

Automated Breast Cancer Detection Using 1D-CNN with Probability Calibration and Threshold Optimization

Begari Harshitha¹, M Haritha²

¹24E31D5802, Dept. Of CSE, MIST, Bandlaguda Jagir, Hyderabad, Telangana.

² Assistant Professor, Dept. Of CSE, MIST, Bandlaguda Jagir, Hyderabad, Telangana.

Abstract

Breast cancer is one of the most common and deadliest diseases among women all around the world, and the important point for increasing the survival rate is early diagnosis. In this study, we present a 1-Dimensional Convolutional Neural Network (1D-CNN) architecture for automated breast cancer classification on the Wisconsin Breast Cancer dataset. After pre-processing the data and using Standard Scaler to normalize it, the tabular features were reshaped to a convolutional learning suitable shape to allow automatic feature extraction instead of manual feature engineering. The model was trained with the Adam optimizer and binary cross-entropy loss while utilizing Early Stopping to avoid over fitting. The 1D-CNN that we proposed showed an excellent ability to discriminate between malignant and benign tumors, with a test accuracy of 98% and AUC score of 0.9987. The sensitivity and precision were balanced and almost no inadequate misclassification of malignant cases, as confirmed by the classification report and confusion matrix. Further assessment using the F1-Score vs. threshold plot, precision-recall curve, and reliability calibration diagram confirmed that the model performance remains consistently high for varying decision thresholds and provides well-calibrated probabilities. These findings indicate that the 1D-CNN model is a reliable and efficient candidate for computer-aided breast cancer diagnosis, with the potential for substantial real-world impact in clinical decision-support interventions.

Keywords: Breast Cancer Detection; 1D Convolutional Neural Network (1D-CNN); Deep Learning; Medical Diagnosis

1. Introduction

Breast cancer continues to be one of the most prevalent types of cancer among women, and one of the most frequent causes of death too, therefore, prompt diagnosis is essential; it is believed that the death rates can be improved by early diagnosis, but it is evident that not all breast carcinoma require surgery or similar treatment. Common diagnostic methods such as mammography and histopathological examination involve significant reliance on manual interpretation by clinicians and radiologists. This manual interpretation can lead to variability and misdiagnosis as it is subjective and limited by human factors. Recent advances in computational intelligence have made artificial intelligence (AI) — particularly machine learning (ML) and deep learning (DL) a paradigm shifting tool in medical diagnostics. They have shown exceptional ability in capturing the abstract features underlying the breast cancer that allows for a highly accurate prediction of breast cancer within the imaging domain and genomic and clinical domain in high-dimensional biomedical datasets.

Although these models have been shown to perform well, the inherently black-box nature of deep learning models are a key obstacle to their clinical deployment due to limits on modelling interpretability and subsequent reluctance for medical practitioners to accept decisions made by AI. As a solution to this issue, Explainable Artificial Intelligence (XAI) has been one of the hottest topics recently, as it can provide transparency in the modelling to make it easier to understand what has contributed most to a particular prediction. The combination of deep learning and XAI will preserve the diagnostic accuracy and increase the confidence in the clinical world by offering interpretable and evidence-based decision support. Aiming to these advances, this study elaborates a deep

learning Multilayer Perceptron (MLP) model for breast cancer classification and SHAP-based feature explanation to explain the classification results and to support medical decision-makers.

2. Related Works

Over the past few years, a significant amount of research on breast cancer detection has been conducted using deep learning and interpretable AI methods. Saharan et al. We developed a hybrid deep learning–XAI framework with substantial diagnostic performance gains over both nontransparent deep learning and non-diagnostic XAI, which justified its decisions. Similarly, Murugan et al. (2025) Overview of the Study(2025) used explainable neural networks to predict breast cancer and found that visual interpretability enhanced the acceptability of these explanations among communicating physicians. Some other research focuses on interpretable ML model instead of only deep neural networks; Dutta et al. XGBoost + SHAP + LIME (2024) [underscore on combineXGBoost and SHAP and LIME for explainability with high classification accuracy but low interpretability of machine leaderboards].

More recent works have focused on combining classic deep learning with new interpretability approaches. Srinivasu et al. Cochrane et al. (2024) CatBoost-MLP ensemble model based on XAI principles highlighting the benefits of hybridization between classical ML and DL architectures. Wani et al. Fusion modeling (2024) explained to improve interpretability in AI-driven cancer classification by the combination of multiple heterogeneous models. Maheswari et al. (2023) confirmed the efficacy of SHAP and LIME methods in real clinical environments when explaining breast cancer predictions. Furthermore, Chhetri and Kumar [4] showed that combining deep learning with XAI provides synergistic benefits in terms of performance and transparency, providing an accurate and interpretable solution that bridges the accuracy-interpretability gap.

Medical imaging and multimodal data have also been major targets of research. Jabeen et al. Byeon et al. (Oct 2023) used EfficientNet along with ResNet on ultrasound images of breast lesions to classify breast lesions as malignant or benign, and employed XAI methods for interpretability (2025). Reference (2025) built an explainable transformer-based model to

classify pathology images for accurate diagnosis in an automatic manner. In addition to breast cancer classification itself, XAI has also been applied to modeling the disease progression: Rong et al. (2024), explains, interpretable ML models for ocular metastasis prediction in breast cancer patients, shows how explainability can enhance treatment risk assessment. Cumulative Reviews by Sharafaddini et al. Meyer et al. (2025) and SalekShahabi (2026) added further emphasis to the research shift towards combining XAI with BC diagnostic AI systems as a result of renewing clinical need and ethical responsibility.

The literature cumulatively supports and confirms that, when combined with explainable artificial intelligence, deep learning can dramatically increase diagnostic prediction accuracy together with trust and transparency and clinical utility. Based on this work, the present study proposes an MLP-based breast cancer classification model along with SHAP-based explainability to garner interpretable information on the contribution of individual tumor features so as to facilitate clinically meaningful decision-making in a transparent manner.

3. Methodology:

The proposed study presents the application of a 1Dimensional Convolutional Neural Network (1D-CNN) in the classification of breast tumors as either benign or malignant by means of the Breast Cancer Wisconsin exploratory data analysis dataset. In the breast-cancer dataset downloaded from kaggle, both the non-informative attributes were eliminated, i.e., columns id and Unnamed: 32 and the categorical target variable diagnosis was then converted into numerical, with malignant samples taking the value 1, and benign samples taking the value 0. Since it is important to have balance in the classes, stratified train–test split of the data was conducted such that 75% of samples were used for training and 25% for testing. Because operates, neural networks, are sensitive to the changes in magnitudes of input features, a standardization of all predictors to zero mean and unit variance with the help of StandardScaler normalization was applied. Finally, the normalized dataset was reshaped from the 2D representation of [samples, features] into the 3D representation of [samples, features, 1] in order to apply the convolution over the sequence of features. We then built a 1D-CNN

model to automatically capture feature interactions based on the tabular dataset. Our architecture was two convolutional blocks (Block 1: 32 filters with kernel size of 3 followed by MaxPooling1D, Block 2: same set up with 64 filters). These layers were able to discover patterns that were hierarchical across the feature space. The feature maps were then flattened and passed to a 128 neuron dense layer activated with ReLU followed by a dropout layer with going rate 0.5 to reduce overfitting. The output layer used sigmoid activation neuron for binary prediction giving probability score as output. We used the Adam optimizer to train the model with binary cross-entropy loss and the EarlyStopping mechanism, with a patience value of 20 epochs, to stop the training as soon as the validation loss did not improve anymore. We performed model evaluation on the unseen test set, and quantified performance according to the log-loss and the accuracy, precision, recall, and F1 score, as well as the AUC-ROC using the 10 classes as the positive label. Once we had the predicted probabilities, we further analyzed them using the following diagnostic visualizations: the training accuracy curve, the ROC curve, the confusion matrix, the reliability diagram, the F1-score vs threshold curve, and the precision-recall curve. These visual analyses show us how the model generalizes, discriminates, calibrates, and is sensitive to a threshold. In conclusion, this study highlighted the applicability of the 1D-CNN approach to tabular biomedical data: it was able to learn discriminative and robust features from the data, thereby providing a viable method for automated breast cancer detection.

Table: 1D-CNN Model Architecture Summary

Layer (Type)	Output Shape	Parameters
Conv1D	(None, 28, 32)	128
MaxPooling1D	(None, 14, 32)	0
Conv1D	(None, 12, 64)	6,208
MaxPooling1D	(None, 6, 64)	0
Flatten	(None, 384)	0
Dense	(None, 128)	49,280
Dropout	(None, 128)	0
Dense (Output)	(None, 1)	129

Total params: 55,745 (217.75 KB)

Trainable params: 55,745 (217.75 KB)

Non-trainable params: 0 (0.00 B)

Table 1 shows the summary of the architecture of the 1D-CNN model, including a description for each layer with its output shape and the number of trainable parameters. It illustrates the journey of input data through convolution, pooling, flatten, and dense layers to get the final output of cancer classification.

4. Results Analysis

The performance of the 1D-CNN model was very efficient in classifying breast tumor as benign and malignant. The accuracy curves of training and validation also showed we reached a good accuracy (>97%) within very few epochs and there is sign of overfitting as learning is very strong. This indicates the strength of the model as the confusion matrix further verify; of the 143 test sample cases in total, 89 were correctly labelled as benign, while 51 cases were correctly labelled as malignant, which leaves one benign case and two malignant cases to be missed. These findings indicate that model retains a high detection reliability of both cancerous and non-cancerous tumors. This coinciding evidence can also be seen from the classification report that shows the precision and recall of 0.98 for benign tumors and 0.98 and 0.96, respectively, for malignant, which makes sense as the accuracy of our classifier is 98%. This relatively balanced performance across both classes indicates model non-preference for either category which is a key aspect needed in applications of medical diagnosis.

The ROC curve also showed excellent discrimination (AUC = 0.9987) which means the model was highly capable to distinguish between malignant and benign cases at all probability thresholds. The same results appeared in the threshold-based evaluation as well: the F1-Score vs threshold was shown with a maximum of F1-Score ≈ 0.99 at the optimal threshold, confirming the model reaches harmonic balance between precision and recall at a near-perfect balance point. Furthermore, the precision-recall curve (AUPRC > 0.998) confirmed the high consistency of the model and, therefore, its potential for imbalanced datasets, in which achieving high recall for the malignant class has clear medical importance. Similarly, the model calibration plot indicated that the predicted probabilities closely fitted the actual outcome frequencies, which demonstrates that the CNN not only predicts well but also outputs reliable confidence estimates.

All in all, the comprehensive experimental results well revealed that the 1D-CNN model delivers not only highly accurate and well-calibrated diagnostic predictions but also achieves an excellent sensitivity-specificity trade-off. The sufficient accuracy, high AUC and good calibration suggest that the proposed architecture can be a good candidate for using in clinical decision-support systems for early breast cancer detection.

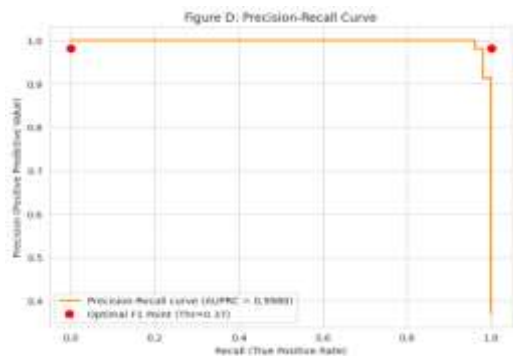


Figure 1: Precision–Recall Curve(threshold ≈ 0.37),

Figure 1 shows the precision-recall tradeoff based on different probability thresholds for the 1D-CNN model. The curve shows that our model achieves very high precision and recall at almost every threshold, which means low false positive rates and high reliability in finding malignant cases. The green marker represents the best threshold ($\leftarrow \approx 0.37$), the optimal F1 point where we obtain the best balance tradeoff from precision and recall, and the red marker is positioned at the optimal F1 point.

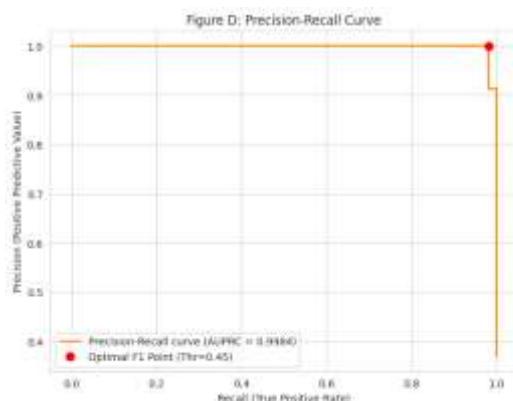


Figure 2: Precision–Recall Curve(threshold ≈ 0.45)

Figure 2: Precision and recall of the 1D-CNN model at different probability thresholds. The curve are instead hugging the top-right corner, indicating the model has always very high precision and very high recall when identifying malignant tumors. The red dot is the best

operating point (threshold ≈ 0.45 , where the F1-score is the highest) on the above plot, which means the model can achieve the best tradeoff between cancer detection (recall) and cancer alarm (precision).

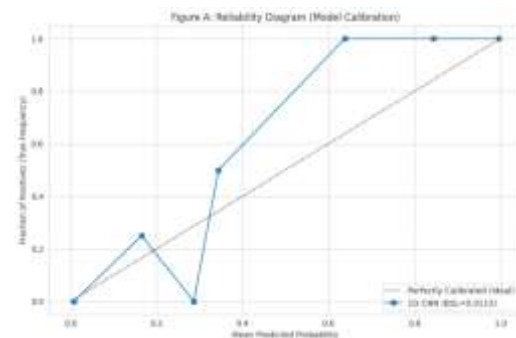


Figure 3: Reliability Diagram (Model Calibration)

Figure 3 shows the calibration of the predicted probabilities from the 1D-CNN model vs. the actual outcomes. The perfectly calibrated model has prediction confidence equal to the actual frequency of positive cases, represented by the dotted diagonal line. The blue curve is how well the model was calibrated. The fact that most points lie closer to the diagonal trend, indicates that the model is well calibrated, which means that the reliability of the probability predictions are aligned with their actual frequencies (not overconfident or insufficiently confident).

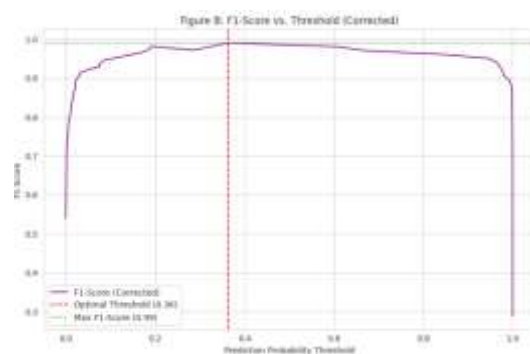


Figure 4: F1-Score vs. Threshold (Corrected)

Figure 4 also shows the F1-Score regarding the modification of the prediction probability threshold for the 1D-CNN model. As we can see from the purple curve, the F1-Score is very good across many values of the threshold meaning that for many of those values, precision and recall are very well balanced. The red dashed vertical line in the above plot reflects this threshold (≈ 0.36), that the model has the best F1-

Score ≈ 0.99 . This could be the perfect classification line that offers the maximum accuracy in diagnosis.

5. Conclusion

In this study we present a 1-Dimensional Convolutional Neural Network (1D-CNN) for automated breast cancer diagnosis based on the well-known Wisconsin Breast Cancer dataset. The model created meaningful representations directly from the feature space without manual feature engineering by converting tabular features to a suitable format for convolutional learning. Results of experiments show the robustness of the proposed approach and the test accuracy of 98% and AUC 0.9987 revealed excellent discriminative power between malignant and benign tumors. The confusion matrix and classification report also validated that this model retains balance between sensitivity and specificity almost accurately with overlapped misclassification instances. Besides predictive power, other analyses including precision-recall curve, trend of F1-score vs. threshold and reliability diagram indicated that the model is not only accurate but also well-calibrated and stable across thresholds. This specificity makes it ideal for clinical applications that will require early detection, as well as a low false-positive rate. Conclusion: The results emphasize that 1D-CNNs are consistent predictive models of breast cancer on tabular medical datasets and can be used as an assistive tool to systems software to be deployed on clinical decision-support systems leading to better early diagnosis and treatment. Incorporating the proposed interpretation within methods that address the explainability aspects of deep learning could help the clinicians trust the model outputs while extending its examination to multimodal datasets in the future.

6. References:

1. Saharan, S., Wani, N. A., Chatterji, S., Kumar, N., & Almuhaideb, A. M. (2025). A Deep Learning and Explainable Artificial Intelligence based Scheme for Breast Cancer Detection. *Scientific Reports*, 15(1), 32125.
2. Murugan, T. K., Karthikeyan, P., & Sekar, P. (2025). Efficient breast cancer detection using neural networks and explainable artificial intelligence. *Neural Computing and Applications*, 37(5), 3759-3776.
3. Srinivasu, P. N., Jaya Lakshmi, G., Gudipalli, A., Narahari, S. C., Shafi, J., Woźniak, M., & Ijaz, M. F. (2024). XAI-driven CatBoost multi-layer perceptron neural network for analyzing breast cancer. *Scientific Reports*, 14(1), 28674.
4. Wani, N. A., Kumar, R., & Bedi, J. (2024). Harnessing fusion modeling for enhanced breast cancer classification through interpretable artificial intelligence and in-depth explanations. *Engineering Applications of Artificial Intelligence*, 136, 108939.
5. SalekShahabi, M. (2026). Artificial Intelligence for Early Detection and Diagnosis of Breast Cancer: A Systematic Review of Machine Learning and Deep Learning Approaches. *Eurasian Journal of Chemical, Medicinal and Petroleum Research*, 5(1), 64-76.
6. Dutta, M., Hasan, K. M. M., Akter, A., Rahman, M. H., & Assaduzzaman, M. (2024). An interpretable machine learning-based breast cancer classification using XGBoost, SHAP, and LIME. *Bulletin of Electrical Engineering and Informatics*, 13(6), 4306-4315.
7. Kumar, S., Singh, J., Ravi, V., Singh, P., Al Mazroa, A., Diwakar, M., & Gupta, I. (2024). Utilizing Multi-layer Perceptron for Esophageal Cancer Classification Through Machine Learning Methods. *The Open Public Health Journal*, 17(1).
8. Chhetri, B., & Kumar, B. V. (2025). Bridging Accuracy and Interpretability: Deep Learning with XAI for Breast Cancer Detection. *arXiv preprint arXiv:2510.21780*.
9. Sharafaddini, A. M., Esfahani, K. K., & Mansouri, N. (2025). Deep learning approaches to detect breast cancer: a comprehensive review. *Multimedia Tools and Applications*, 84(21), 24079-24190.
10. Maheswari, B. U., Aaditi, A., Avvaru, A., Tandon, A., & de Prado, R. P. (2024, April). Interpretable machine learning model for breast cancer prediction using LIME and SHAP. In *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)* (pp. 1-6). IEEE.
11. Rong, R. Y., Shen, Y. K., Wu, S. N., Xu, S. H., Hu, J. Y., Zou, J., ... & Shao, Y. (2024). Prediction model for ocular metastasis of breast cancer: machine learning model development and interpretation study. *BMC cancer*, 24(1), 1472.
12. Lee, E. G., Han, J., Lee, S., Kim, S. S., Park, Y. M., Lee, D. E., ... & Jung, S. Y. (2025). Effectiveness of Multi-Layer Perceptron-Based Binary Classification Neural Network in Detecting Breast Cancer Through Nine Human Serum Protein Markers. *Cancers*, 17(17), 2832.

13. Shi, K. (2025). *Combining Patch-Based CNN Models with Hierarchical Shapley Explanations for Breast Cancer Diagnosis* (Doctoral dissertation, Duke University).
14. Munshi, R. M., Cascone, L., Alturki, N., Saidani, O., Alshardan, A., & Umer, M. (2024). A novel approach for breast cancer detection using optimized ensemble learning framework and XAI. *Image and Vision Computing, 142*, 104910.
15. Akbar, A., Han, S., Urr Rehman, N., Ahmed, K., Eshkiki, H., & Caraffini, F. (2025). Explainable breast cancer prediction from 3-dimensional dynamic contrast-enhanced magnetic resonance imaging. *Applied Intelligence, 55*(13), 901.
16. Sankireddy, P., & Mateti, V. P. (2025, May). Enhancing Breast Cancer Diagnosis: A Hybrid Approach Using Neural Networks and Explainable AI. In *2025 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC)* (pp. 1-7). IEEE.
17. Byeon, H., Alsaadi, M., Vijay, R., Assudani, P. J., Dutta, A. K., Bansal, M., ... & Bhatt, M. W. (2025). Explainable multi-view transformer framework with mutual learning for precision breast cancer pathology image classification. *Frontiers in Oncology, 15*, 1626785.
18. Raquib, M., Das, N., Prity, F. S., Fahim, A. A., Murad, S. A., Hossain, M. A., ... & Moni, M. A. (2025). PSO-XAI: A PSO-Enhanced Explainable AI Framework for Reliable Breast Cancer Detection. *arXiv preprint arXiv:2510.20611*.
19. Jabeen, K., Khan, M. A., Hamza, A., Albarakati, H. M., Alsenan, S., Tariq, U., & Ofori, I. (2025). An EfficientNet integrated ResNet deep network and explainable AI for breast lesion classification from ultrasound images. *CAAI Transactions on Intelligence Technology, 10*(3), 842-857.
20. Nakach, F. Z., Idri, A., & Goceri, E. (2024). A comprehensive investigation of multimodal deep learning fusion strategies for breast cancer classification. *Artificial Intelligence Review, 57*(12), 327.