

Fuzzy logic and linear regression modelling in breast cancer detection: A review

Reham A. Ahmed^{1*}, Muhammad Ammar Shafi¹, Nor Faezan Abdul Rashid², Suraya Othman², Rozin Badeel³, Banan Badeel Abdal⁴

¹Department of Technology and Management, Faculty of Technology Management and Business, Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, Malaysia; rehamabdul.ahmed@gmail.com (R.A.A.).

²Surgery department, Hospital Al-Sultan Abdullah, Universiti Teknologi MARA, 42300 Bandar Puncak Alam, Selangor, Malaysia.

³Department of Communication Technology and Network, University Putra Malaysia (UPM), Seri Kembangan, 43300, Malaysia.

⁴College of Administration and Economics, University of Duhok, Duhok Kurdistan region -Iraq.

Abstract: The research investigates the effectiveness of breast cancer detection using linear regression models and fuzzy logic approaches, together with an analysis of their medical diagnostic applications and their associated limitations. The research evaluates performance results by analyzing both methods through a review of current studies, where linear regression demonstrates ease of interpretation alongside simplicity, but fuzzy logic shows strength in dealing with uncertainty along with nonlinear relationships. The research shows that while linear regression works simply, it fails to handle the complexity of medical data, but fuzzy logic handles complex medical diagnosis settings better, which suggests that adding fuzzy logic features to linear regression can boost diagnosis quality. The research finds that the hybrid technique involving fuzzy logic and linear regression may increase the accuracy of breast cancer detection. Furthermore, it highlights the requirement for further investigation of sophisticated artificial intelligence strategies, like neural networks, for addressing the basic techniques' limitations. Practical Implications: The study offers a useful guide to medical and research professionals, indicating that beyond the intriguing integration of fuzzy logic from AI capabilities, there is the potential to improve diagnostic performance in a clinical setting. Future developments in computer AI-driven models will certainly create an even better workflow for breast cancer examination.

Keywords: Artificial intelligence, Cancer detection, Fuzzy models, Integrated models, Linear predictors, Medical testing.

1. Introduction

Breast cancer remains a public health problem because it has turned into the most frequent female cancer in all the countries of the world. In the case of cancer, there must be an early detection as the probability rate of survival, together with the effectiveness of the treatment, is high. In health care, advances have been recorded on a breathtaking scale, further scaled up by applying artificial intelligence and machine learning in diagnostics. Out of these techniques, it is prudent to examine fuzzy logic and linear regression modelling in detail due to the complicated and uncertain medical data. This review discusses how these methods are applied in detecting breast cancer, emphasizing linear regression modelling accompanied by fuzzy logic to enhance performance [1-5] Fuzzy logic, developed in the 1960s, is essential for illness diagnosis, particularly in scenarios with ambiguous or insufficient data [4]. Conversely, linear Regression, a recognized statistical technique, seeks to forecast outcomes by modelling the connection among variables. Its simplicity and interpretability have facilitated its use in medical procedures, particularly in cancer detection. Notwithstanding its advantages, the exclusive use

of either method of fuzzy logic or linear Regression exhibits constraints [3]. Consequently, researchers are investigating the incorporation of linear Regression into fuzzy expert systems to enhance diagnostic precision by using the advantages of both methodologies. The main screening method used in breast cancer is mammography as shown in Figure 1.

This work is to provide a thorough examination of the many approaches now used in breast cancer detection. This will assess the efficacy of various strategies, together with their constraints and recent developments. Furthermore, it examines the current initiatives aimed at enhancing and expanding these methodologies, specifically emphasizing prospective advancements in accuracy, early diagnosis, and patient outcomes.

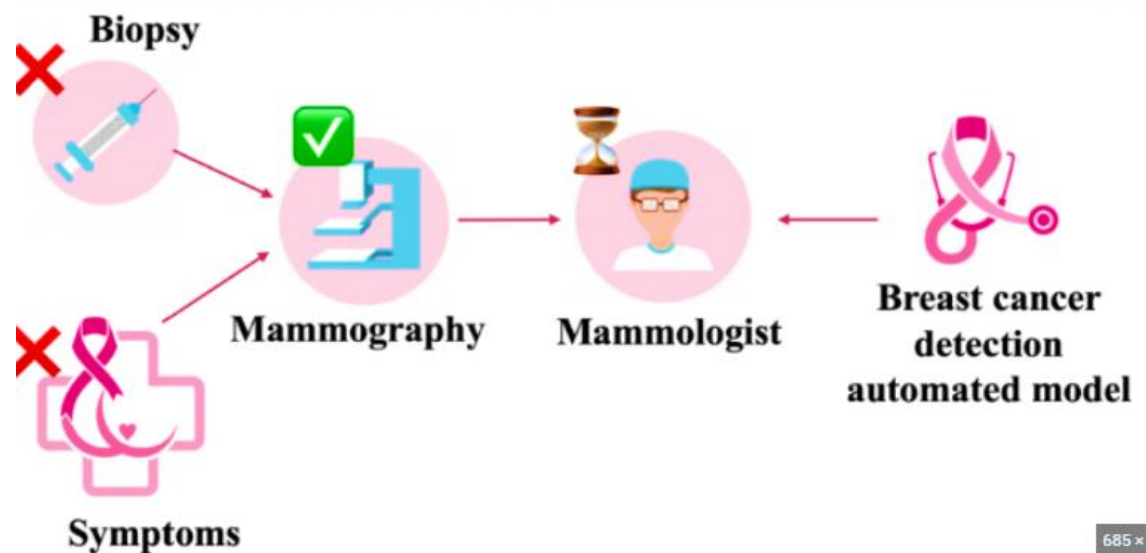


Figure 1.
Breast cancer screening [6].

This paper is structured as follows: The first part presents an extensive Literature Review of pertinent methodologies and their applications. Subsequently, this work examines Linear Regression in Medical Concepts, emphasizing its simplicity and prevalent use in diagnostic methods and the integration of fuzzy logic systems with linear Regression, highlighting the synergistic advantages of amalgamating both methodologies. The following section examines the limitations of Linear Regression and Fuzzy Logic when used independently. Then, we will concentrate on the use of linear Regression in breast cancer detection, elucidating its particular function and influence. Ultimately, this work provides Recommendations for Future Research to address current problems and enhance diagnosis accuracy, followed by a summary of significant insights in the Conclusion.

2. Literature Review

Fuzzy logic is a rather intricate methodology that offers appropriate tools to address issues regarding the diagnostic practice of common diseases, including breast cancer. Some authors, such as Tjendra, et al. [7] note that converting machine learning to binary classification is a problem when the situation is entirely different. This, according to them, will be disadvantageous if patients' possible severity groups are categorized because disease processes may be different. According to Jindal, et al. [8] there is a certain level of truth towards which this perspective leans by demonstrating how fuzzy logic can make propositions at least partially true. They also explain how fuzzy logic systems can not only refer to tumour results as malignant or non-malignant, as most models do but also can express the probability of malignancy as 70 percent, for instance. The same idea is pointed out in both of the studies.

While Tjendra, et al. [7] provided the theoretical contribution of fuzzy logic, Jindal, et al. [8] have described the applicative utility of such systems, arguing how such systems can increase the accuracy of diagnosis. In addition, Jindal, et al. [8] also labelled the computational part of the fuzzy system as being potentially more challenging in the resource-constraint environment; this was not elucidated by Tjendra, et al. [7]. Hence, using fuzzy logic in conjunction with medical diagnosis yields a more attractive approach than conventional diagnosis. If more categories of patient data can be discerned than a traditional sharp set of categories, then the use of fuzzy logic may minimize the chances of an improper diagnosis. These asymmetries increase the need for theoretical analysis and methodization in the advancement of clinical diagnostic technologies while at the same time provoking negative externality costs in terms of resources. Moreover, much research has been conducted in the medical Area using leaner regressions. Linear Regression is widely applied for data analysis in Medical Research because they have a basic understanding of them and their interpretations. However, arguing differently from the above approach, the authors [9] held the opinion that instead of linearity, polynomial Regression could be much more effective because of its power and capability to deal with nonlinearity. This opens a third dimension in arguing that while linear Regression may be practical, it is essential to be able to think of other forms of regression analysis that could be useful in managing medical data configurations. Thus, linear regression analysis is a valuable method for breast cancer risk prediction, but its usage is only appropriate. It also implies that more complex modelling methods are needed, which is even more apparent when considering the amount of data produced in biological applications. To effect better diagnostic results in the future, it will be helpful in studies to attempt to extend the implementation of linear Regression with other forms of Regression, such as polynomial Regression.

Gomila [10] also describes how this model's use in developing risk scores lets clinicians assess the probability of breast cancer based on various patient descriptors, such as age and tumour. Stressed the possibility of using linear Regression in order to make an initial estimation of risk on the same subject. However, according to Mullahy and Norton [11] this approach has been refuted since linear Regression is a deficit when considering the medical data with large dimensions processed. They stress that biological datasets may encompass relationships of the second and higher orders, which are not adequately described in linear components. Again, both authors use the linear regression model, but while acknowledging the merits of this model across different areas of analysis, where it could really be easy to apply, the authors diverge in relation to its applicability in clinical practice. Mullahy and Norton [11] Established that fixed association, in this sense, oversimplifies the matter.

Much research has been conducted on Integrating Fuzzy Logic Systems and Linear Regression. By integrating both methodologies, the system can manage ambiguous and imprecise input data using fuzzy logic while simultaneously delivering accurate predictions through Regression when feasible. Integrating Fuzzy Logic with Linear Regression capitalizes on the advantages of both methodologies: fuzzy logic's proficiency in managing ambiguity and uncertainty and linear Regression's capability for accurate, linear predictive modelling. This results in enhanced performance in intricate, real-world situations.

Linear Regression with a degree of fuzzy logic added helps to increase the model's reliability in diagnosing breast cancer. Petrović, et al. [12] Described how these methodologies could be integrated, pointing out, for instance, that fuzzy logic could be utilized to address uncertainty while linear Regression could be used for interpretability; on the other hand, Guo, et al. [13] on the other hand is interested in the application of the synergy of the fuzzy linear regression hybrid models where it is pointed out that it leads to improvement in model stability As such, both studies support the use of the combination of fuzzy logic and linear Regression. However, they have conceptual differences in their methodologies. Petrović, et al. [12] provided a rationale for the integration, and the authors of the current manuscript make the conceptual claim for integrating these approaches. However, Guo, et al. [13] provided concrete figures on how much a hybrid model increases predictive efficiency. In addition to this, the author also fixed the hybrid models against linear Regression to demonstrate a comparable

increase in both accuracy and recall, consequently proving not only an enhancement in the predictive ability but also the alleviation of some of the disadvantages occasioned by the applicability of linear Regression alone [13]. Consequently, the utilization of fuzzy logic and linear Regression is a promising way to develop the existing state of breast cancer detection further. Integrated approaches would present better models and diagnostic tools because the two integration strategies are harmonious. These differences in focus imply that there is a need for practical validation of this integration besides rationality in building this integration and the capacity of such hybrid techniques to offer better results than purely classical methods.

3. Limitations of Linear Regression and Fuzzy Logic

Several issues arise about its relevance and limitations offered by linear Regression and fuzzy logic. Discussing the methods for detecting breast cancer, the results presented come with disappointments that a researcher cannot help but encounter. Some claim that while linear Regression is helpful in gaining some basic introduction, the model deteriorates when there are multiple interactions between predictors. Also, Xu, et al. [14] elaborate the same, asserting that linear Regression is as basic as it gets yet utterly incapable of predicting medical data. Besides that, they also find that linear Regression could lead to inaccurate outcomes should there be significant outliers or a skewed data set.

Conversely, Wang, et al. [9] provide a means for managing some of the vices observed when performing linear Regression. It is not an easy task. Another critical argument presented is that fuzzy logic systems depend on the degree of accuracy defining membership functions and employing them is very much like being an expert [14]. Furthermore, one must pay attention to the fact that the results obtained through the identification and usage of the structure of fuzzy models depend on the quality of input information, which proves the exceptional significance of data correction and management. A comparative analysis by Silva Araújo, et al. [15] suggests that the usage of fuzzy logic can be more precise and recall a higher number of cases than a linear regression model, thus noting that the process of applying the fuzzy system can be complicated due to the system's complexity, as well as not so suitable for the clinical setting.

These differences in applicability indicate that a combination of these approaches may be required in order to get the best of both methodologies without the pitfalls. For example, they improve the input variables by using fuzzy logic to make some linear regression models more accurate while maintaining their interpretability. Therefore, even though linear Regression and fuzzy logic can be used for breast cancer detection, their drawbacks must be considered. These findings indicate that combined approaches may be more effective for dealing with medical data complexity and enhancing diagnosis. Further work should be aimed at creating the theory for modelling using a linear regression approach with elements of fuzzy logic.

4. Application of Linear Regression in Breast Cancer Detection

Linear Regression is one of the most important tools for making predictions in statistics and the most popular method of regression analysis. It helps explain the relationship between certain diagnostic features of the tumour – size, texture, shape, and possibility of the tumour being malignant when applied to the detection of breast cancer. For example, a linear regression may recommend the probability of breast cancer given the size of the tumour, the age of the patient, and her hormonal status if she is a female. As mentioned, ordinary least square Linear Regression is primarily used with continuous data. However, it can be employed for such assignments as breast tumour diagnosis where some predefined threshold other than zero has been obtained for distinguishing between malignant and benign tumour volumes. Applications of linear regression in breast cancer can be seen in Figure 2.

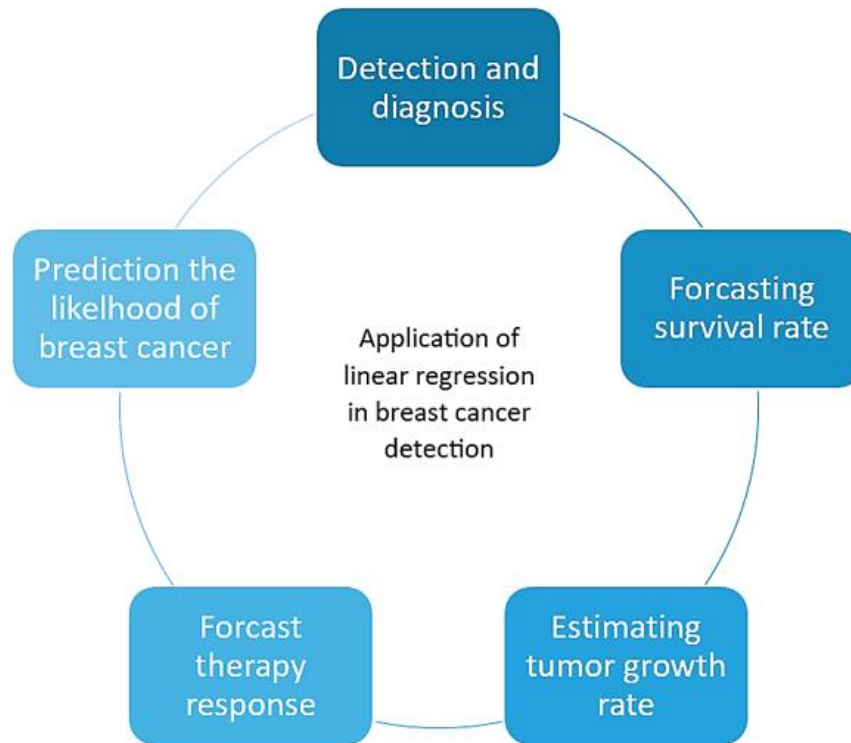


Figure 2.
Application of linear regression in breast cancer detection.

Linear Regression is an effective instrument in breast cancer detection and diagnosis, offering significant insights for early identification, prognosis, and tailored treatment strategies. This methodology can be utilized to forecast tumour dimensions and associated risks, analyse breast cancer survival, examine correlations among clinical characteristics, and conduct genetic and molecular biomarker assessments. Additionally, it facilitates tumour growth rate estimation, risk factor quantification, recurrence prediction, breast density classification, mammogram image analysis, and treatment response forecasting [1, 16].

Moreover, Linear regression models elucidate the association between independent factors such as age, tumour size, and other clinical characteristics and the likelihood of malignancy. It furthermore aids in forecasting patient survival rates based on these variables, informing individualized therapy strategies. It also aids in identifying links between clinical characteristics and cancer risk, assisting oncologists in pinpointing critical elements that contribute to cancer development [17].

In addition, Genetic and molecular biomarkers may be analysed using linear Regression to uncover associations between certain biomarkers and cancer incidence, facilitating early identification or tailored therapies. Estimating tumor growth rate involves examining variations in tumor size from sequential imaging scans, tracking cancer development, and assessing treatment efficacy over time [18].

Moreover, linear Regression may be used to identify breast density, characterize imaging attributes, and forecast therapy response. Through the analysis of clinical and genetic data, it may aid in determining the most efficacious treatment approach for patients. Linear Regression is an essential instrument in breast cancer detection and diagnosis, offering data-driven insights that improve early detection, prognosis, and individualized treatment strategies [19]. By integrating both methodologies, the system can manage ambiguous and imprecise input data using fuzzy logic, while simultaneously delivering accurate predictions when feasible through Regression. Integrating Fuzzy Logic with Linear

Regression capitalizes on the advantages of both methodologies: fuzzy logic's proficiency in managing ambiguity and uncertainty, and linear Regression's capability for accurate, linear predictive modelling. This results in enhanced performance in intricate, real-world situations.

To be more precise, Wang, et al. [9] in one of their studies, pointed out that linear Regression could predict the likelihood of breast cancer by using parameters such as age, family history, and tumor size. However, assuming linear relationships are very unrealistic in most of the big biological datasets, linear Regression is used as the first step to identify trends among medical data due to its simplicity. Also, applying linear regression models works because the overall types of models are rather interpretable. This is beneficial because the physicians can easily discern how each variable contributes to the models to design the models' recommendation systems. The difference between these models and more elaborate models like gross neural nets, which are often accused of making predictions without explaining them [20, 21] As shown in Table 1, a comparison of fuzzy logic (linear regression) with other models such as decision trees and neural networks. The comparison handling nonlinearity, interpretability, handling uncertainty, computational complexity, accuracy, flexibility in medical diagnosis, sensitivity to outliers, and data requirements.

Table 1.
Comparison of Fuzzy Logic (Linear Regression) with Other Models.

Feature	Fuzzy Logic (with Linear Regression)	Decision Trees	Neural Networks
Handling nonlinearity	Nonlinearity is managed to some extent using fuzzy logic, but it suffers from having a linear regression model.	The decision trees can easily manage nonlinearity through multiple splits of the tree.	It does exceptionally well when capturing interactions of second and higher order.
Interpretability	Somewhat interpretable, fuzzy rules and linear coefficients can at least be explained (see Fig 1.).	It is highly interpretable; it is easy to visualize and understand the decision-making process at each tree node.	It is not very interpretable; architectures are densely complex. Thus, it is famously referred to as the 'black box.'
Handling Uncertainty	Copes well with uncertainty using fuzzy sets and degrees of membership.	It was resolved by making dichotomy decisions, which were less in comparison with fuzzy logic than statistics.	It is good at working with uncertainty but, unlike fuzzy logic, does not natively deal with ambiguity.
Computational Complexity	Moderate because of integrating the fuzzy logic concept with the linear regression technique.	Vary from a low to moderate level, depending on how detailed and extensive the tree is.	Those have high computational complexity, especially when using deep neural networks.
Accuracy	When used in uncertain data conditions, high accuracy is obtained when the data is analyzed with fuzzy logic as well as linear Regression.	High accuracy has been demonstrated on structured data, while performance has significantly deteriorated on noisy or complex data.	When large numbers are used as samples, very high accuracy is possible in complicated chores.
Flexibility in Medical Diagnosis	Fuzzy logic is very flexible while handling medical data, while linear Regression gives a clean output of the likely prediction.	A decision process is standardized and convenient to determine; it could be more suitable for ambiguous situations.	Such flexibility in modeling is particularly suitable for image analysis and multiple-factor predictions.
Sensitivity to Outliers	Superior to simple linear Regression due to the mature fuzzy logic of classifying the data.	Noisy data pose a difficulty, but it is not significant compared to other problems, and pruning counteracts overfitting.	They are significantly influenced by outliers unless techniques such as regularization are used.
Data Requirements	Fuzzy logic is sensitive to small to moderate amounts of data; it can learn from and reason with limited or even ambiguous data.	Gains a medium amount of information; when the data are too small, it tends to overfit.	It is limited by the demand for large datasets in order to get the best performance, especially in deep learning.

5. Recommendations for Future Research

It is suggested that future work on the detection of breast cancer should continue to improve the hybrid model that combines fuzzy logic with better artificial intelligence mechanisms. Although I fundamentally agree with the idea of using fuzzy logic systems over the linear regression methods when it comes to breast cancer risk assessment, Silva Araújo, et al. [15] pointed out better accuracy and recall. As per their recommendations, they argued that fuzzy logic can enhance risk assessment outcomes in cases where data are questionable. Altameem, et al. [22] affirm this claim by analyzing the role of fuzzy logic with linear Regression in the assessment of mammograms. Researchers identify enhanced performance measures and thus conclude that, overall, hybrid strategies have great potential to outcompete conventional methods. As both these studies acknowledge that the application of both fuzzy logic and linear Regression for integration is feasible, their approaches deviate with respect to the considerations of particular areas of use and ways of their application. Silva Araújo, et al. [15] elaborate on the theoretical benefits; however, Altameem, et al. [22]; Murad and Badeel [23] and Adday, et al. [24]. Show better results from the research. It is essential to continue research in this field as this example indicates the versatility of the use of fuzzy logic.

In addition, the researchers should look forward to applying fuzzy logic combined with other higher-order intelligent mechanisms like deep learning algorithms. A paper by Baldwin [25] and Murad, et al. [26] shows that higher numbers, such as Top 5 errors, can be reduced through integrating deep learning the linear regression formula, even though this decreases performance substantially in accuracy in comparison to standard models. It would be exciting to investigate how fuzzy logic might help deepen architectures of deep learning for breast cancer detection and whether new venues for better possible diagnosis can be accomplished.

Hence, there is a proposition that combining fuzzy logic with other higher-order modeling tools like neural nets and decision trees may improve the prospects for breast cancer detection. Future studies should focus on broadening such models to deal with the challenges in clinical data and enhance the accuracy of diagnosis. In this context, it will be possible to strengthen the potential of fuzzy logic combined with improved AI approaches that can open the right avenue towards breast cancer diagnosis with higher efficiency and accuracy.

6. Conclusions

Conclusively, though easy to understand and interpret, linear Regression tends to produce poor results in the case of breast cancer detection because it assumes linearity and is highly sensitive to noisy data. At the same time, it can prove helpful in understanding certain relationships between the parameters, for instance, the tumor size and the risk of malignancy, while being much less accurate than the neural networks. The integration of fuzzy logic is quite significant by providing a solution to data uncertainty besides dealing with nonlinearity. To overcome the limitations of linear regression models are made fuzzy, the predictions are more accurate and outperform the other parameters like precision and recall, mainly in the conditions when the medical data varies. Some works prove that adding fuzzy logic to the linear Regression improves the results obtained by the linear Regression alone, showing that a hybrid approach of these two techniques can be a good solution for the first stage of breast cancer diagnosis.

Funding:

This research was supported by the Ministry of Higher Education (MOHE) through the Fundamental Research Grant Scheme (FRGS/1/2024/STG06/UTHM/02/2).

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

© 2025 by the authors. This open-access article is distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

References

- [1] S. K. Ali and W. K. Mutlag, "Early detection for breast cancer by using fuzzy logic," *Journal of Theoretical and Applied Information Technology*, vol. 96, no. 17, pp. 5717-5728, 2018.
- [2] R. Badeel, S. K. Subramaniam, Z. M. Hanapi, and A. Muhammed, "A review on LiFi network research: Open issues, applications and future directions," *Applied Sciences*, vol. 11, no. 23, p. 11118, 2021. <https://doi.org/10.3390/app112311118>
- [3] R. Belohlavek, J. W. Dauben, and G. J. Klir, *Fuzzy logic and mathematics: A historical perspective*. United Kingdom: Oxford University Press, 2017.
- [4] J. Yen, "Fuzzy logic-a modern perspective," *IEEE Transactions on Knowledge and Data Engineering*, vol. 11, no. 1, pp. 153-165, 1999. <https://doi.org/10.1109/69.755624>
- [5] R. Badeel, S. K. Subramaniam, A. Muhammed, and Z. M. Hanapi, "A multicriteria decision-making framework for access point selection in hybrid LiFi/WiFi networks using integrated AHP-VIKOR technique," *Sensors*, vol. 23, no. 3, p. 1312, 2023. <https://doi.org/10.3390/s23031312>
- [6] A. Alloqmani, Y. B. Abushark, and A. I. Khan, "Anomaly detection of breast cancer using deep learning," *Arabian Journal for Science and Engineering*, vol. 48, no. 8, pp. 10977-11002, 2023. <https://doi.org/10.1007/s13369-023-07945-z>
- [7] Y. Tjendra *et al.*, "Predicting disease severity and outcome in COVID-19 patients: A review of multiple biomarkers," *Archives of Pathology & Laboratory Medicine*, vol. 144, no. 12, pp. 1465-1474, 2020. <https://doi.org/10.5858/arpa.2020-0471-SA>
- [8] N. Jindal *et al.*, "Fuzzy logic systems for diagnosis of renal cancer," *Applied Sciences*, vol. 10, no. 10, p. 3464, 2020. <https://doi.org/10.3390/app10103464>
- [9] H. Wang, R. J. MacInnis, and S. Li, "Family history and breast cancer risk for Asian women: A systematic review and meta-analysis," *BMC Medicine*, vol. 21, no. 1, p. 239, 2023. <https://doi.org/10.1186/s12916-023-02950-3>
- [10] R. Gomila, "Logistic or linear? Estimating causal effects of experimental treatments on binary outcomes using regression analysis," *Journal of Experimental Psychology: General*, vol. 150, no. 4, p. 700, 2021. <https://doi.org/10.1037/xge0000920>
- [11] J. Mullahy and E. C. Norton, "Why transform Y? A critical assessment of dependent-variable transformations in regression models for skewed and sometimes-zero outcomes (No. w30735)," National Bureau of Economic Research, 2022.
- [12] D. V. Petrović, M. Tanasijević, S. Stojadinović, J. Ivaz, and P. Stojković, "Fuzzy model for risk assessment of machinery failures," *Symmetry*, vol. 12, no. 4, p. 525, 2020. <https://doi.org/10.3390/sym12040525>
- [13] Y. Guo, W. Wang, and X. Wang, "A robust linear regression feature selection method for data sets with unknown noise," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 1, pp. 31-44, 2021. <https://doi.org/10.1109/TKDE.2021.3076891>
- [14] Y. Xu, Z. Wang, Z. Li, Y. Yuan, and G. Yu, "SiamFC++: Towards robust and accurate visual tracking with target estimation guidelines," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 7, pp. 12549-12556, 2020. <https://doi.org/10.1609/aaai.v34i07.6944>
- [15] V. J. Silva Araújo, A. J. Guimarães, P. V. de Campos Souza, T. S. Rezende, and V. S. Araújo, "Using resistin, glucose, age and BMI and pruning fuzzy neural network for the construction of expert systems in the prediction of breast cancer," *Machine Learning and Knowledge Extraction*, vol. 1, no. 1, pp. 466-482, 2019. <https://doi.org/10.3390/make1010028>
- [16] R. Badeel, *Is LiFi technology ready for manufacturing and adoption? An end-user questionnaire-based study*. Iraq: Mesopotamian Press, 2024.
- [17] Q. Al-Tashi *et al.*, "Machine learning models for the identification of prognostic and predictive cancer biomarkers: A systematic review," *International Journal of Molecular Sciences*, vol. 24, no. 9, p. 7781, 2023. <https://doi.org/10.3390/ijms24097781>
- [18] C. Rödel *et al.*, "Prognostic significance of tumor regression after preoperative chemoradiotherapy for rectal cancer," *Journal of Clinical Oncology*, vol. 23, no. 34, pp. 8688-8696, 2005. <https://doi.org/10.1016/j.jco.2004.11.040>

- [19] P. Lambin *et al.*, "Radiomics: The bridge between medical imaging and personalized medicine," *Nature Reviews Clinical Oncology*, vol. 14, no. 12, pp. 749-762, 2017. <https://doi.org/10.1038/nrclinonc.2017.141>
- [20] S. S. Murad, S. Yussof, and R. Badeel, "Wireless technologies for social distancing in the time of COVID-19: Literature review, open issues, and limitations," *Sensors*, vol. 22, no. 6, p. 2313, 2022. <https://doi.org/10.3390/s22062313>
- [21] R. Badeel, "Introduction to Wi-Fi 7: A review of history, applications, challenges, economical impact, and research development," *Mesopotamian Journal of Computer Science and Communication*, pp. 1-9, 2024. <https://doi.org/10.58496/MJCSC/2024/009>
- [22] A. Altameem, C. Mahanty, R. C. Poonia, A. K. J. Saudagar, and R. Kumar, "Breast cancer detection in mammography images using deep convolutional neural networks and fuzzy ensemble modeling techniques," *Diagnostics*, vol. 12, no. 8, p. 1812, 2022. <https://doi.org/10.3390/diagnostics12081812>
- [23] S. Murad and R. Badeel, "Optimized Min-Min task scheduling algorithm for scientific workflows in a cloud environment," *J. Theor. Appl. Inf. Technol.*, vol. 100, no. 2, pp. 480-506, 2022.
- [24] G. H. Adday, S. K. Subramaniam, Z. A. Zukarnain, and N. Samian, "Friendship degree and tenth man strategy: A new method for differentiating between erroneous readings and true events in wireless sensor networks," *IEEE Access*, vol. 11, pp. 127651-127668, 2023. <https://doi.org/10.1109/ACCESS.2023.1234567>
- [25] J. D. Baldwin, "Propensity and generalized propensity score estimation among nonlinearity and high dimensionality, using common and machine learning techniques," Doctoral Dissertation, The University of Oklahoma Health Sciences Center. ProQuest Dissertations & Theses Global, 2024.
- [26] S. S. Murad, R. Badeel, R. A. Ahmed, and S. Yussof, "Using drones and robots for social distancing: Literature review, challenges and issues," presented at the 2024 Panhellenic Conference on Electronics & Telecommunications (PACET), IEEE, 2024.