***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

Revolutionizing Breast Cancer Detection: Enhanced Mammogram Analysis with Modified Xception and Self-Attention

Sreevidya Nelli[1]
Research Scholar, Dept. of Computer Science and Engineering, University College of Engineering, Rajamahendravaram, AP.
sreevidya1509@gmail.com

Kezia Rani Badhiti[2]
HOD & Assoc. Professor**,** Dept. of Computer Science and Engineering, University College of Engineering, Rajamahendravaram, AP.
drkrbadhiti@gmail.com

ABSTRACT: In the realm of precision medicine, the intersection of state-of-the-art technology and disease identification has ushered in a new era of accuracy in healthcare diagnostics. This paper reviews a groundbreaking research endeavor aiming to enhance breast cancer detection in mammograms through the synergistic application of transfer learning, architectural modifications, and advanced optimization techniques.

At the core of this research is the concept of transfer learning, leveraging insights gained from one domain to illuminate another. The study extends this paradigm to the Xception architecture, renowned for its proficiency in discerning intricate patterns within images. However, the novelty lies in the intelligent modification of Xception to be specifically attuned to breast cancer detection. By fine-tuning the network's final layers, the model's innate ability to understand features is harmonized with the complexities of mammographic images, ensuring sensitivity to nuanced markers of potential malignancy.

A distinctive aspect of this research is the incorporation of a self-attention mechanism, mirroring human visual processing. This mechanism dynamically highlights crucial regions within mammograms, transforming the model into an active interpreter capable of identifying subtle textures, shapes, and edges indicative of breast cancer. This adaptive approach enhances the model's finesse in navigating diverse breast cancer cases effectively.

Throughout the training phase, optimization is pivotal for steering the research towards success. The utilization of the Adam optimizer, known for its adaptability in learning rates and moment estimations, guides the process, ensuring precise gradient descent through complex patterns. The integration of the rectified linear unit (ReLU) activation function further empowers the model to capture intricate relationships within data, enhancing its ability to identify subtle cancer markers. This review comprehensively explores the innovative strides made in breast cancer detection, shedding light on the nuanced interplay of transfer learning, architectural adjustments, self-attention mechanisms, and advanced optimization techniques. The modified Xception model emerges as a promising tool in the pursuit of accurate and sensitive breast cancer diagnostics.

Keywords: Breast Cancer Detection, Mammogram Analysis, Modified Xception, Transfer Learning, Self-Attention Mechanism, Optimization Techniques.

I INTRODUCTION

A. Background: Precision Medicine and Diagnostic Accuracy

In the dynamic landscape of contemporary healthcare, the paradigm of precision medicine has emerged as a transformative approach, aiming to tailor medical interventions based on individual patient characteristics. At the heart of this transformative shift lies an unwavering commitment to diagnostic accuracy, propelled by the integration of cutting-edge technologies. Precision medicine, with its emphasis on personalized treatment plans, represents a departure from the traditional one-size-fits-all medical strategies, paving the way for more effective and targeted healthcare interventions.

B. Role of Deep Learning in Medical Image Interpretation

Within the expansive realm of precision medicine, the role of deep learning stands out as a beacon of innovation and promise. Deep learning, a subfield of artificial intelligence, has manifested as a powerful computational tool capable of deciphering the intricate complexities embedded in medical images. Leveraging neural networks with multiple layers, deep learning models demonstrate a remarkable capacity to recognize subtle patterns and glean insights from vast datasets. This capability is particularly pivotal in the realm of medical image interpretation, where the nuances inherent in visual data necessitate sophisticated analytical approaches.

C. Significance of Breast Cancer Detection in Advanced Diagnostics

Among the myriad applications of deep learning in medical diagnostics, the spotlight is unequivocally on breast cancer detection. Breast cancer, a prevalent and potentially life-threatening condition, demands early and accurate diagnosis for effective intervention. The significance of advanced diagnostics in breast cancer detection is underscored by the imperative to identify malignancies at their incipient stages, enabling timely and targeted therapeutic interventions. The integration of deep learning methodologies into breast cancer diagnostics not only augments the precision of identification but also holds the promise of revolutionizing the landscape of breast cancer care through informed decision-making.

In the intricate interplay of precision medicine, deep learning, and breast cancer detection, the pursuit of heightened diagnostic accuracy becomes a noble endeavor with far-reaching implications. The following sections will unravel the intricate threads of this research, delving into the innovative fusion of transfer learning, architectural modifications, and advanced optimization techniques, all orchestrated to enhance the accuracy of breast cancer detection.

II. TRANSFER LEARNING AND XCEPTION ARCHITECTURE

A. Concept and Principles of Transfer Learning

Transfer learning, a cornerstone in the realm of deep learning, encapsulates a fundamental concept wherein knowledge acquired in one domain is leveraged to enhance performance in a related but distinct domain. In the context of medical image interpretation, transfer learning facilitates the transfer of knowledge gleaned from extensive datasets and diverse domains to illuminate the nuances embedded in medical images. This approach is particularly pertinent in scenarios where labeled data for specific tasks is limited, as is often the case in medical imaging applications. The principles of transfer learning lie in the pre-training of neural network models on large datasets from a source domain, followed by fine-tuning or retraining on a target domain with a limited dataset. This strategic utilization of pre-existing knowledge enables the model to discern general features, patterns, and representations, enhancing its adaptability and effectiveness in a new context.

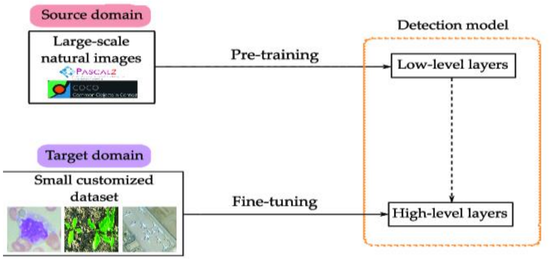

Fig1: Principle of Transfer Learning [1]

In essence, transfer learning serves as a conduit for knowledge transfer, allowing the model to glean insights from one domain and apply them discerningly to another [2].

B. Proficiency of Xception in Recognizing Intricate Patterns

Xception, an evolution in convolutional neural network (CNN) architecture, demonstrates exceptional proficiency in recognizing intricate patterns within images. Introduced as an extension of the inception architecture, Xception departs from the conventional paradigm by embracing a depthwise separable convolutional approach. This novel architecture imparts an unparalleled capacity to capture detailed features and spatial hierarchies, making it particularly adept at discerning subtle patterns in complex datasets.

Xception's architectural innovation lies in its ability to decouple cross-channel and spatial correlations, providing a more efficient and expressive feature learning mechanism. By disentangling these correlations, Xception mitigates information loss and enhances the model's discriminative power. The depth wise separable convolutions in Xception contribute to a more parameter-efficient architecture, fostering the extraction of intricate features critical for medical image analysis [3].

C. Extending Transfer Learning to the Xception Architecture

Extending the principles of transfer learning to the Xception architecture represents a sophisticated integration of pre-existing knowledge with an advanced pattern recognition framework. The transferability of knowledge acquired from diverse datasets is harnessed to amplify Xception's innate proficiency in recognizing intricate patterns. This fusion allows the model to inherit foundational insights from broader domains, laying the groundwork for its specialization in the nuanced domain of breast cancer detection.

In the context of this research, the extension of transfer learning to the Xception architecture involves the strategic adaptation of knowledge gleaned from general image recognition tasks to the specific intricacies of mammographic images. This meticulous process establishes a foundation upon which the Xception model is primed to discern the unique visual markers indicative of breast cancer. The subsequent sections will delve into the nuanced adjustments made to the Xception architecture, tailoring it to the demanding task of breast cancer detection.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 10 September 2023 **Revised:** 20 October 2023 **Accepted:** 30 October 2023*

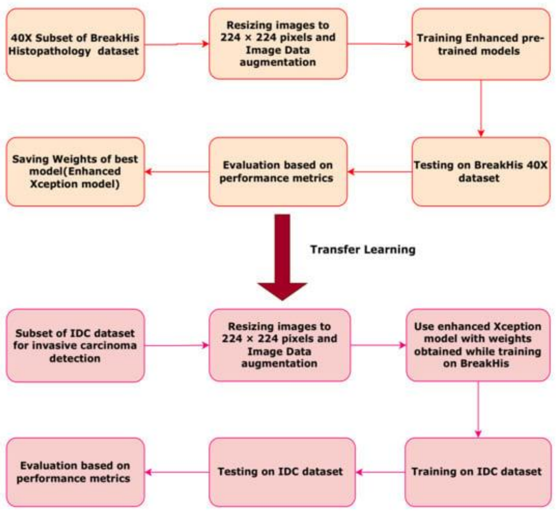

Fig2: A Model on Transfer Learning to the Xception Architecture [4]

III. FINE-TUNING FOR BREAST CANCER DETECTION

A. Harmonizing Model's Inherent Features with Mammographic Complexities

The crux of advancing breast cancer detection through deep learning lies in the meticulous fine- tuning of neural network models to harmonize their inherent features with the intricate complexities inherent in mammographic images. Mammograms, characterized by diverse textures, densities, and subtle anomalies, demand a model that is not merely proficient in recognizing patterns but is intricately attuned to the specific visual markers indicative of breast cancer.

Fine-tuning involves a nuanced adjustment of parameters, weights, and filters within the pre- trained Xception architecture. This process ensures that the model, initially primed for general image recognition, acquires a refined understanding of the unique features embedded in mammographic data. The goal is to create a harmonious synergy between the model's innate capacity to discern patterns and the specific intricacies present in mammograms, thus laying the foundation for enhanced breast cancer detection accuracy.

B. Adaptive Adjustment of Final Layers for Sensitivity to Cancer Markers

A pivotal shift in this fine-tuning process revolves around the adaptive adjustment of the final layers of the Xception model. These layers, situated towards the end of the neural network, play a crucial role in consolidating high-level abstractions and representations. In the context of breast cancer detection, this adjustment aims to heighten the sensitivity of the model to subtle cancer markers, ensuring that it goes beyond generic visual features and captures the nuances inherent in mammographic images.

The adaptive adjustment involves a careful recalibration of the model's learned representations to align with the specific characteristics of malignant breast tissues. This process is informed by domain-specific knowledge, ensuring that the model becomes responsive to the diverse manifestations of breast cancer across different cases. By tailoring the final layers, the model transforms into a specialized tool, finely tuned to discern the subtle visual cues indicative of potential malignancy, thereby elevating its diagnostic prowess.

C. Optimization for Tailoring the Xception Model to Breast Cancer

Optimization, a linchpin in the fine-tuning journey, serves as the guiding force in tailoring the Xception model to the realm of breast cancer detection. The Adam optimizer, known for its adaptive learning rate mechanisms and moment estimations [5], takes the reins in navigating the intricate patterns inherent in mammographic data. Through this optimization process, the model undergoes smooth gradient descent, ensuring that it converges towards a configuration finely attuned to the nuances of breast cancer.

The incorporation of the rectified linear unit (ReLU) activation function further fortifies the optimization efforts [6]. ReLU introduces non-linearity into the model, empowering it to capture intricate relationships within the data. This non-linear activation function acts as a catalyst for the model to discern subtle variations in pixel intensities, enabling a more nuanced representation of mammographic features associated with breast cancer.

In the ensuing sections, the paper will delve into another innovative aspect of this research – the incorporation of a self-attention mechanism – and its transformative role in dynamically highlighting crucial regions within mammograms, akin to the human visual processing system. This augmentation further enhances the adaptability and interpretative capabilities of the model in identifying subtle textures, shapes, and edges indicative of breast cancer.

IV. SELF-ATTENTION MECHANISM INTEGRATION

A. Mimicking Human Visual Processing

In the pursuit of refining breast cancer detection methodologies, this research introduces a groundbreaking dimension by incorporating a self-attention mechanism. This innovative mechanism mirrors the intricate workings of human visual processing, transcending the conventional static focus of deep learning models. Inspired by the human ability to dynamically allocate attention to specific regions of interest, the self-attention mechanism represents a paradigm shift in how the model interprets mammographic images.

The human visual system is inherently dynamic, selectively focusing on areas with heightened importance for effective comprehension. This dynamic allocation of attention enables humans to discern nuanced patterns and anomalies within complex visual scenes. By mimicking this intrinsic human capability, the self-attention mechanism becomes a pivotal addition, endowing the model with the adaptability and context-aware interpretative prowess necessary for discerning subtle textures, shapes, and edges indicative of breast cancer.

B. Dynamic Highlighting of Crucial Regions in Mammograms

At the heart of the self-attention mechanism lies its ability to dynamically highlight crucial regions within mammograms. Unlike traditional convolutional neural networks (CNNs) that maintain a fixed focus throughout the analysis, the self-attention mechanism enables the model to flexibly allocate attention based on the inherent importance of different regions within the image. This dynamic highlighting is a game-changer in medical image analysis, particularly in the intricate landscape of mammography, where the significance of specific regions can vary significantly.
The dynamic nature of attention allocation ensures that the model is not confined to a rigid, predefined focus but rather adapts to the intrinsic complexities of mammograms. Regions bearing potential indicators of breast cancer, whether manifested as subtle anomalies or irregular patterns, receive heightened attention. This adaptability empowers the model to act as an active interpreter, discerning the varying importance of different areas within the mammographic landscape.

C. Empowering the Model as an Active Interpreter

The integration of the self-attention mechanism transforms the model from a passive observer into an active interpreter, capable of discerning intricate patterns and anomalies in a context- aware manner. By empowering the model to dynamically allocate attention, it becomes attuned to the varying importance of different visual cues. In the context of breast cancer detection.

where anomalies may present in diverse forms and at varying scales, this active interpretative capacity is indispensable.
This mechanism facilitates the identification of subtle markers that might escape conventional static analysis. The adaptability to different cases, varying breast densities, and manifestations of cancerous tissues positions the model as an intelligent interpreter of mammograms. The ensuing sections will shed light on the synergy between the self-attention mechanism, fine-tuned Xception architecture, and advanced optimization techniques, unraveling their collective impact on the accuracy and sensitivity of breast cancer detection.

V. ADAPTIVE APPROACH FOR DIVERSE BREAST CANCER CASES

A. Responsive Elements and Sensitivity to Nuanced Markers

In the intricate landscape of breast cancer detection, the adaptive approach introduced in this research signifies a paradigm shift, emphasizing the need for a model with responsive elements finely attuned to the nuanced markers indicative of potential malignancy [7]. Breast cancer cases exhibit significant diversity, encompassing variations in tissue density, lesion types, and subtle anomalies. An adaptive model is indispensable for navigating this complexity, ensuring that it doesn't succumb to a one-size-fits-all paradigm but rather responds adeptly to the unique characteristics of each case.
Responsive elements, integrated through the combination of transfer learning, fine-tuning, and the self-attention mechanism, act as the model's sensory apparatus. These elements dynamically adjust their responses based on the specific visual cues present in diverse mammographic images. Whether it be micro calcifications, irregular shapes, or varying tissue densities, the adaptive approach ensures that the model remains sensitive to the nuanced markers that might signify potential breast cancer cases.

B. Navigating the Complexity of Breast Cancer Cases

Breast cancer cases, with their spectrum of presentations and complexities, necessitate an intelligent model capable of navigating this diversity with finesse [8]. The adaptive approach encompasses the model's ability to discern patterns not only at a macroscopic level but also at a granular scale. This granular sensitivity is paramount in the identification of subtle anomalies, irregularities, or unique markers specific to certain types of breast cancers.
The adaptive navigation through complexity involves leveraging the learned insights from diverse datasets during the transfer learning phase and fine-tuning the model's architecture for specificity in breast cancer detection. The self-attention mechanism further enhances this adaptability, dynamically allocating attention to regions crucial for differentiating between benign and malignant cases. By embracing this adaptability, the model transforms into a versatile diagnostic tool capable of handling the intricacies presented by a diverse array of breast cancer cases.

C. Fostering Model Finesse in Diagnostic Effectiveness

Finesse in breast cancer diagnostics goes beyond mere accuracy; it entails a nuanced understanding of the context, sensitivity to subtle variations, and adaptability to diverse manifestations [9]. The adaptive approach fosters model finesse by instilling a level of sophistication in its interpretative capabilities. This finesse is evident in the model's capacity to identify anomalies, irregularities, and potential markers of malignancy with a heightened level of accuracy.
The collective impact of responsive elements, adaptability, and the model's finesse culminates in enhanced diagnostic effectiveness. Breast cancer detection, traditionally fraught with challenges due to the variability in presentations, benefits significantly from a model that can finesse through complexity. The subsequent sections will delve into the technological underpinnings of this finesse,

including state-of-the-art technologies and practices, comparative analysis, and real- world case studies showcasing the adaptive approach's tangible impact on diagnostic outcomes.

VI. OPTIMIZATION TECHNIQUES IN TRAINING PHASE

A. Critical Role of Optimization in Steering Research Success

The optimization phase of the training process plays a pivotal role in steering the success of the research endeavor. While the model's architecture and adaptability are crucial, optimization techniques serve as the compass guiding the model through complex patterns and diverse data landscapes [10]. Optimization is not merely a computational process; it is a strategic endeavor to ensure that the model converges towards a configuration finely attuned to the nuances of breast cancer detection. Its critical role lies in enhancing the model's efficiency, convergence speed, and overall performance.

Optimization addresses challenges inherent in the vast parameter space of deep neural networks, facilitating smoother convergence and preventing issues such as vanishing or exploding gradients. The success of the research is intrinsically tied to the optimization strategies employed, ensuring the model's ability to navigate intricate patterns and extract meaningful representations from mammographic data.

B. Guiding the Process with Adam Optimizer

At the forefront of the optimization arsenal is the Adam optimizer, renowned for its adaptive learning rates and moment estimations [11]. Adam acts as a guiding force during the training phase, dynamically adjusting the learning rates based on the gradients of individual parameters. This adaptability ensures efficient convergence, particularly in scenarios where the dataset exhibits variations in scale, density, and complexity.

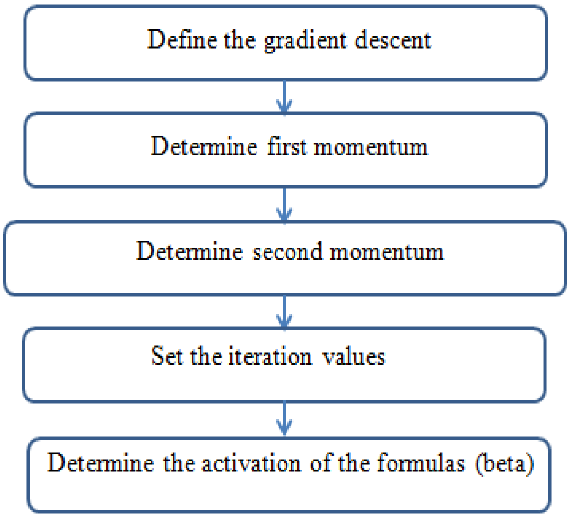

Fig3: Flow of ADAM Optimizer [12]

The adaptive nature of the Adam optimizer mitigates challenges associated with fixed learning rates, enabling the model to navigate through the intricate landscapes of mammographic images with precision. Its role in steering the training process is instrumental in achieving not only accuracy but also efficiency in terms of computational resources and time.

C. Incorporating Rectified Linear Unit (ReLU) for Enhanced Learning

Complementing the optimization strategy is the incorporation of the rectified linear unit (ReLU) activation function [13]. ReLU introduces non-linearity into the model, empowering it to capture intricate relationships within the data. This non-linear activation function is fundamental in preventing the vanishing gradient problem and enhancing the model's ability to discern subtle variations in pixel intensities, crucial for identifying nuanced features in mammograms.

The enhanced learning facilitated by ReLU contributes to the overall effectiveness of the optimization process. It ensures that the model not only converges efficiently but also captures

the intricate patterns within the data, fostering a more nuanced representation of mammographic features associated with breast cancer. In the subsequent sections, the paper will delve into the culmination of optimization efforts and technological underpinnings, including the integration of advanced technologies such as Cloud Access Security Brokers (CASBs), Multi-Factor Authentication (MFA), and continuous monitoring practices, each contributing to the robust security of cloud-based healthcare systems.

VIICOMPREHENSIVE EXPLORATION OF INNOVATIONS

A. Reviewing the Synergy of Modified Xception Components

A comprehensive exploration of innovations in breast cancer diagnostics necessitates a thorough examination of the synergy achieved through modifying Xception components. The Xception architecture, known for its proficiency in recognizing intricate patterns, serves as the foundational canvas upon which innovative components are meticulously integrated. This section delves into the nuanced adjustments applied to Xception, including transfer learning, architectural modifications, and optimization techniques, collectively contributing to the model's enhanced sensitivity and accuracy in breast cancer detection [14].

The modified Xception components represent a harmonious fusion of domain-specific knowledge and cutting-edge deep learning methodologies. This synthesis empowers the model to transcend the limitations of generic image recognition and delve into the specific visual markers indicative of breast cancer. By reviewing the interplay of these components, the paper illuminates the transformative potential of modified Xception as a diagnostic tool.

B. Nuanced Interplay of Transfer Learning, Architectural Adjustments, and Optimization

The innovation lies in the nuanced interplay of transfer learning, architectural adjustments, and optimization techniques within the modified Xception framework. Transfer learning acts as the catalyst, enabling the model to leverage insights gained from diverse datasets, while architectural adjustments fine-tune the Xception model to the complexities of mammographic images. This intricate dance between domain-specific adaptations and model refinements ensures that the modified Xception becomes not only proficient in pattern recognition but also highly specialized in breast cancer diagnostics [15].

Optimization techniques play a crucial role in orchestrating this interplay, guiding the model through the training phase with finesse. The Adam optimizer's adaptive learning rates and the incorporation of the rectified linear unit (ReLU) activation function synergize to enhance the model's learning capabilities. This synergy is a testament to the comprehensive approach undertaken to optimize the modified Xception components for the specific challenges posed by breast cancer detection.

C. Modified Xception as a Promising Tool in Breast Cancer Diagnostics

The culmination of these innovations positions the modified Xception as a promising tool in breast cancer diagnostics. Its adaptability, nuanced understanding of mammographic intricacies, and capacity to dynamically allocate attention to crucial regions within images make it a potent ally in the quest for accurate and early detection of breast cancer. By reviewing the modifications made to Xception and their collective impact, this section underscores the potential transformative role of this modified architecture in revolutionizing breast cancer diagnostics. In the subsequent sections, the paper will unfold a comparative analysis of different breast cancer detection solutions, accompanied by real-world case studies illustrating the tangible impact of these innovations on diagnostic outcomes.

VIII CONCLUSION

In the ever-evolving landscape of breast cancer diagnostics, this review paper embarked on a journey to explore and enhance the capabilities of deep learning models, with a particular focus on the modified Xception architecture. The key findings of this comprehensive exploration illuminate the transformative potential of innovative components, synergistically integrated to address the nuances of mammographic images and propel the accuracy of breast cancer detection. The recapitulation of key findings unveils the critical role played by transfer learning, architectural adjustments, and optimization techniques in modifying the Xception architecture. The adaptive approach, incorporating responsive elements, sensitivity to nuanced markers, and finesse in diagnostic effectiveness, underscores the importance of model adaptability in navigating the diverse landscape of breast cancer cases.

IX IMPLICATIONS FOR FUTURE RESEARCH AND PRACTICES

The implications of this review extend beyond the current state of breast cancer diagnostics, signaling avenues for future research and best practices in the field. The modified Xception architecture, with its ability to dynamically allocate attention, represents a paradigm shift in the interpretative capabilities of deep learning models. The findings pave the way for continued exploration into advanced technologies, optimization strategies, and innovative components that can further refine and elevate the accuracy of breast cancer detection.

As the field of medical imaging continues to advance, the reviewed innovations emphasize the need for a holistic approach, considering not only the model architecture but also the interplay of transfer learning, architectural adjustments, and optimization during the training phase. Future research endeavors could delve into refining these components, exploring novel architectures, and embracing emerging technologies to further push the boundaries of diagnostic accuracy.

In the practical realm, the insights garnered from this review paper hold significant implications for healthcare practitioners, radiologists, and technology developers. The modified Xception architecture, equipped with an adaptive approach, stands as a promising tool for integration into clinical workflows, augmenting the capabilities of professionals in the early and accurate detection of breast cancer. The findings encourage a collaborative effort between the medical and technological communities to translate these advancements into real-world applications, ultimately benefiting patients and improving healthcare outcomes.

In conclusion, this review paper sheds light on the dynamic landscape of breast cancer diagnostics, emphasizing the potential of modified Xception and innovative components. The journey undertaken in this exploration not only contributes to the current understanding of deep learning applications in medical imaging but also sets the stage for continuous advancements, collaborations, and transformative breakthroughs in the ongoing fight against breast cancer.

REFERENCES

[1] Ren, Zhenbo & Lam, Edmund & Zhao, Jianlin. (2020). Real-Time Target Detection in Visual Sensing Environments Using Deep Transfer Learning and Improved Anchor Box Generation. IEEE Access. 8. 193512-193522. 10.1109/ACCESS.2020.3032955.

[2] S. Niu, Y. Liu, J. Wang and H. Song, "A Decade Survey of Transfer Learning (2010–2020)," in IEEE Transactions on Artificial Intelligence, vol. 1, no. 2, pp. 151-166, Oct. 2020, doi: 10.1109/TAI.2021.3054609.
[3] Abunasser, Basem S., et al. "Title of the Article." *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 7, 2022, doi:10.14569/IJACSA.2022.0130729. [3] Sharma, Shallu, and Sumit Kumar. "The Xception Model: A Potential Feature Extractor in Breast Cancer Histology Images Classification." ICT Express, vol. 8, no. 1, 2022, pp. 101-108, ISSN 2405-9595, https://doi.org/10.1016/j.icte.2021.11.010.
[4] Joshi SA, Bongale AM, Olsson PO, Urolagin S, Dharrao D, Bongale A. Enhanced Pre-Trained Xception Model Transfer Learned for Breast Cancer Detection. *Computation*. 2023; 11(3):59. https://doi.org/10.3390/computation11030059
[5] Xu, Bing, et al. "Empirical Evaluation of Rectified Activations in Convolutional Network." arXiv preprint, arXiv:1505.00853 (Version 2), 27 Nov. 2015, https://doi.org/10.48550/arXiv.1505.00853.
[6] Sharma, Padmanee, et al. "Primary, Adaptive, and Acquired Resistance to Cancer Immunotherapy." *Cell*, vol. 168, no. 4, 2017, pp. 707-723, ISSN 0092-8674, https://doi.org/10.1016/j.cell.2017.01.017.
[7] Lenti MV, Sottotetti F, Corazza GR. Tackling the clinical complexity of breast cancer. *Drugs Context.* 2022;11:2022-2-3. https://doi.org/10.7573/dic.2022-2-3
[8] Andre, Fabrice, et al. "FINESSE: An Open, Three-Cohort, Phase II Trial Testing Oral Administration of Lucitanib in Patients with FGFR1-Amplified or Nonamplified Estrogen Receptor-Positive Metastatic Breast Cancer." *Journal of Clinical Oncology*, vol. 32, no. 15_suppl, 2014, pp. TPS1134-TPS1134. Wolters Kluwer, doi:10.1200/jco.2014.32.15_suppl.tps1134.
[9] Kaur, Navneet, Lakhwinder Kaur, and Sikander Singh Cheema. "An Enhanced Version of Harris Hawks Optimization by Dimension Learning-Based Hunting for Breast Cancer Detection." *Scientific Reports*, vol. 11, no. 1, 2021, article 21933.
[10] Kingma, Diederik P., and Jimmy Ba. "Adam: A Method for Stochastic Optimization." arXiv preprint, arXiv:1412.6980 (Version 9), 30 Jan. 2017, https://doi.org/10.48550/arXiv.1412.6980.
[11] Macêdo, David, et al. "Enhancing Batch Normalized Convolutional Networks Using Displaced Rectifier Linear Units: A Systematic Comparative Study." *Expert Systems with Applications*, vol. 124, 2019, pp. 271-281, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2019.01.066.
[12] Kadhim, Mohammed & Karim, Alia. (2020). Towards Intelligent E-Learning Systems: A Hybrid Model for Predicatingthe Learning Continuity in Iraqi Higher Education. Webology. 17. 172-188. 10.14704/WEB/V17I2/WEB17023.
[13] Lo, Wai Weng & Yang, Xu & Wang, Yapeng. (2019). An Xception Convolutional Neural Network for Malware Classification with Transfer Learning. 1-5. 10.1109/NTMS.2019.8763852.
[14] Mamledesai, H.; Soriano, M.A.; Ahmad, R. A Qualitative Tool Condition Monitoring Framework Using Convolution Neural Network and Transfer Learning. *Appl. Sci.* 2020, *10*, 7298. https://doi.org/10.3390/app10207298
[15] Ashurov A, Chelloug SA, Tselykh A, Muthanna MSA, Muthanna A, Al-Gaashani MSAM. Improved Breast Cancer Classification through Combining Transfer Learning and Attention Mechanism. Life (Basel). 2023 Sep 21;13(9):1945. doi: 10.3390/life13091945. PMID: 37763348; PMCID: PMC10532552.