
IIR		Infinite Impulse Response
IP	–	Intellectual Property
IPC	–	Inter-Process-Communication
ISA		Instruction Set Architecture
ISE	–	Identity Services Engine
JTAG	–	Joint Test Action Group
LGA	–	Local Grey Level Appearance
LS	–	Least-Squares
LUT	–	Look-Up Table
MBD		Mammography Breast Density

MCU	–	Multipoint Control Unit
MIAS	–	Mammographic Image Analysis Society
MLO	–	Mediolateral
MMU	–	Memory Management Units
MOH	–	Ministry of Health
MPU	–	Microprocessor units
MRI	–	Magnetic Resonance Imaging
MSE	–	Mean Squared Error
NPI	–	Native Port Interface
NRE	–	Non-Recurring Engineering
OSes	–	Operating Systems
PC	–	Personal Computer
PCC	–	Pearson Correlation Coefficient
PEIPA	–	Pilot European Image Processing Archive
PFCM	–	Proficient Fuzzy C-Means
PHCM	–	Proficient Hard C-Means
PhD	–	Doctor of Philosophy
PIO	–	Programmed Input / Output
PR	–	Partial Reconfiguration
PRM	–	Partially Reconfigurable Module
PRR	–	Partially Reconfigurable Region
PSNR	–	Peak Signal-To-Noise Ratio
RAM	–	Random Access Memory
RAMB	–	RAM Block
RH	–	Reconfigurable Hardware
RICE		Region of Interest Contrast Enhancement
RNU		Regional Non-Uniformity
ROC	–	Receiver Operating Characteristic
ROI		Region of Interest
RTL	–	Register Transfer Level
SDRAM	–	Synchronous Dynamic Random Access Memory
SFTA	–	Segmented Fractal Texture Analysis

SIMD	–	Single-Instruction Multiple-Data
SoC	–	System-on-Chips
SoPC	–	System on a Programmable Chips
SPCNN		Simple Pulse Coupled Neural Network
SRAM	–	Static Random-Access Memory
SSE	–	Sum of Squares Due to Error
SSIM	–	Structural Similarity Index Measure
SVM		Supported Vector Machine
SW	–	Software
TN	–	True Negatives
TNM	–	The Tumour, Node and Metastasis
TP	–	True Positives
UART	–	Universal Asynchronous Receiver / Transmitter
UCSF	–	University of California, San Francisco
US	–	Ultrasound
VHDL	–	Very High-Speed Hardware Description Language
VLSI	–	Very Large Scale Integrated Circuits
xSPI		Expanded Serial Peripheral Interface
ZBT	–	Zero Bus Turnaround

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Medical imaging is an essential tool in modern medicine, but it is also one of the most challenging fields to master, with virtually limitless potential. Computer-Aided Diagnosis (CAD) is widely used in mammography, but advances in segmentation and clustering have improved the accuracy of predictions (Qi *et al.,* 2020). Advances in mammography equipment are always important when it comes to medical imaging requirements. According to Anton *et al.* (2021), mammography is a time-consuming procedure that may require up to eight (8) sessions. Neelam Siddiqui stated that procedure on the symptoms and treatment plan of breast cancer is essential for future generations. Meanwhile, the breasts are submerged in water or gel, bypassing breast pressure, which makes routine mammograms uncomfortable and even difficult for some women (Dhamija & Khandelwal, 2022; Atiq & Buzdar, 2021; Dzidzornu *et al.,* 2021). Multiple CAD readers support the sensitivity of calcifications in their performance, rate of cancer detection rate, and stage of diagnosis, as well as emerging technologies in this lateral study, bringing out the importance of identifying micro-calcification (Azam *et al.,* 2021; Hamed, *et al.,* 2021). Breast cancer research by Wang *et al.* (2021) and Carter *et al.* (2020) shows that with the right information, the speed and effectiveness of results are expected to improve over time, as the right information ensures innovation.

Multiple CAD readers support the sensitivity of calcification in its performance, increase cancer detection rate and stage of diagnosis, as well as the new technique in this cross-sectional study that highlights the importance of identifying micro-calcifications. Mammography requires great care in real-time image acquisition and evaluation. However, most computerized mammography image applications typically manage large amounts of information. Norsa'adah *et al.* (2021) revealed an interesting reality about this problem. This is consistent with data obtained from the University of Malaya Medical Centre, a mid-sized rehabilitation facility with about 1,050 beds and screening about 30,000 patients annually. For each case, the screener provided approximately 110 megabytes of information in a digitized simple image environment and approximately 25 megabytes of data for direct computerized events. This means that the radiographic measure created per year is 4.05 TB, or approximately 11 GB per day. Screening is complete within 45 minutes. The radiologist then interpreted it within seven (7) to ten (10) days of work.

To further highlight the themes and challenges in the healthcare sector in 2020, there were more than 29,530 cancer deaths in Malaysia in 2020, most of which were due to breast cancer. According to a poll released by the Global Cancer Observatory, the number of new cases (men, women, and children) in Malaysia in 2020 showed that there were 48,639 cases of cancer in Malaysia, with breast cancer accounting for 17.3% (8,418 cases), as shown in Figure 1.1. Polls show that breast cancer ranks first among 36 specific cancer types and all cancers (CANCER TODAY, 2021). This hypothesis reveals that they impartially investigate, mediate and assist when all routine avenues have been exhausting. Genuine attention to this matter is critical for reducing the risk of death from breast cancer. Then, there is the implication of how the most effective countermeasures are developed and investigated.

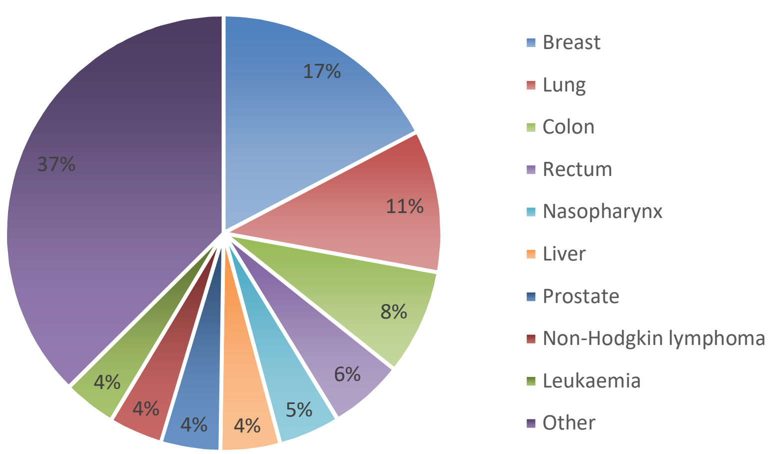

Figure 1.1: The number of new cases in Malaysia 2020, both sexes, all ages (CANCER TODAY, 2021).

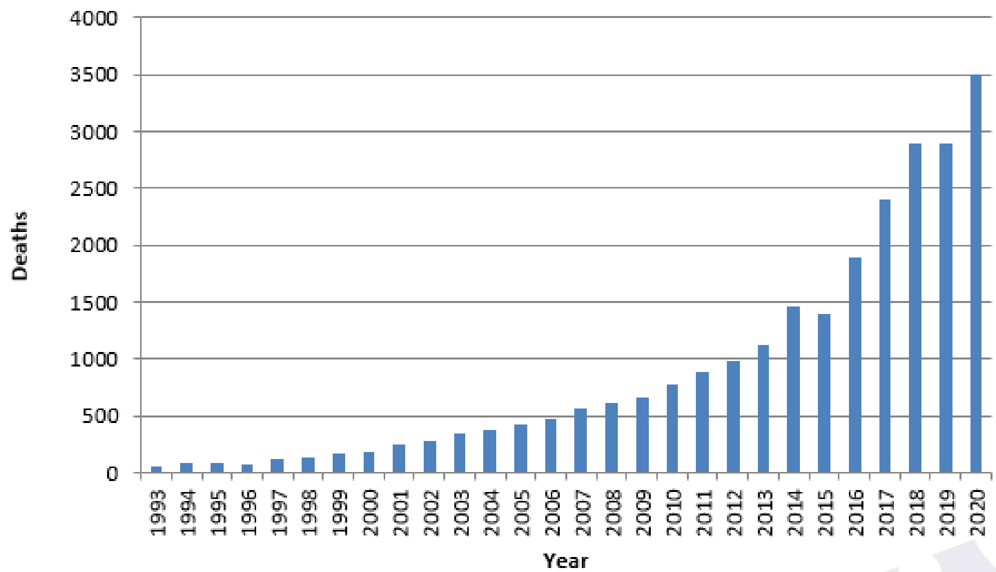

Figure 1.2: Breast cancer Statistics **(**Ghee *et al.,* 2014, CANCER TODAY, 2021).

According to the annual statistics from the Global Cancer Observatory, the risk of dying from cancer in Malaysia has increased over the past 28 years, as shown in Figure 1.2. In addition, about 26% of breast cancer patients are under the age of 45, which is an alarmingly young age for such a disease (CANCER TODAY, 2021). Nevertheless, not an explicit age or specific frequency, the population within its control is impacted by the availability of interpreters in their medical facilities. The younger generation in urban areas makes use of this facility, whereas the elderly in rural areas prefer traditional discourse. About 30% to 40% of advanced patients have tiny tumours, but this does not mean a substantial reduction in size (CANCER TODAY, 2021).

Quantitative constraints clearly differentiate benign and malignant tumors based on radiological data. Radiologists use digital mammography and CAD support to discover and scan irregular density ranges. However, due to limitations in processing power and supervised learning, most CAD fails in tiny breast tissue in the irregular density range, especially at early stages (Batchu *et al.,* 2021). This digital medical image preparation (shown in Table 1.1) covers the major factors (such as super-resolution, filtering, sensitivity, transition, compression, parallelism, architecture, precision data, and deep learning) in the varying composition of density mapping results. This major factor comes from the review by Hassan *et al.* (2022) and Mohammed *et al.* (2021), on how to improve CAD using significant developments in machine learning and image processing techniques. From here, this study selects the best results from an improved technical perspective based on the preferences of society, leading industry, and academia.

Table 1.1: Major factor in digital medical image preparation.

No	Reference	Research in digital medical image preparing
1.	Boudraa *et al.,* 2020	The super-resolution reconstruction improves distinguishing feature extraction but results in a large number of observed classes.
2.	de Santana *et al.,* 2021	This technique uses image filtering to improve classification but is not suitable for detecting breast lesions.
3.	Henriksen *et al.,* 2019	Case studies using Computer-Aided Detection (CAD) improve sensitivity in screening but require a longer follow-up period.
4.	Farber *et al.,* 2021	When data from multiple screens were combined in case studies involving the transition from film to digital mammography, there was no difference in interpretation.
5.	Jo *et al.,*2021	The impact of compression on the model's classification performance is presented, but only for binary classification.
6.	Forooshani *et al.,*2021	The use of machine learning algorithms to identify abnormal lesions in mammography images increases sensitivity to noise.
7.	Abdou, 2022	According to their review, the Deep Neural Network architecture is still in its early stages for medical image processing analysis, requires extensive training time, and may lead to overfitting.
8.	Huang & Lin 2021	The accuracy of data of the computer method decreases as the density of the breast increases.
9.	Sahiner *et al.,* 2019	There are still ongoing research challenges designed to reduce large data sets in medical imaging without implementing such architectures and algorithms.

Table 1.2: Trends in image analysis.

Refs.	**Applications**						**Image**		**Implementations**		
	1	2	3	4	5	6	2-D	3-D	HW	SW	MM
Sharma *et al.* 2019		✓	✓		✓		✓		✓		
Radzi *et al.* 2020		✓			✓		✓			✓	
ALmaremi, 2020	✓	✓		✓	✓	✓	✓			✓	
Jo *et al.* 2021	✓	✓					✓			✓	
García *et al.* 2021		✓	✓				✓	✓	✓		
MehmoodGondal *et al.* 2021				✓			✓			✓	
Ketabi *et al.* 2021		✓		✓			✓				
Al-Rubaye 2021		✓			✓		✓				✓
Das *et al.* 2021		✓			✓		✓			✓	

Note:

HW: Hardware, SW: Software, MM: Mammography Machine 1: Compression,

2: Segmentation and cluster, 3: Registration, 4: Enhancement and de-noising,

5: Quantification, 6: Others.

As a result, Table 1.2 depicts the current state of image analysis in order to identify the appropriate applications and implementations. All of these works are categorized based on the following criteria:

1. The majority of medical image processing applications are constituted of compression, enhancement, registration, segmentation cluster, de-noising, quantification;
2. Hardware design and development, software simulation, and algorithm creation and optimization are all examples of system implementation.; and
3. Types of images utilize Two-Dimensional (2-D) and Three-Dimensional (3-D).

Given the trend of research in medical image processing conducted by leading experts in the field, the following conclusions are reached:

1. The use of digital medical images is increasing dramatically because of the remarkable benefits that they provide not only for diagnostic assistance but also for planning and surgical radiotherapy procedures.
2. This application has dominated most of the work reported, with significant contributions in segmentation and clustering, as well as registration aspects. A gap between the programming models, accelerators, and sizes identified.
3. The progression of both algorithm development and hardware implementation aspect is established from cross intra-disciplinary advancement.

Their investigation required an architectural phase, including programming and hardware expansion. Computer analysis can solve some of these problems, and it was found that most of the foundation's operations contained hyper-parameters. (Martin *et al.,* 2021; Reddy & Das, 2020). Unlike explicit spectral ranges, improvements in the speed of medical image processing hardware have given rise to a great deal of consideration for innovative work. Until now, building a dedicated hardware accelerator required creating a special front-end program that communicated with the accelerator at the same time. This procedure is tedious and limits the adaptability of both the software and the hardware.

REFERENCES

Abbas, M., El-Zoghabi, A., & Shoukry, A. (2021). DenMune: Density peak based clustering using mutual nearest neighbors. Pattern Recognition, 109, 107589.

Abdou, M. A. (2022). Literature review: Efficient deep neural networks techniques for medical image analysis. Neural Computing and Applications, 1-22.

Abdullah, P., Alabousi, M., Ramadan, S., Zawawi, I., Zawawi, M., Bhogadi, Y., ... & Alabousi, A. (2021). Synthetic 2D mammography versus standard 2D digital mammography: a diagnostic test accuracy systematic review and meta-analysis. American Journal of Roentgenology, 217(2), 314-325.

Abideen, Z. U., Perez, T. D., & Pagliarini, S. (2021). From FPGAs to Obfuscated eASICs: Design and Security Trade-offs. arXiv preprint arXiv:2110.05335.

AboAlNaga, B. M., Said, L. A., Madian, A. H., & Radwan, A. G. (2021). Analysis and FPGA of semi-fractal shapes based on complex Gaussian map. Chaos, Solitons & Fractals, 142, 110493.

Afifi, S., GholamHosseini, H., & Sinha, R. (2020). FPGA implementations of SVM classifiers: a review. SN Computer Science, 1(3), 1-17.

Ajao, L. A., Adegboye, M. A., Agajo, J., Ajao, A. O., & Yunus, A. A. (2017). FPGA Logic Circuit Implementation and Synthesis with VHDL Programming: A Learning Approach. International Journal of Computer Science and Communications, 2(1), 1-11.

Ajili, M. T., & Hara-Azumi, Y. (2022). Multimodal Neural Network Acceleration on a Hybrid CPU-FPGA Architecture: A Case Study. IEEE Access.

Alam, N., RE Denton, E., & Zwiggelaar, R. (2019). Classification of microcalcification clusters in digital mammograms using a stack generalization based classifier. Journal of Imaging, 5(9), 76.

Alcaín, E., Fernández, P. R., Nieto, R., Montemayor, A. S., Vilas, J., Galiana-Bordera, A., ... & Torrado-Carvajal, A. (2021). Hardware Architectures for Real-Time Medical Imaging. Electronics, 10(24), 3118.

Almalki, Y. E., Soomro, T. A., Irfan, M., Alduraibi, S. K., & Ali, A. (2022). Impact of Image Enhancement Module for Analysis of Mammogram Images for Diagnostics of Breast Cancer. Sensors, 22(5), 1868.

Al-Rubaye, M. (2021). Automatic Quality Assessment in Mammography Screening: a Deep Learning Based Segmentation Method. (Bachelor's Thesis, University of Oulu).

ALmaremi, F. A. (2020). Mammogram Image Enhancement For Breast Cancer Detection (Doctoral dissertation, Al zawiya – Libya).

Altamimi, A., & Ben Youssef, B. (2021). A Systematic Review of Hardware-Accelerated Compression of Remotely Sensed Hyperspectral Images. Sensors, 22(1), 263.

AlZu'bi, S., Shehab, M., Al-Ayyoub, M., Jararweh, Y., & Gupta, B. (2020). Parallel implementation for 3d medical volume fuzzy segmentation. Pattern Recognition Letters, 130, 312-318.

Amid, A., Ou, A., Asanović, K., Shao, Y. S., & Nikolić, B. (2021). Vertically integrated computing labs using open-source hardware generators and cloud-hosted FPGAs. In 2021 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 1-5). IEEE.

Andrich, D., & Marais, I. (2019). A course in Rasch measurement theory. D. Andrich y I. Marais (Coords.), Measuring in the Educational, Social and Health Sciences, 41-53.

Anton, M., Reginatto, M., Elster, C., Mäder, U., Schopphoven, S., Sechopoulos, I., & van Engen, R. (2021). The regression detectability index RDI for mammography images of breast phantoms with calcification-like objects and anatomical background. Physics in Medicine & Biology, 66(22), 225015.

Anwar, R., Farouk, M. A., Abdel Hamid, W. R., Abu El Maati, A. A., & Eissa, H. (2021). Breast cancer in dense breasts: comparative diagnostic merits of contrast-enhanced mammography and diffusion-weighted breast MRI. Egyptian Journal of Radiology and Nuclear Medicine, 52(1), 1-13.

Astley, S. M., Harkness, E. F., Sergeant, J. C., Warwick, J., Stavrinos, P., Warren, R., ... & Evans, D. G. (2018). A comparison of five methods of measuring mammographic density: a case-control study. Breast Cancer Research, 20(1), 1-13.

Athamnah, S. I., Oglat, A. A., & Fohely, F. (2021). Diagnostice breast elastography estimation from doppler imaging using central difference (CD) and least-squares (LS) algorithms. Biomedical Signal Processing and Control, 68, 102667.

Atiq, A., & Buzdar, S. A. (2021). Fabrication and Determination of Radiation Sensitive Features of Tissue Equivalent Gels in Radiation Dosimetry and Diagnostic Radiology. FRONTIERS IN CHEMICAL SCIENCES, 2(2), 195-206.

Azam, S., Eriksson, M., Sjölander, A., Gabrielson, M., Hellgren, R., Czene, K., & Hall, P. (2021). Mammographic microcalcifications and risk of breast cancer. British journal of cancer, 125(5), 759-765.

Baltzer, P. A. T., Freiberg, C., Beger, S., Vag, T., Dietzel, M., Herzog, A. B., ... & Kaiser, W. A. (2009). Clinical MR-mammography: are computer-assisted methods superior to visual or manual measurements for curve type analysis? A systematic approach. Academic radiology, 16(9), 1070-1076.

Banks, J. (2014). The Spartan-3E Tutorial 1: Introduction to FPGA Programming, Version 2.0.

Basile, T. M. A., Fanizzi, A., Losurdo, L., Bellotti, R., Bottigli, U., Dentamaro, R., ... & Tamborra, P. (2019). Microcalcification detection in full-field digital mammograms: A fully automated computer-aided system. Physica Medica, 64, 1-9.

Batchu, S., Liu, F., Amireh, A., Waller, J., & Umair, M. (2021). A review of applications of machine learning in mammography and future challenges. Oncology, 99(8), 483-490.

Boutros, A., & Betz, V. (2021). FPGA architecture: Principles and progression. IEEE Circuits and Systems Magazine, 21(2), 4-29.

Bekker, D., Smith, R., & Tran, M. Q. (2021). Guiding DART to Impact—the FPGA SoC Design of the DRACO Image Processing Pipeline. In 2021 IEEE Space Computing Conference (SCC) (pp. 122-133). IEEE.

Bezdek, J. C. (2013). Pattern recognition with fuzzy objective function algorithms. Springer Science & Business Media.

Bharadwaj, A., Afsar, M., Khaitan, K. K., & Gururaj, C. (2021). Optimized FPGA Implementation and Synthesis of Image Segmentation Techniques. In 2021 IEEE Mysore Sub Section International Conference (MysuruCon) (pp. 191-196). IEEE.

Bhattacherjee, A., Sanyal, S., & Abraham, A. (2021). Reducing Time Complexity of Fuzzy C Means Algorithm. In International Conference on Innovations in Bio-Inspired Computing and Applications (pp. 332-347). Springer, Cham.

Biookaghazadeh, S. (2021). FPGA-Based Edge-Computing Acceleration (Doctoral dissertation, Arizona State University).

Blochwitz, C., Philipp, L., Berekovic, M., & Pionteck, T. (2021). StreamGrid-An AXI-Stream-Compliant Overlay Architecture. In International Symposium on Applied Reconfigurable Computing (pp. 156-170). Springer, Cham.

Boudraa, S., Melouah, A., & Merouani, H. F. (2020). Improving mass discrimination in mammogram-CAD system using texture information and super-resolution reconstruction. Evolving Systems, 11(4), 697-706.

Boumaraf, S., Liu, X., Wan, Y., Zheng, Z., Ferkous, C., Ma, X., ... & Bardou, D. (2021). Conventional machine learning versus deep learning for magnification dependent histopathological breast cancer image classification: A comparative study with visual explanation. Diagnostics, 11(3), 528.

Bragança, L., Canesche, M., Penha, J., Campos, J., Nacif, J. A. M., & Ferreira, R. S. (2022). Fast flow cloud: A stream dataflow framework for cloud FPGA accelerator overlays at runtime. Concurrency and Computation: Practice and Experience, e6977.

Bustio-Martínez, L., Cumplido, R., Letras, M., Hernández-León, R., Feregrino-Uribe, C., & Hernández-Palancar, J. (2021). FPGA/GPU-based Acceleration for Frequent Itemsets Mining: A Comprehensive Review. ACM Computing Surveys (CSUR), 54(9), 1-35.

Carter, S. M., Rogers, W., Win, K. T., Frazer, H., Richards, B., & Houssami, N. (2020). The ethical, legal and social implications of using artificial intelligence systems in breast cancer care. The Breast, 49, 25-32.

Castellana, V. G., Tumeo, A., & Ferrandi, F. (2021). High-level synthesis of parallel specifications coupling static and dynamic controllers. In 2021 IEEE International Parallel and Distributed Processing Symposium (IPDPS) (pp. 192-202). IEEE.

CANCER TODAY (2021). Data visualization tools for exploring the global cancer burden in 2021, Available in https://gco.iarc.fr/today/data/factsheets/populations/458-malaysia-fact-sheets.pdf [Accessed in 30 May 2022].

Chakravarthy, S. S., & Rajaguru, H. (2022). Automatic detection and classification of mammograms using improved extreme learning machine with deep learning. IRBM, 43(1), 49-61.

Chang-Chien, S. J., Nataliani, Y., & Yang, M. S. (2021). Gaussian-kernel c-means clustering algorithms. Soft Computing, 25(3), 1699-1716.

Charitopoulos, G., Pnevmatikatos, D. N., & Gaydadjiev, G. (2021). Mc-def: Creating customized cgras for dataflow applications. ACM Transactions on Architecture and Code Optimization (TACO), 18(3), 1-25.

Chen, Y., Wang, M., Heidari, A. A., Shi, B., Hu, Z., Zhang, Q., ... & Turabieh, H. (2022). Multi-threshold Image Segmentation using a Multi-strategy Shuffled Frog Leaping Algorithm. Expert Systems with Applications, 116511.

Chen, T., & Andersen, M. S. (2021). On semiseparable kernels and efficient implementation for regularized system identification and function estimation. Automatica, 132, 109682.

Choudhary, R., & Shukla, S. (2021). A clustering based ensemble of weighted kernelized extreme learning machine for class imbalance learning. Expert Systems with Applications, 164, 114041.

Chugh, S., Goyal, S., Pandey, A., Joshi, S., & Azad, M. (2021). Density-Assessment for Breast Cancer Diagnosis Using Deep Learning on Mammographic Image: A Brief Study. In Machine Vision and Augmented Intelligence—Theory and Applications (pp. 313-320). Springer, Singapore.

Cock, D., Ramdas, A., Schwyn, D., Giardino, M., Turowski, A., He, Z., ... & Roscoe, T. (2022, February). Enzian: an open, general, CPU/FPGA platform for systems software research. In Proceedings of the 27th ACM International Conference on Architectural Support for Programming Languages and Operating Systems (pp. 434-451).

Cui, Y., Chen, R., Chu, W., Chen, L., Tian, D., Li, Y., & Cao, D. (2021). Deep learning for image and point cloud fusion in autonomous driving: A review. IEEE Transactions on Intelligent Transportation Systems.

Dafir, Z., Lamari, Y., & Slaoui, S. C. (2021). A survey on parallel clustering algorithms for big data. Artificial Intelligence Review, 54(4), 2411-2443.

Danganan, A. E., & De Los Reyes, E. M. (2021). eHMCOKE: an enhanced overlapping clustering algorithm for data analysis. Bulletin of Electrical Engineering and Informatics, 10(4), 2212-2222.

Das, K., & Das, A. (2021). Segmentation of Brain Tumor Using Cluster Validity Index-Based Fuzzy C-Means Algorithm. In Advances in Medical Physics and Healthcare Engineering (pp. 45-56). Springer, Singapore.

Datta, D., & Dutta, H. S. (2021). High performance IIR filter implementation on FPGA. Journal of Electrical Systems and Information Technology, 8(1), 1-9.

Dayaratna, S., & Jackson, R. (2022). The conundrum of breast density; guidance for healthcare providers. Best Practice & Research Clinical Obstetrics & Gynaecology.

Daye, D., Joseph, E., Flores, E., Kambadakone, A., Chinn, G., Bennett, S., & Sahani, D. (2021). Point-of-care virtual radiology consultations in primary care: a feasibility study of a new model for patient-centered care in radiology. Journal of the American College of Radiology, 18(9), 1239-1245.

de Fine Licht, J., Kuster, A., De Matteis, T., Ben-Nun, T., Hofer, D., & Hoefler, T. (2021). StencilFlow: Mapping large stencil programs to distributed spatial computing systems. In 2021 IEEE/ACM International Symposium on Code Generation and Optimization (CGO) (pp. 315-326). IEEE.

Dell'Eva, A., Pizzati, F., Bertozzi, M., & de Charette, R. (2021). Leveraging Local Domains for Image-to-Image Translation. arXiv preprint arXiv:2109.04468.

De Menezes, D. Q. F., Prata, D. M., Secchi, A. R., & Pinto, J. C. (2021). A review on robust M-estimators for regression analysis. Computers & Chemical Engineering, 147, 107254.

de Santana, M. A., Pereira, J. M. S., da Silva, W. W. A., & dos Santos, W. P. (2021). Breast Cancer Diagnosis in Mammograms Using Wavelet Analysis, Haralick Descriptors, and Autoencoder. In AI Innovation in Medical Imaging Diagnostics (pp. 76-91). IGI Global.

Dhamija, E., & Khandelwal, N. (2022). Imaging in Breast Cancer. In Breast Cancer (pp. 139-151). Springer, Singapore.

Dice, L. R. (1945). Measures of the amount of ecologic association between species. Ecology, 26(3), 297-302.

Dreizin, D., Zhou, Y., Zhang, Y., Tirada, N., & Yuille, A. L. (2020). Performance of a deep learning algorithm for automated segmentation and quantification of traumatic pelvic hematomas on CT. Journal of Digital Imaging, 33(1), 243-251.

Duc, T. Q. (2021). LabVIEW and Open Embedded System. In LabVIEW-A Flexible Environment for Modeling and Daily Laboratory Use. IntechOpen.

Dzidzornu, E., Angmorterh, S. K., Ofori-Manteaw, B. B., Aboagye, S., Ofori, E. K., Owusu-Agyei, S., & Hogg, P. (2021). Compression force variability in mammography in Ghana–a baseline study. Radiography, 27(1), 150-155.

Elbatel, M. (2022). Mammograms Classification: A Review. arXiv preprint arXiv:2203.03618.

Elmoufidi, A. (2022). Deep Multiple Instance Learning for Automatic Breast Cancer Assessment using Digital Mammography. IEEE Transactions on Instrumentation and Measurement.

Fang, J., Mulder, Y. T., Hidders, J., Lee, J., & Hofstee, H. P. (2020). In-memory database acceleration on FPGAs: a survey. The VLDB Journal, 29(1), 33-59.

Farber, R., Houssami, N., Wortley, S., Jacklyn, G., Marinovich, M. L., McGeechan, K., ... & Bell, K. (2021). Impact of full-field digital mammography versus film-screen mammography in population screening: a meta-analysis. JNCI: Journal of the National Cancer Institute, 113(1), 16-26.

Farahpour, N., Hao, Y., Fang, Z., & Reinman, G. (2020). Reconfigurable Accelerator Compute Hierarchy: A Case Study using Content-Based Image Retrieval. In 2020 IEEE International Symposium on Workload Characterization (IISWC) (pp. 276-287). IEEE.

Farooq, U., & Mehrez, H. (2021). Pre-Silicon Verification Using Multi-FPGA Platforms: A Review. Journal of Electronic Testing, 37(1), 7-24.

Forooshani, M. K. (2021). Breast Tumor Detection by Mammogram Image Segmentation (Doctoral dissertation, Politecnico di Torino).

Garcia, R., Volkova, A., Kumm, M., Goldsztejn, A., & Kuhle, J. (2022). Hardware-aware Design of Multiplierless Second-Order IIR Filters with Minimum Adders. IEEE Transactions on Signal Processing.

Gaona, Y. J., Rodríguez-Álvarez, M. J., Freire, J., Castillo, D., & Lakshminarayanan, V. (2021). Preprocessing fast filters and mass segmentation for mammography images. In Applications of Digital Image Processing XLIV (Vol. 11842, p. 1184213). International Society for Optics and Photonics.

George, D. N., Chyad, H. S., & Mustafa, R. A. (2021). Subject Review: Diagnoses cancer diseases systems for most body's sections using image processing techniques. Global Journal of Engineering and Technology Advances, 6(3), 056-062.

George, M. (2021). Breast density estimation and micro-calcification classification (Doctoral dissertation, Aberystwyth University).

George, M., & Zwiggelaar, R. (2019). Comparative study on local binary patterns for mammographic density and risk scoring. Journal of Imaging, 5(2), 24.

Ghalati, M. K., Nunes, A., Ferreira, H., Serranho, P., & Bernardes, R. (2021). Texture analysis and its applications in biomedical imaging: A survey. IEEE Reviews in Biomedical Engineering.

Ghee, L. K., Wei, L. A., & Pin, G. P. (2014). Introducing a Collection of Reviews on Major Diseases in Malaysia. Med J Malaysia, 69.

Ghieh, D., Saade, C., Najem, E., El Zeghondi, R., Rawashdeh, M. A., & Berjawi, G. (2021). Staying abreast of imaging–current status of breast cancer detection in high density breast. Radiography, 27(1), 229-235.

Ghosh, S. K., Mitra, A., & Ghosh, A. (2021a). A novel intuitionistic fuzzy soft set entrenched mammogram segmentation under multigranulation approximation for breast cancer detection in early stages. Expert Systems with Applications, 169, 114329.

Ghosh, S., Samanta, G., & De la Sen, M. (2021b). Multi-Model Approach and Fuzzy Clustering for Mammogram Tumor to Improve Accuracy. Computation, 9(5), 59.

Groth, S., Teich, J., & Hannig, F. (2021). Efficient Application of Tensor Core Units for Convolving Images. In Proceedings of the 24th International Workshop on Software and Compilers for Embedded Systems (pp. 1-6).

Goh, Y. L. E., Lee, Z. Y., & Lai, C. (2021). Spatial Distribution and Quantification of Mammographic Breast Density, and Its Correlation with BI-RADS Using an Image Segmentation Method. Life, 11(6), 516.

Guerroudji, M. A., Amara, K., Aouam, D., Zenati, N., Djekoune, O., & Benbelkacem, S. (2022). Segmentation of the Breast Masses in Mammograms Using Active Contour for Medical Practice: AR Based Surgery. In International Conference on Artificial Intelligence and its Applications (pp. 447-457). Springer, Cham.

Haldorai, A., & Ramu, A. (2021). Survey of Image Processing Techniques in Medical Image Assessment Methodologies. In Computational Vision and Bio-Inspired Computing (pp. 795-811). Springer, Singapore.

Hall, L. O. (2018). A Primer on Cluster Analysis by James C. Bezdek [By the Book]. IEEE Systems, Man, and Cybernetics Magazine, 4(1), 48-50.

Hamed, G., Marey, M., Amin, S., & Tolba, M. (2021). Comparative study and analysis of recent computer aided diagnosis systems for masses detection in mammograms. International Journal of Intelligent Computing and Information Sciences, 21(1), 33-48.

Han, Y., Moore, J. X., Colditz, G. A., & Toriola, A. T. (2022). Family history of breast cancer and mammographic breast density in premenopausal women. JAMA network open, 5(2), e2148983-e2148983.

Hassan, N. M., Hamad, S., & Mahar, K. (2022). Mammogram breast cancer CAD systems for mass detection and classification: a review. Multimedia Tools and Applications, 1-33.

Hassan, B. A., & Rashid, T. A. (2021). A multidisciplinary ensemble algorithm for clustering heterogeneous datasets. Neural Computing and Applications, 33(17), 10987-11010.

Hassanein, A., El-Abd, M., Damaj, I., & Rehman, H. U. (2020). Parallel hardware implementation of the brain storm optimization algorithm using FPGAs. Microprocessors and Microsystems, 74, 103005.

Henriksen, E. L., Carlsen, J. F., Vejborg, I. M., Nielsen, M. B., & Lauridsen, C. A. (2019). The efficacy of using computer-aided detection (CAD) for detection of breast cancer in mammography screening: a systematic review. Acta Radiologica, 60(1), 13-18.

Hernández, A., Miranda, D., & Pertuz, S. (2021). Algorithms and Methods for Computerized Analysis of Mammography Images in Breast Cancer Risk Assessment. Computer Methods and Programs in Biomedicine, 106443.

Herwanto, W., Khumaidi, A., & Putro, H. P. (2022). Feature Extraction and Classification of Tissue Mammograms Based on Grayscale and Gray Level

Co-occurrence Matrix. In 2021 International Seminar on Machine Learning, Optimization, and Data Science (ISMODE) (pp. 131-134). IEEE.

Hoozemans, J., Peltenburg, J., Nonnemacher, F., Hadnagy, A., Al-Ars, Z., & Hofstee, H. P. (2021). FPGA Acceleration for Big Data Analytics: Challenges and Opportunities. IEEE Circuits and Systems Magazine, 21(2), 30-47.

Hu, S., Lou, Z., & Ye, Y. (2021). View-Wise Versus Cluster-Wise Weight: Which Is Better for Multi-View Clustering?. IEEE Transactions on Image Processing, 31, 58-71.

Huang, M. L., & Lin, T. Y. (2021). Considering breast density for the classification of benign and malignant mammograms. Biomedical Signal Processing and Control, 67, 102564.

Huang, Q., Miao, Z., Zhou, S., Chang, C., & Li, X. (2021). Dense prediction and local fusion of superpixels: A framework for breast anatomy segmentation in ultrasound image with scarce data. IEEE Transactions on Instrumentation and Measurement, 70, 1-8.

Huang, Y., Wang, Z., Lyu, Z., Dai, H., Zhao, Y., Liu, P., ... & Chen, K. (2022). Screening performance in high-risk groups of breast cancer by integrating classical risk factors, mammographic density and polygenic risk.

Huber, P. J. (1964). Robust estimation of a location parameter: Annals Mathematics Statistics, 35.

Huber, P. J. (1992). Robust estimation of a location parameter. In Breakthroughs in statistics (pp. 492-518). Springer, New York, NY.

Huber, P. J., & Ronchetti, E. M. (1981). Robust Statistics John Wiley & Sons. New York, 1(1).

Ibrahim, Y., Wang, H., Liu, J., Wei, J., Chen, L., Rech, P., ... & Guo, G. (2020). Soft errors in dnn accelerators: A comprehensive review. Microelectronics Reliability, 115, 113969.

Ijaz, Q., Bourennane, E. B., Bashir, A. K., & Asghar, H. (2020). Revisiting the high-performance reconfigurable computing for future datacenters. Future Internet, 12(4), 64.

Janan, F., & Brady, M. (2021). RICE: A method for quantitative mammographic image enhancement. Medical image analysis, 71, 102043.

Jeyamogan, S., Khan, N. A., & Siddiqui, R. (2021). Application and Importance of Theranostics in the Diagnosis and Treatment of Cancer. Archives of medical research, 52(2), 131-142.

Jiang, X., Wang, J., Lin, Y., & Wang, Z. (2022). FPGA-Accelerated Maze Routing Kernel for VLSI Designs. In 2022 27th Asia and South Pacific Design Automation Conference (ASP-DAC) (pp. 592-597). IEEE.

Jo, Y. Y., Choi, Y. S., Park, H. W., Lee, J. H., Jung, H., Kim, H. E., ... & Hwangbo, Y. (2021). Impact of image compression on deep learning-based mammogram classification. Scientific Reports, 11(1), 1-9.

John, J. S., Herwig, C., Kafkes, D., Mitrevski, J., Pellico, W. A., Perdue, G. N., ... & Keller, R. (2021). Real-time artificial intelligence for accelerator control: A study at the Fermilab Booster. Physical Review Accelerators and Beams, 24(10), 104601.

Junior, G. B., da Rocha, S. V., de Almeida, J. D., de Paiva, A. C., Silva, A. C., & Gattass, M. (2019). Breast cancer detection in mammography using spatial diversity, geostatistics, and concave geometry. Multimedia Tools and Applications, 78(10), 13005-13031.

Kailemia, P. N., Lee, E. C., Taylor, C., & Renfrew, M. J. (2020). Exploring determinants of, and interventions for, delayed presentation of women with breast symptoms: A systematic review. European Journal of Oncology Nursing, 44, 101677.

Kashyap, K. L., Bajpai, M. K., & Khanna, P. (2018). An efficient algorithm for mass detection and shape analysis of different masses present in digital mammograms. Multimedia Tools and Applications, 77(8), 9249-9269.

Katzen, J. T., Grimm, L. J., & Brem, R. F. (2021). The American College of Radiology/Society of Breast Imaging updated fellowship training curriculum for breast imaging. Journal of Breast Imaging, 3(4), 498-501.

Kavitha, T., Mathai, P. P., Karthikeyan, C., Ashok, M., Kohar, R., Avanija, J., & Neelakandan, S. (2022). Deep learning based capsule neural network model for breast cancer diagnosis using mammogram images. Interdisciplinary Sciences: Computational Life Sciences, 14(1), 113-129.

Ketabi, H., Ekhlasi, A., & Ahmadi, H. (2021). A computer-aided approach for automatic detection of breast masses in digital mammogram via spectral clustering and support vector machine. Physical and Engineering Sciences in Medicine, 44(1), 277-290.

Khin, T., Srujan Raju, K., Sinha, G. R., Khaing, K. K., & Kyi, T. M. (2020). Review of optimization methods of medical image segmentation. In Proceedings of the Third International Conference on Computational Intelligence and Informatics (pp. 213-218). Springer, Singapore.

Kim, K. (2022). Accelerating Genome Quantification in FPGA (Doctoral dissertation, Arizona State University).

Kim, S., & Park, B. (2021). Association between changes in mammographic density category and the risk of breast cancer: A nationwide cohort study in East-Asian women. International Journal of Cancer, 148(11), 2674-2684.

Kumar, V., Sharma, D. K., & Mishra, V. K. (2021). Mille Cheval: a GPU-based in-memory high-performance computing framework for accelerated processing of big-data streams. The Journal of Supercomputing, 77(7), 6936-6960.

Kwon, W., Yu, G. I., Jeong, E., & Chun, B. G. (2020). Nimble: Lightweight and parallel gpu task scheduling for deep learning. Advances in Neural Information Processing Systems, 33, 8343-8354.

Lai, Y. H., Rong, H., Zheng, S., Zhang, W., Cui, X., Jia, Y., ... & Dubey, P. (2020). Susy: A programming model for productive construction of high-performance systolic arrays on FPGAs. In 2020 IEEE/ACM International Conference On Computer Aided Design (ICCAD) (pp. 1-9). IEEE.

Lai, Y. H., Ustun, E., Xiang, S., Fang, Z., Rong, H., & Zhang, Z. (2021). Programming and Synthesis for Software-defined FPGA Acceleration: Status and Future Prospects. ACM Transactions on Reconfigurable Technology and Systems (TRETS), 14(4), 1-39.

Langhammer, M., Nurvitadhi, E., Gribok, S., & Pasca, B. (2022). Stratix 10 NX Architecture. ACM Transactions on Reconfigurable Technology and Systems (TRETS).

Lbachir, I. A., Daoudi, I., & Tallal, S. (2021). Automatic computer-aided diagnosis system for mass detection and classification in mammography. Multimedia Tools and Applications, 80(6), 9493-9525.

Le Blanc, J. M., Heller, D. R., Friedrich, A., Lannin, D. R., & Park, T. S. (2020). Association of Medicaid expansion under the Affordable Care Act with breast cancer stage at diagnosis. JAMA surgery, 155(8), 752-758.

Lee, C. S., Moy, L., Hughes, D., Golden, D., Bhargavan-Chatfield, M., Hemingway, J., ... & Rosenkrantz, A. B. (2021). Radiologist Characteristics Associated with Interpretive Performance of Screening Mammography: A National Mammography Database (NMD) Study. Radiology, 300(3), 518-528.

Lee, J., Ha, Y., Lee, S., Woo, J., Lee, J., Jang, H., & Kim, Y. (2022, June). GCoM: a detailed GPU core model for accurate analytical modeling of modern GPUs. In Proceedings of the 49th Annual International Symposium on Computer Architecture (pp. 424-436).

Lee, R. S., Dunnmon, J. A., He, A., Tang, S., Re, C., & Rubin, D. L. (2021). Comparison of segmentation-free and segmentation-dependent computer-aided diagnosis of breast masses on a public mammography dataset. Journal of biomedical informatics, 113, 103656.

Lee, S. H., Ryu, H. S., Jang, M. J., Yi, A., Ha, S. M., Kim, S. Y., ... & Moon, W. K. (2021). Glandular Tissue Component and Breast Cancer Risk in Mammographically Dense Breasts at Screening Breast US. Radiology, 301(1), 57-65.

Leena Nesamani, S., Nirmala Sugirtha Rajini, S., Josphine, M. S., & Jacinth Salome, J. (2021). Deep Learning-Based Mammogram Classification for Breast Cancer Diagnosis Using Multi-level Support Vector Machine. Advances in Automation, Signal Processing, Instrumentation, and Control, 371-383.

Leveque, L., Young, P., & Liu, H. (2021). Studying the gaze patterns of expert radiologists in screening mammography: A case study with Breast Test Wales. In 2020 28th European Signal Processing Conference (EUSIPCO) (pp. 1249-1253). IEEE.

Li, A., & Wentzlaff, D. (2021). PRGA: An Open-Source FPGA Research and Prototyping Framework. In The 2021 ACM/SIGDA International Symposium on Field-Programmable Gate Arrays (pp. 127-137).

Li, J., Pei, Y., & Yasin, A. (2022). A review on machine learning techniques for the assessment of image grading in breast mammogram. International Journal of Machine Learning and Cybernetics, 1-27.

Liu, X., Song, L., Liu, S., & Zhang, Y. (2021). A review of deep-learning-based medical image segmentation methods. Sustainability, 13(3), 1224.

Liu, Y., Feng, C., Zhou, Y., Shao, X., & Chen, M. (2022). Simulating the Dynamic Intra-Tumor Heterogeneity and Therapeutic Responses. Cancers, 14(7), 1645.

Logullo, A. F., Prigenzi, K. C., Nimir, C. C., Franco, A. F., & Campos, M. S. (2022). Breast microcalcifications: Past, present and future. Molecular and Clinical Oncology, 16(4), 1-8.

Ma, Y., Wang, Z., Yang, H., & Yang, L. (2020). Artificial intelligence applications in the development of autonomous vehicles: a survey. IEEE/CAA Journal of Automatica Sinica, 7(2), 315-329.

Maghsoudi, O. H., Gastounioti, A., Scott, C., Pantalone, L., Wu, F. F., Cohen, E. A., ... & Kontos, D. (2021). Deep-LIBRA: An artificial-intelligence method for robust quantification of breast density with independent validation in breast cancer risk assessment. Medical image analysis, 73, 102138.

Malathi, M., Sinthia, P., Mary, G. A. A., Nalini, M., & Wahed, F. F. (2022). Segmentation of breast cancer using fuzzy C means and classification by SVM based on LBP features. In AIP Conference Proceedings (Vol. 2405, No. 1, p. 020002). AIP Publishing LLC.

Martin, T., Areibi, S., & Grewal, G. (2021). Effective Machine-Learning Models for Predicting Routability During FPGA Placement. In 2021 ACM/IEEE 3rd Workshop on Machine Learning for CAD (MLCAD) (pp. 1-6). IEEE.

Mazio, C., Casale, C., Imparato, G., Urciuolo, F., & Netti, P. A. (2018). Recapitulating spatiotemporal tumor heterogeneity in vitro through engineered breast cancer microtissues. Acta Biomaterialia, 73, 236-249.

MehmoodGondal, R., Lashari, S. A., Saare, M. A., & Sari, S. A. (2021). A hybrid de-noising method for mammogram images. Indonesian Journal of Electrical Engineering and Computer Science, 21(3), 1435-1443.

Meyer-Baese, U. (2021). Embedded Microprocessor System Design Using FPGAs. Springer.

Michael, E., Ma, H., Li, H., Kulwa, F., & Li, J. (2021). Breast cancer segmentation methods: current status and future potentials. BioMed Research International, 2021.

Militello, C., Rundo, L., Dimarco, M., Orlando, A., Conti, V., Woitek, R., ... & Russo, G. (2022). Semi-automated and interactive segmentation of contrast-enhancing masses on breast DCE-MRI using spatial fuzzy clustering. Biomedical Signal Processing and Control, 71, 103113.

Minutoli, M., Castellana, V. G., Saporetti, N., Devecchi, S., Lattuada, M., Fezzardi, P., ... & Ferrandi, F. (2021). Svelto: High-level synthesis of multi-threaded accelerators for graph analytics. IEEE Transactions on Computers.

Mittal, H., & Saraswat, M. (2020). A New Fuzzy Cluster Validity Index for Hyperellipsoid or Hyperspherical Shape Close Clusters With Distant Centroids. IEEE Transactions on Fuzzy Systems, 29(11), 3249-3258.

Mohamed, S. K., Sakr, N. A., & Hikal, N. A. (2021). A Review of Breast Cancer Classification and Detection Techniques. International Journal of Advanced Science Computing and Engineering, 3(3), 128-139.

Mokhtary, A., Karakatsanis, A., & Valachis, A. (2021). Mammographic Density Changes over Time and Breast Cancer Risk: A Systematic Review and Meta-Analysis. Cancers, 13(19), 4805.

Mroczek, K. (2021). SoPC-based DMA for PCI Express DAQ cards. International Journal of Electronics and Telecommunications, 67(4), 565-570.

Mulhem, S., Mars, A., & Adi, W. (2020). Low-Complexity Nonlinear Self-Inverse Permutation for Creating Physically Clone-Resistant Identities. Cryptography, 4(1), 6.

Murti, K. C. S. (2021). Design Principles For Embedded Systems. Springer Verlag, Singapore.

Nagarajan, D., Jacob, K., Mustapha, A., Boppana, U. M., & Chaini, N. (2021). Comparative analysis of filtering methods in fuzzy C-means: Environment for DICOM image segmentation. In Generative Adversarial Networks for Image-to-Image Translation (pp. 81-98). Academic Press.

Nazarian, S., Glover, B., Ashrafian, H., Darzi, A., & Teare, J. (2021). Diagnostic accuracy of artificial intelligence and computer-aided diagnosis for the detection and characterization of colorectal polyps: systematic review and meta-analysis. Journal of medical Internet research, 23(7), e27370.

Nguyen, T. L., Schmidt, D. F., Makalic, E., Maskarinec, G., Li, S., Dite, G. S., ... & Hopper, J. L. (2021). Novel mammogram-based measures improve breast cancer risk prediction beyond an established mammographic density measure. International Journal of Cancer, 148(9), 2193-2202.

Nithya, A., & Shanmugavadivu, P. (2021). An Introspective Performance Analysis of Threshold-based Segmentation Techniques on Digital Mammograms.

Nithya, R., & Santhi, B. (2021). Mammogram density classification using deep convolutional neural network. Journal of Instrumentation, 16(01), P01019.

Norsa'adah, B., Rampal, K. G., & Mohd Amin, R. (2021). Time Taken for Symptom Recognition, First Consultation, Diagnosis and First Definitive Treatment and Its Associated Factors among Women with Breast Cancer. Asian Pacific Journal of Cancer Prevention, 22(11), 3623-3631.

Nourian, M. (2021). Analysis of Finite State Automata and Transducers Processing Acceleration on Disparate Hardware Technologies. North Carolina State University.

Nuño-Maganda, M. A., Jiménez-Arteaga, J. H., Barron-Zambrano, J. H., Hernández-Mier, Y., Elizondo-Leal, J. C., Díaz-Manríquez, A., ... & Polanco-Martagón, S. (2022). Implementation and integration of image processing blocks in a real-time bottle classification system. Scientific Reports, 12(1), 1-11.

Nykänen, A., Okuma, H., Sutela, A., Masarwah, A., Vanninen, R., & Sudah, M. (2021). The mammographic breast density distribution of Finnish women with breast cancer and comparison of breast density reporting using the 4th and 5th editions of the Breast Imaging-Reporting and Data System. European Journal of Radiology, 137, 109585.

O'Grady, S., & Morgan, M. P. (2018). Microcalcifications in breast cancer: From pathophysiology to diagnosis and prognosis. Biochimica et Biophysica Acta (BBA)-Reviews on Cancer, 1869(2), 310-320.

Olowookere, T. A. (2022). Hybridized Deep Convolutional Neural Network and Fuzzy Support Vector Machines for Breast Cancer Detection.

Oyetade, I. S., Ayeni, J. O., Ogunde, A. O., Oguntunde, B. O., & Olowookere, T. A. (2022). Hybridized Deep Convolutional Neural Network and Fuzzy Support Vector Machines for Breast Cancer Detection. SN Computer Science, 3(1), 1-14.

Omer, A. M. (2019). Detection of breast cancer in mammogram images using texture analysis methods (Doctoral dissertation, Sudan University of Science and Technology).

Osman, M. A., Darwish, A., Khedr, A. E., Ghalwash, A. Z., & Hassanien, A. E. (2017). Enhanced breast cancer diagnosis system using fuzzy clustering means approach in digital mammography. In Handbook of Research on Machine Learning Innovations and Trends (pp. 925-941). IGI Global.

Otsu, N. 1975. A threshold selection method from gray-level histograms. Automatica, 11(285-296), 23-27.

Oza, P., Sharma, P., Patel, S., & Bruno, A. (2021). A bottom-up review of image analysis methods for suspicious region detection in mammograms. Journal of Imaging, 7(9), 190.

Pal, N. R. (2017). A primer on cluster analysis: 4 basic methods that (usually) work [book review]. IEEE computational intelligence magazine, 12(4), 98-100.

Park, B., Cho, H. M., Lee, E. H., Song, S., Suh, M., Choi, K. S., ... & Cha, J. H. (2018). Does breast density measured through population-based screening independently increase breast cancer risk in Asian females?. Clinical epidemiology, 10, 61.

Park, G. E., Kang, B. J., Kim, S. H., & Lee, J. (2022). Retrospective Review of Missed Cancer Detection and Its Mammography Findings with Artificial-Intelligence-Based, Computer-Aided Diagnosis. Diagnostics, 12(2), 387.

Patel, P. G., Ahmadi, A., & Khalid, M. (2021). Implementing An Improved Image Enhancement Algorithm On FPGA. In 2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE) (pp. 1-6). IEEE.

Patil, R. S., Biradar, N., & Pawar, R. (2022). A new automated segmentation and classification of mammogram images. Multimedia Tools and Applications, 1-34.

Pawar, S. D., Sharma, K. K., Sapate, S. G., & Yadav, G. Y. (2021). Segmentation of pectoral muscle from digital mammograms with depth-first search algorithm towards breast density classification. Biocybernetics and Biomedical Engineering, 41(3), 1224-1241.

Pham-Quoc, C., Nguyen, X. Q., & Thinh, T. N. (2021). Hardware/Software Co-design for Convolutional Neural Networks Acceleration: A Survey and Open Issues. In International Conference on Context-Aware Systems and Applications (pp. 164-178). Springer, Cham.

Plancher, B., Neuman, S. M., Bourgeat, T., Kuindersma, S., Devadas, S., & Reddi, V. J. (2021). Accelerating robot dynamics gradients on a CPU, GPU, and FPGA. IEEE Robotics and Automation Letters, 6(2), 2335-2342.

Punithavathi, V., & Devakumari, D. (2021). A new proposal for the segmentation of breast lesion in mammogram images using optimized kernel fuzzy clustering algorithm. Materials Today: Proceedings.

Qi, Y., Yang, Z., Lei, J., Lian, J., Liu, J., Feng, W., & Ma, Y. (2021). Morph_SPCNN model and its application in breast density segmentation. Multimedia Tools and Applications, 80(2), 2821-2845.

Qiao, S., Hu, C., Brebner, G., Zou, J., & Guan, X. (2020). Adaptable Switch: A Heterogeneous Switch Architecture for Network-Centric Computing. IEEE Communications Magazine, 58(12), 64-69.

Radzi, S. F. M., Karim, M. K. A., Saripan, M. I., Abd Rahman, M. A., Osman, N. H., Dalah, E. Z., & Noor, N. M. (2020). Impact of Image Contrast Enhancement on Stability of Radiomics Feature Quantification on a 2D Mammogram Radiograph. IEEE Access, 8, 127720-127731.

Raju, A., & Sinha, N. (2022). SSEGEP: Small Segment Emphasized Performance evaluation metric for medical image segmentation. Journal of Machine Learning in Fundamental Sciences, 2022(1).

Rätze, M. A., Koorman, T., Sijnesael, T., Bassey-Archibong, B., van de Ven, R., Enserink, L., ... & Derksen, P. W. (2022). Loss of E-cadherin leads to Id2-dependent inhibition of cell cycle progression in metastatic lobular breast cancer. Oncogene, 1-13.

Reddy A, N., & Das, R. (2020). Color image segmentation using adaptive particle swarm optimization and fuzzy C-means. arXiv e-prints, arXiv-2004.

Ren, Y., Kamath, U., Domeniconi, C., & Xu, Z. (2019). Parallel boosted clustering. Neurocomputing, 351, 87-100.

Ribeiro, R. G., & Rios, R. (2021). Temporal gap statistic: A new internal index to validate time series clustering. Chaos, Solitons & Fractals, 142, 110326.

Retsky, M., Demicheli, R., Hrushesky, W., James, T., Rogers, R., Baum, M., ... & Forget, P. (2020). Breast cancer and the black swan. ecancermedicalscience, 14.

Rezaei, Z. (2021). A review on image-based approaches for breast cancer detection, segmentation, and classification. Expert Systems with Applications, 182, 115204.

Rowell, E. (2016). Know thy complexities. Big-O Cheat Sheet, Available in http://bigocheatsheet. com/# sorting. [Accessed in 30 May 2022].

Roy, A., Singh, B. K., Banchhor, S. K., & Verma, K. (2022). Segmentation of malignant tumours in mammogram images: A hybrid approach using convolutional neural networks and connected component analysis. Expert Systems, 39(1), e12826.

Rudin W. (1976), Principles of Mathematical Analysis, McGraw-Hill Book Company, New York.

Ryoo, J. H., Park, S., Kim, S., & Ryoo, H. S. (2020). Efficiency of cluster validity indexes in fuzzy clusterwise generalized structured component analysis. Symmetry, 12(9), 1514.

Sadeghi, V., & Etemadfard, H. (2022). Optimal cluster number determination of FCM for unsupervised change detection in remote sensing images. Earth Science Informatics, 1-13.

Saffari, N., Rashwan, H. A., Abdel-Nasser, M., Kumar Singh, V., Arenas, M., Mangina, E., ... & Puig, D. (2020). Fully automated breast density segmentation and classification using deep learning. Diagnostics, 10(11), 988.

Sahiner, B., Pezeshk, A., Hadjiiski, L. M., Wang, X., Drukker, K., Cha, K. H., ... & Giger, M. L. (2019). Deep learning in medical imaging and radiation therapy. Medical physics, 46(1), e1-e36.

Salaris, M., Damiani, A., Putti, E., & Stornaiuolo, L. (2021). FPGA-based implementation of 2D Normalized Cross-Correlation for Large Scale Signals. In 2021 IEEE 6th International Forum on Research and Technology for Society and Industry (RTSI) (pp. 300-305). IEEE.

Salazar, A. S., & Toriola, A. T. (2021). Reply to Hopper, Nguyen, and Li. JNCI Cancer Spectrum, 5(4), pkab052.

Sarić, R., Jokić, D., Beganović, N., Pokvić, L. G., & Badnjević, A. (2020). FPGA-based real-time epileptic seizure classification using Artificial Neural Network. Biomedical Signal Processing and Control, 62, 102106.

Savaridas, S. L., & Tennant, S. L. (2022). Quantifying lesion enhancement on contrast-enhanced mammography: a review of published data. Clinical Radiology.

Schliemann, D., Ismail, R., Donnelly, M., & Su, T. T. (2021). Anticipated delay in help-seeking for cancer symptoms: Findings from a nationwide study of Malaysian adults. Cancer epidemiology, 71, 101882.

Setiadi, D. R. I. M. (2021). PSNR vs SSIM: imperceptibility quality assessment for image steganography. Multimedia Tools and Applications, 80(6), 8423-8444.

Shaikh, K., Krishnan, S., & Thanki, R. M. (2021). Artificial intelligence in breast cancer early detection and diagnosis. Springer.

Shao, L., & He, W. (2019). Application of IIR Digital Filter with A New LMS Adaptive Algorithm. In IOP Conference Series: Materials Science and Engineering (Vol. 677, No. 5, p. 052003). IOP Publishing.

Sharma, M. K., Jas, M., Karale, V., Sadhu, A., & Mukhopadhyay, S. (2019). Mammogram segmentation using multi-atlas deformable registration. Computers in biology and medicine, 110, 244-253.

Shi, C., Wei, B., Wei, S., Wang, W., Liu, H., & Liu, J. (2021). A quantitative discriminant method of elbow point for the optimal number of clusters in clustering algorithm. EURASIP Journal on Wireless Communications and Networking, 2021(1), 1-16.

Shiri, A., Prakash, B., Mazumder, A. N., Waytowich, N. R., Oates, T., & Mohsenin, T. (2021). An energy-efficient hardware accelerator for hierarchical deep reinforcement learning. In 2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS) (pp. 1-4). IEEE.

Siddiqui, F., Amiri, S., Minhas, U. I., Deng, T., Woods, R., Rafferty, K., & Crookes, D. (2019). FPGA-Based Processor Acceleration for Image Processing Applications. Journal of Imaging, 5(1), 16.

Simon, W. A., Ray, V., Levisse, A., Ansaloni, G., Zapater, M., & Atienza, D. (2021). Exact Neural Networks from Inexact Multipliers via Fibonacci Weight Encoding. In 2021 58th ACM/IEEE Design Automation Conference (DAC) (pp. 805-810). IEEE.

Sobri, F. B., Bachtiar, A., Panigoro, S. S., Ayuningtyas, D., Gustada, H., Yuswar, P. W., ... & Widihidayati, A. D. (2021). Factors Affecting Delayed Presentation and Diagnosis of Breast Cancer in Asian Developing Countries Women: A Systematic Review. Asian Pacific Journal of Cancer Prevention, 22(10), 3081-3092.

Songsaeng, C., Woodtichartpreecha, P., & Chaichulee, S. (2021). Multi-Scale Convolutional Neural Networks for Classification of Digital Mammograms With Breast Calcifications. IEEE Access, 9, 114741-114753.

Soulami, K. B., Ghribi, E., Saidi, M. N., Tamtaoui, A., & Kaabouch, N. (2019). Breast Cancer: Segmentation of Mammograms using Invasive Weed optimization and SUSAN algorithms. In 2019 IEEE International Conference on Electro Information Technology (EIT) (pp. 1-7). IEEE.

Sowmyayani, S., & Murugan, V. (2021). Multi-Type Classification Comparison of Mammogram Abnormalities. International Journal of Image and Graphics, 21(03), 2150027.

Sreedevi, S., & Sherly, E. (2021). Fuzzy soft set approach for classifying malignant and benign breast tumours. International Journal of Healthcare Technology and Management, 18(3-4), 228-249.

Stamenković, Zoran, Bojan Dimitrijević, and Mile Stojčev. "Digital Circuit Models." Silicon Systems For Wireless Lan 22 (2020): 111.

Suckling, J., Parker, J., Dance, D., Astley, S., Hutt, I., Boggis, C., ... & Taylor, P. (2015). Mammographic image analysis society (MIAS) database v1. 21.

Sudin, E., Roy, D., Kadi, N., Triantafyllakis, P., Atwal, G., Gale, A., ... & Chen, Y. (2021). Eye tracking in digital pathology: identifying expert and novice patterns in visual search behaviour. In Medical Imaging 2021: Digital Pathology (Vol. 11603, p. 116030Z). International Society for Optics and Photonics.

Suradi, S. H., Abdullah, K. A., & Isa, N. A. M. (2021). Breast lesions detection using FADHECAL and Multilevel Otsu Thresholding Segmentation in digital mammograms. In International Conference on Medical and Biological Engineering (pp. 751-759). Springer, Cham.

Suradi, S. H., Abdullah, K. A., & Mat Isa, N. A. (2021). Improvement of image enhancement for mammogram images using Fuzzy Anisotropic Diffusion Histogram Equalisation Contrast Adaptive Limited (FADHECAL). Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 1-9.

Surendhar, S. P. A., & Vasuki, R. (2021). Breast cancer detection using deep belief network by applying feature extraction on various classifiers. Turkish Journal of Computer and Mathematics Education, 12(1S), 471-487.

Talib, M. A., Majzoub, S., Nasir, Q., & Jamal, D. (2021). A systematic literature review on hardware implementation of artificial intelligence algorithms. The Journal of Supercomputing, 77, 1897-1938.

Tampouratzis, N., Papaefstathiou, I., Nikitakis, A., Brokalakis, A., Andrianakis, S., Dollas, A., ... & Plebani, E. (2020). A novel, highly integrated simulator for parallel and distributed systems. ACM Transactions on Architecture and Code Optimization (TACO), 17(1), 1-28.

Tariq Jamal, A., Ben Ishak, A., & Abdel-Khalek, S. (2021). Tumor edge detection in mammography images using quantum and machine learning approaches. Neural Computing and Applications, 33(13), 7773-7784.

Tian, R., Sun, G., Liu, X., & Zheng, B. (2021). Sobel edge detection based on weighted nuclear norm minimization image denoising. Electronics, 10(6), 655.

Tirandaz, Z., Akbarizadeh, G., & Kaabi, H. (2020). PolSAR image segmentation based on feature extraction and data compression using weighted neighborhood filter bank and hidden Markov random field-expectation maximization. Measurement, 153, 107432.

Torres, G. F., Sassi, A., Arponen, O., Holli-Helenius, K., Lääperi, A. L., Rinta-Kiikka, I., ... & Pertuz, S. (2019). Morphological Area Gradient: System-independent Dense Tissue Segmentation in Mammography Images. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 4855-4858). IEEE.

Tsai, H. H., Wei, C. S., Hsieh, Y. C., Chen, I. M., Yeh, P. Y., Shih, D., & Chin, C. L. (2022). Calcification Clusters And Lesions Analysis In Mammogram Using Multi-Architecture Deep Learning Algorithms. Biomedical Engineering: Applications, Basis and Communications, 2250022.

Ullah, S., Rehman, S., Shafique, M., & Kumar, A. (2021). High-performance accurate and approximate multipliers for fpga-based hardware accelerators. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems.

Valencia-Hernandez, I., Peregrina-Barreto, H., Reyes-Garcia, C. A., & Lopez-Armas, G. C. (2021). Density map and fuzzy classification for breast density by using BI-RADS. Computer Methods and Programs in Biomedicine, 200, 105825.

Venieris, S. I., Panopoulos, I., Leontiadis, I., & Venieris, I. S. (2021). How to Reach Real-Time AI on Consumer Devices? Solutions for Programmable and Custom Architectures. In 2021 IEEE 32nd International Conference on Application-specific Systems, Architectures and Processors (ASAP) (pp. 93-100). IEEE.

Vijay, V., Rao, V. S., Chaitanya, K., Venkateshwarlu, S. C., Pittala, C. S., & Vallabhuni, R. R. (2022, February). High-Performance IIR Filter Implementation Using FPGA. In 2021 4th International Conference on Recent Trends in Computer Science and Technology (ICRTCST) (pp. 354-358). IEEE.

Vuttipittayamongkol, P., Elyan, E., & Petrovski, A. (2021). On the class overlap problem in imbalanced data classification. Knowledge-based systems, 212, 106631.

Vyshnavi, V., Vijayan, D., & Lavanya, R. (2021). Breast Density Classification in Mammogram Images. In 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII) (pp. 1-5). IEEE.

Wang, J., Zhu, H., Wang, S. H., & Zhang, Y. D. (2021). A review of deep learning on medical image analysis. Mobile Networks and Applications, 26(1), 351-380.

Wang, L., Liu, K., & Li, Y. (2021). Quality map guided parallel phase unwrapping algorithm for multi-lateral shearing interferometry. In Optical Technology and Measurement for Industrial Applications Conference 2021 (Vol. 11927, pp. 87-93). SPIE.

Wang, S. P. (2021). Design high-confidence computers using trusted instructional set architecture and emulators. High-Confidence Computing, 1(2), 100009.

Wang, X., Xie, L., Hu, W., Yan, J., Qian, X., & Zhu, L. (2021). Apatinib treatment is effective for metastatic malignant phyllodes tumors of the breast: a case report. BMC women's health, 21(1), 1-5.

Wang, Y., Yang, F., Zhang, J., Wang, H., Yue, X., & Liu, S. (2021). Application of artificial intelligence based on deep learning in breast cancer screening and imaging diagnosis. Neural Computing and Applications, 33(15), 9637-9647.

Wang, Y., Yan, X., & Zhang, J. A. (2021). Research on GPU parallel algorithm for direct numerical solution of two-dimensional compressible flows. The Journal of Supercomputing, 77(10), 10921-10941.

Warner, E. T., Rice, M. S., Zeleznik, O. A., Fowler, E. E., Murthy, D., Vachon, C. M., ... & Tamimi, R. M. (2021). Automated percent mammographic density, mammographic texture variation, and risk of breast cancer: a nested case-control study. NPJ breast cancer, 7(1), 1-8.

Watt, G. P., Knight, J. A., Nguyen, T. L., Reiner, A. S., Malone, K. E., John, E. M., ... & Bernstein, J. L. (2022). Association of contralateral breast cancer risk with mammographic density defined at higher-than-conventional intensity thresholds. International journal of cancer.

Wen, Y., Zhang, Y., Wen, L., Cao, H., Ai, G., Gu, M., ... & Chen, H. (2022). A 65nm/0.448 mW EEG processor with parallel architecture SVM and lifting wavelet transform for high-performance and low-power epilepsy detection. Computers in Biology and Medicine, 144, 105366.

Wijeratne, S., Pattnaik, S., Chen, Z., Kannan, R., & Prasanna, V. (2021). Programmable fpga-based memory controller. In 2021 IEEE Symposium on High-Performance Interconnects (HOTI) (pp. 43-51). IEEE.

Wijtvliet, M., Waeijen, L. J. W., Adriaansen, M., & Corporaal, H. (2016). Reaching intrinsic compute efficiency requires adaptable micro-architectures. In 9th International Workshop on Programmability and Architectures for Heterogeneous Multicores (MULTIPROG-2016), January 18, 2016, Prague, Czech Republic.

Wind, S., & Hua, C. (2021). Rasch Measurement Theory Analysis in R: Illustrations and Practical Guidance for Researchers and Practitioners. Bookdown. org,[Epub].

Xilinx, D. (2008). Spartan-3E FPGA Family: Complete Data Sheet, Xilinx.

Yang, L., Wang, Y., Wu, Z., & Wang, X. (2021). FPGA Implementation of Threshold-Type Binary Memristor and Its Application in Logic Circuit Design. Micromachines, 12(11), 1344.

Yang, Y., Yuan, Q., & Liu, J. (2021). An Architecture of Area-Effective High Radix Floating-Point Divider With Low-Power Consumption. IEEE Access, 9, 40039-40048.

Yao, Z., Chen, R., Zang, B., & Chen, H. (2021). Wukong+ G: Fast and Concurrent RDF Query Processing Using RDMA-Assisted GPU Graph Exploration. IEEE Transactions on Parallel and Distributed Systems, 33(7), 1619-1635.

Yin, F., & Shi, F. (2021). A Comparative Survey of Big Data Computing and HPC: From a Parallel Programming Model to a Cluster Architecture. International Journal of Parallel Programming, 1-38.

Yoshida, S., Ukon, Y., Ohteru, S., Uzawa, H., Ikeda, N., & Nitta, K. (2020). FPGA-Based Network Microburst Analysis System with Flow Specification and Efficient Packet Capturing. In 2020 IEEE 31st International Conference on Application-specific Systems, Architectures and Processors (ASAP) (pp. 29-32). IEEE.

Young, S. I., Dalca, A. V., Ferrante, E., Golland, P., Fischl, B., & Iglesias, J. E. (2022). SUD: Supervision by Denoising for Medical Image Segmentation. arXiv preprint arXiv:2202.02952.

Zadeh, L. A. (1965). Fuzzy sets. Information and control, 8(3), 338-353.

Zakaria, R., Abdelmajid, H., & Zitouni, D. (2022). Deep Learning in Medical Imaging: A Review. Applications of Machine Intelligence in Engineering, 131-144.

Zebari, D. A., Ibrahim, D. A., Zeebaree, D. Q., Haron, H., Salih, M. S., Damaševičius, R., & Mohammed, M. A. (2021). Systematic Review of Computing Approaches for Breast Cancer Detection Based Computer Aided Diagnosis Using Mammogram Images. Applied Artificial Intelligence, 1-47.

Zebari, D. A., Zeebaree, D. Q., Abdulazeez, A. M., Haron, H., & Hamed, H. N. A. (2020). Improved threshold based and trainable fully automated segmentation for breast cancer boundary and pectoral muscle in mammogram images. IEEE Access, 8, 203097-203116.

Zeiser, F. A., da Costa, C. A., Zonta, T., Marques, N., Roehe, A. V., Moreno, M., & da Rosa Righi, R. (2020). Segmentation of masses on mammograms using data augmentation and deep learning. Journal of digital imaging, 33(4), 858-868.

Zhang, M. (2021). Weighted clustering ensemble: A review. Pattern Recognition, 108428.

Zhang, R., Zhang, H., & Li, X. (2021). Maximum joint probability with multiple representations for clustering. IEEE transactions on neural networks and learning systems.

Zhao, D., Liu, L., Yu, F., Heidari, A. A., Wang, M., Liang, G., ... & Chen, H. (2021). Chaotic random spare ant colony optimization for multi-threshold image segmentation of 2D Kapur entropy. Knowledge-Based Systems, 216, 106510.

Zhao, W., Wang, R., Qi, Y., Lou, M., Wang, Y., Yang, Y., ... & Ma, Y. (2021). BASCNet: Bilateral adaptive spatial and channel attention network for breast density classification in the mammogram. Biomedical Signal Processing and Control, 70, 103073

Zhou, Q., Zuley, M., Guo, Y., Yang, L., Nair, B., Vargo, A., ... & Wu, S. (2021). A machine and human reader study on AI diagnosis model safety under attacks of adversarial images. Nature communications, 12(1), 1-11.