

Hybrid Deep Learning and Machine Learning Approaches for Enhanced Breast Cancer Detection and Early Diagnosis

[1]Amol N. Dumbare, [2]Dr. Vijay Bhandari,

[1]Department of Computer Science and Engineering, Research Scholar, Madhyanchal Professional University, Bhopal, MP (India). amoldumbare12@gmail.com

[2]Professor, Department of Computer Science & Engineering, Madhyanchal Professional University, Bhopal, MP (India). bhandarivijay314@gmail.com

Abstract - Breast cancer remains one of the most critical health challenges worldwide, necessitating advancements in early detection to improve patient survival rates. This study aims to analyze the effectiveness of machine learning and swarm intelligence techniques in breast cancer detection, and to develop a multilayer deep learning model for accurate symptom identification. A cascaded model based on deep learning is proposed for enhancing the detection of early-stage breast cancer, which is vital for reducing invasive treatments like chemotherapy and surgery. The research also compares the performance of the proposed algorithm with existing techniques to demonstrate its superior accuracy and diagnostic efficiency.

The study introduces a Convolutional Neural Network (CNN) model for detecting invasive ductal carcinoma (IDC) in whole-slide images (WSIs), achieving 87% accuracy. By leveraging pre-stage data processing and a Recurrent Neural Network (RNN) as a meta classifier, the proposed model further enhances breast cancer detection, reaching an impressive validation accuracy of 98.08%. Despite these promising results, the research highlights the limitations of relying on secondary datasets and calls for the inclusion of primary data in future studies. Incorporating gene sequence data and attention mechanisms could provide more comprehensive predictions and improve classification accuracy. Furthermore, the study proposes a hybrid classifier combining CNN and Long Short-Term Memory (LSTM) networks, with future work focused on applying the model to various breast cancer types and investigating hardware implementation for real-time diagnostics.

Keywords - Breast cancer detection, Convolutional Neural Network (CNN), Deep learning, Machine learning algorithms, Hybrid classifier.

I. INTRODUCTION

Breast cancer remains one of the most prevalent and life-threatening diseases affecting women worldwide, as highlighted by the World Health Organization (WHO). The high incidence and mortality rates associated with breast cancer make it a critical public health issue. Early detection is crucial because it significantly increases the chances of successful treatment and survival. Early-stage detection of breast cancer can prevent the disease from advancing to more severe stages, thereby saving millions of lives globally.

The importance of early detection has driven extensive research into developing more accurate and efficient methods for identifying breast cancer in its initial stages. Traditional approaches to breast cancer detection often involve mammography, ultrasound, and biopsy, followed by pathological analysis to confirm the presence of cancerous cells. While these methods are effective, they are time-consuming, expensive, and require highly specialized medical expertise. Moreover, the accuracy of these methods can sometimes be compromised by human error, particularly in the interpretation of mammographic images.

As a result, there is a growing need for automated systems that can assist radiologists in detecting breast cancer more accurately and efficiently. These automated systems are designed to reduce the workload of medical professionals while increasing the precision of diagnosis, thus enabling earlier and more effective treatment.

In recent years, the advent of deep learning has revolutionized the field of medical imaging, particularly in breast cancer detection. Deep learning, a subset of artificial intelligence (AI), involves the use of neural networks with multiple layers to analyze and interpret complex patterns in data. One of the most widely used deep learning algorithms in breast cancer detection is the

Convolutional Neural Network (CNN). CNNs are particularly well-suited for image analysis because they can automatically learn and extract relevant features from images, such as shapes, textures, and edges, without the need for manual feature selection. This capability makes CNNs highly effective in identifying abnormalities in mammographic images that may indicate the presence of cancer.

The integration of deep learning techniques into breast cancer detection systems has led to significant improvements in accuracy and precision. These systems can analyze vast amounts of data quickly and accurately, which is essential for early-stage detection. By providing a more accurate initial diagnosis, these systems can help streamline the diagnostic process and reduce the time and cost associated with breast cancer detection.

1.4 Objective of the Study

The extensive review of breast cancer detection methodologies indicates the need for modifications and improvements to enhance early-stage detection and improve survival rates. The objectives of this study are:

1. **To analyze the behavior of breast cancer in response to machine learning and swarm intelligence techniques.**
2. **To design a multilayer deep learning model for the detection of breast cancer.**
3. **To develop a cascaded model based on deep learning for the detection of breast cancer symptoms.**
4. **To study different approaches for improving the detection of breast cancer.**
5. **To compare the proposed algorithm with existing algorithms to enhance the effectiveness of breast cancer detection.**

II. LITERATURE REVIEW

The integration of machine learning and deep learning has led to the development of models that can analyze large volumes of medical imaging data, such as mammograms and biopsies, with high precision. These models are designed to recognize patterns and anomalies that may be imperceptible to the human eye, thereby improving diagnostic accuracy. Continuous advancements in these algorithms, driven by large datasets and sophisticated computational techniques, are pushing the boundaries of cancer detection technology. This progress offers promising new avenues for more effective screening programs and early interventions in breast cancer management.

The author [1] highlights the challenges of low classification accuracy in cancer detection, particularly in fuzzy mammography images. The study introduces Traditional Convolutional Neural Networks (TCNN) and Supported Convolutional Neural Networks (SCNN) to address issues related to scale and shift in these images. The Flipped Rotation-based Approach (FRbA) is proposed to improve prediction accuracy by considering various directions of malignant masses. TCNN and SCNN methods, tested on 200 mammography images from the MIAS Medical Dataset, show improved performance compared to systems based on K-Nearest Neighbors (KNN) and Random Forest (RF), particularly in terms of accuracy and sensitivity.

The author [2] explores the integration of AI in breast cancer imaging, focusing on MRI. AI's capabilities in precise tumor volume delineation and risk prediction are discussed, emphasizing the potential for personalized treatment through the integration of imaging data with genetic and clinical information. The study reviews the current applications and limitations of AI in breast cancer imaging and highlights the evolving role of radio-genomics in clinical decision-making.

The author [3] presents a deep neural network model designed for identifying malignant breast cancer. Using the Wisconsin Breast Cancer Dataset, the model achieves an F1 score exceeding 98, demonstrating the effectiveness of deep learning techniques in computer-aided diagnosis. The study underscores that while AI assists in diagnosis, it is intended to complement rather than replace medical professionals.

The author [4] describes a clinical study involving 240 digital mammography images evaluated by 14 radiologists. The study finds that AI assistance improves radiologists' performance in reading mammograms, with enhancements in sensitivity, specificity, and overall diagnostic accuracy. The study suggests that AI can increase productivity by enabling radiologists to focus on more suspicious cases while providing reassurance on less concerning ones.

The author [5] notes that while AI systems have shown promise in mimicking radiologists' performance, most studies have been conducted in controlled lab settings. The potential for AI to triage normal screening mammograms and reduce the workload for radiologists is highlighted, though more research is needed to validate these findings in real-world screening programs.

The author [6] reviews the role of AI in digital pathology for breast cancer diagnosis. The paper discusses how AI techniques can enhance diagnostic accuracy and provide additional insights beyond traditional visual inspections. The widespread adoption of whole-slide imaging technology is expected to facilitate the integration of AI in breast pathology.

The author [7] introduces a multi-stage mitotic cell detection technique using deep CNNs and Faster R-CNN. The method demonstrates superior performance compared to existing techniques, with high precision and recall rates. This approach could support pathologists by providing a reliable second opinion and highlighting areas requiring further attention.

The author [8] emphasizes the need for external validation of AI-powered mammography screening tools across diverse patient demographics. The paper advocates for ongoing monitoring and recalibration of AI systems to ensure their effectiveness and generalizability in clinical practice.

The author [9] proposes a three-step technique to predict breast tumor response to chemotherapy, involving tumor segmentation, feature extraction, and response prediction using deep learning. The study suggests that radionics features can improve prediction accuracy, though further research is needed to expand the dataset and refine the approach.

The author [10] evaluates the Thermalytix Risk Score (TRS), a personalized risk framework using AI to assess breast cancer risk from thermal images. The TRS demonstrates high accuracy in risk assessment and could offer a non-invasive, cost-effective screening method for a wide age range of women.

The author [11] investigates how AI can enhance cancer detection and reduce radiologist workload by simulating screening scenarios. The study finds that AI can effectively triage mammograms, reducing the need for radiologist assessment and improving overall screening efficiency.

The author [12] explores the use of data mining techniques, specifically the C4.5 algorithm enhanced by Particle Swarm Optimization (PSO) and bagging, to improve breast cancer classification accuracy. The study shows that these methods significantly enhance the performance of classification algorithms.

The author [13] compares the performance of DenseNet-169 and EfficientNet-B5 in identifying breast cancer from combined mammography images. The study finds high accuracy in detecting malignancies, particularly in less dense breast tissues, and highlights the importance of algorithms in reducing interpretation variability.

The author [14] discusses the challenges of high-dimensional data in cancer diagnosis and the application of Particle Swarm Optimization (PSO) for feature selection. The study demonstrates that PSO can improve the performance of several classification algorithms, with SVM showing the best results.

The author [15] presents an AI model based on deep neural networks for evaluating bone scintigraphy images in cancer diagnosis. The model achieves high diagnostic efficacy and could aid in diagnosing bone metastases, providing valuable support to nuclear medicine doctors.

III. PROPOSED ALGORITHM

The hybrid detection model is combination of CNN and RNN algorithms. The CNN and RNN algorithms is variants of deep learning. The deep learning classification and detection rate is very high instead of others machine learning algorithms. Here we describe the processing of hybrid algorithm, one part of hybrid algorithm work with spider monkey optimization algorithm for the dimension reduction of features. The reduce features process through the hybrid models. the hybrid model is connected feedforwarded neural network model. The 1st phase of hybrid algorithm work as training of sample data using CNN and RNN models work as prediction of stock price. The processing of algorithm describes here.

The sampling of data as

$SMO_F : F^{Tf} \rightarrow D^{Tf}$, where $F_T \in D^{Tf}$

The set of reduces dimension features of stock data.

S the transformed vectors $y_j \in D^T$ to mapped the input of CNN network

$$y_j = S_j\,(f_j) + Z, \quad \forall\, Z \le j \le Z + K$$

The above mention expression represents the data of stock.

Hybrid RNN training of prediction as

$$RNN = yi_0 \to z(f_0) + Z$$

Define the variance matrix of samples of CNN and RNN Ck and Rk

Now prediction of hybrid model is

$$Pre(model) = \text{Class}\left\{ \|D - D_k\|\, R_k^{-1} + \sum_{j=k}^{k+z} \left\|ZF_j(f) - y_j\right\| C_j^{-1} \right\}$$

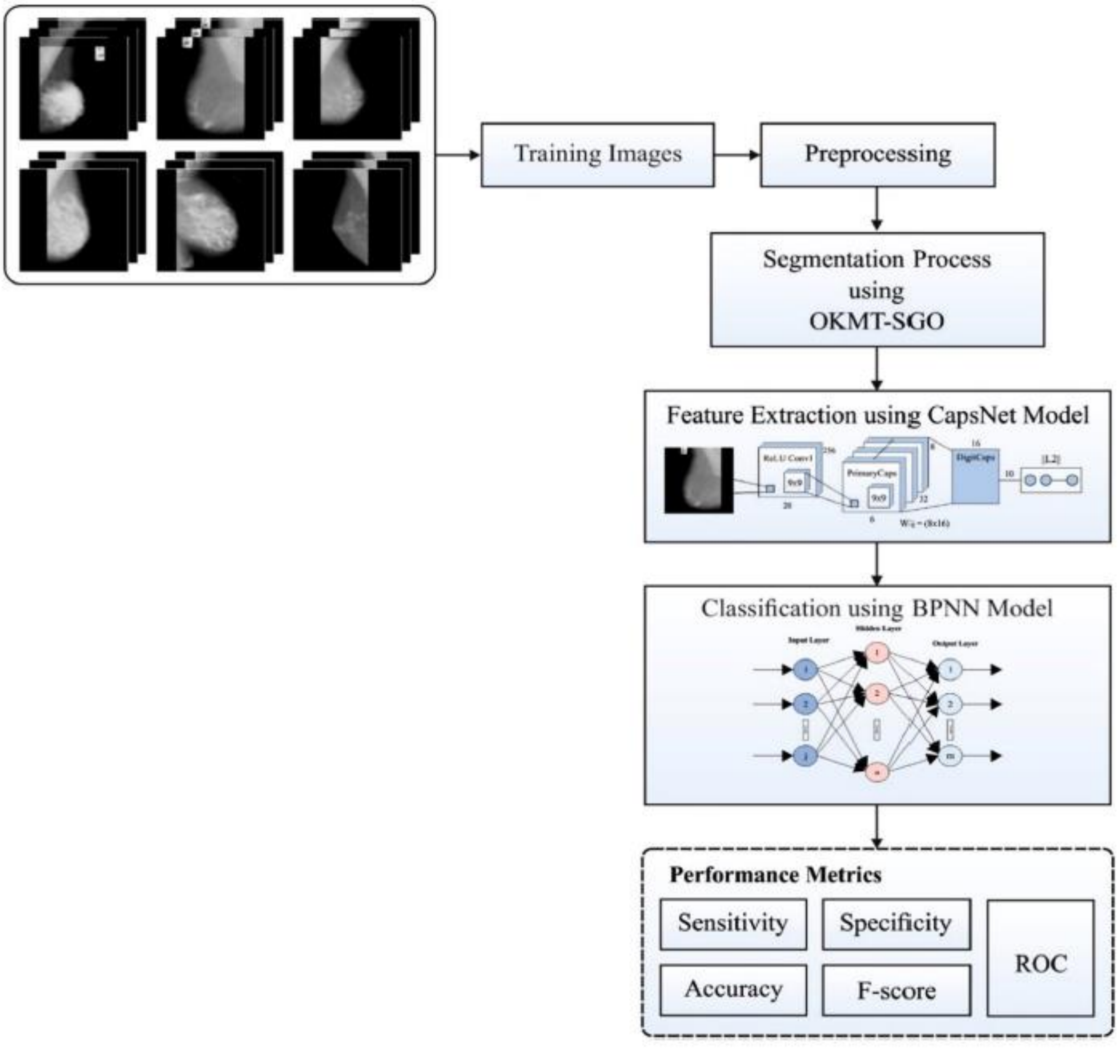

Figure 1 proposed model of breast cancer detection

IV. IMPLEMENTATION & RESULT ANALYSIS

A. OVERVIEW

This chapter focuses on the implementation and simulation of breast cancer detection algorithms using MATLAB software version 2018R. MATLAB is renowned for its advanced functions in deep learning and image processing, making it an ideal platform for developing and testing breast cancer detection models. The software's extensive library of functions and toolboxes supports complex algorithm applications, enabling researchers to simulate and refine models for accurate cancer detection in medical images.

The comparison explores the potential of integrating new approaches, including hybrid algorithms that combine deep learning with traditional image processing methods. This exploration underscores the need for continuous innovation to meet the evolving demands of medical diagnostics.

B. DATASET & PERFORMANCE PARAMETERS

The **CBIS-DDSM (Curated Breast Imaging Subset of DDSM)** dataset is a critical resource for advancing research in breast cancer detection. It offers a comprehensive collection of mammographic images, featuring both benign and malignant cases. This dataset is instrumental in training and testing machine learning models for early breast cancer detection.

Dataset Example: The dataset is categorized into different cases of cancer patients, with sample images shown in Figure 2. This visual representation provides insights into the dataset's content and aids in understanding the types of images used for model training and evaluation.

By leveraging the CBIS-DDSM dataset and MATLAB's capabilities, researchers can enhance their breast cancer detection algorithms, leading to more accurate and timely diagnoses in clinical settings.

The sample of dataset is shown in figure 2.

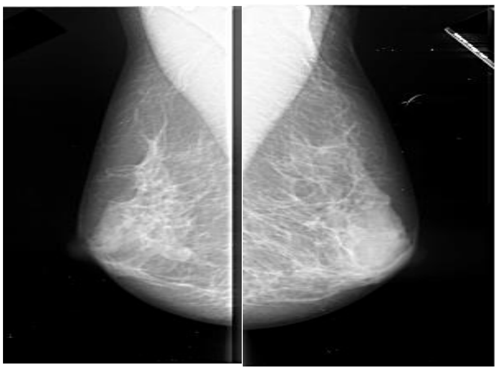

Figure 2 Breast cancer image dataset of left and right breast ring of cancer cell.

The process of evaluation also evaluates the existing methods of breast cancer detection, such. The estimation of results formula is mentioned here [25,26,27,30].

$$Accuracy = \frac{Total\ No.of\ Correctly\ Classified\ Instances}{Total\ No.of\ Instances} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

$$F1 = \frac{2TP}{2TP + FN + FN}$$

$$MCC = \frac{TP\ XTN - FP\ X\ FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

C. SIMULATION PROCESS

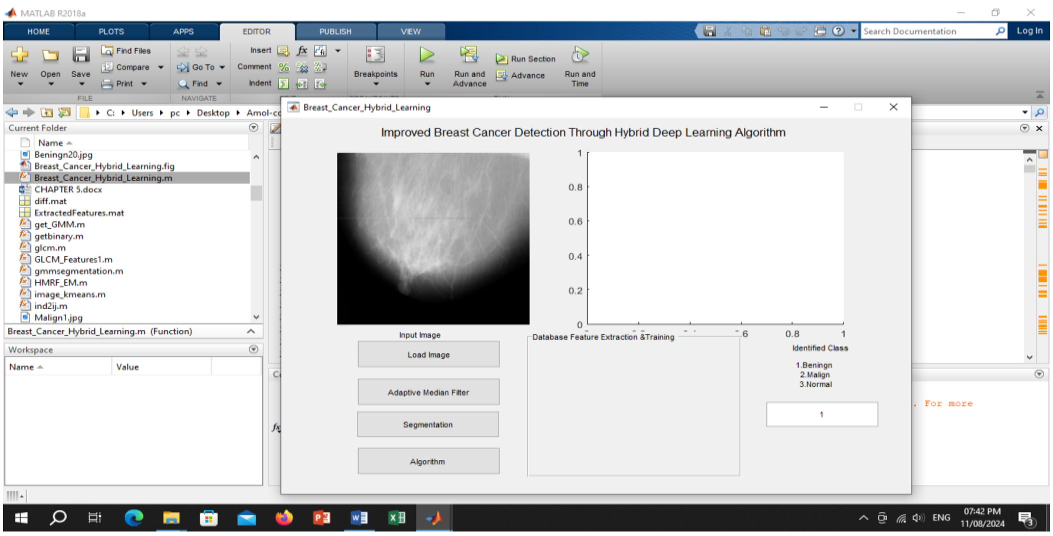

Figure 3 windows show that the improved breast cancer detection through hybrid deep learning algorithm

Figure 3 windows show that the improved breast cancer detection through hybrid deep learning algorithm for adaptive median filter segmentation and identified class 1beningn, 2 malign and 3 normal.

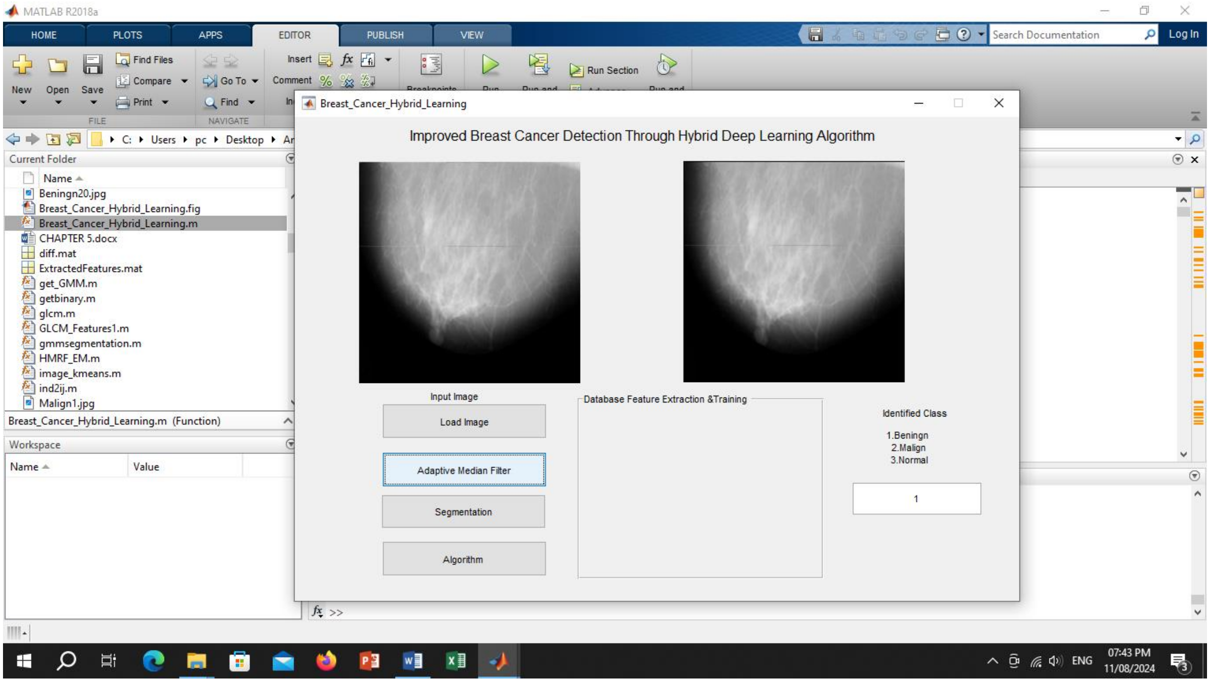

Figure 4 windows show that the improved breast cancer detection through hybrid deep learning algorithm

Figure 4 windows show that the improved breast cancer detection through hybrid deep learning algorithm for adaptive median filter segmentation and identified class 1beningn, 2 malign and 3 normal.

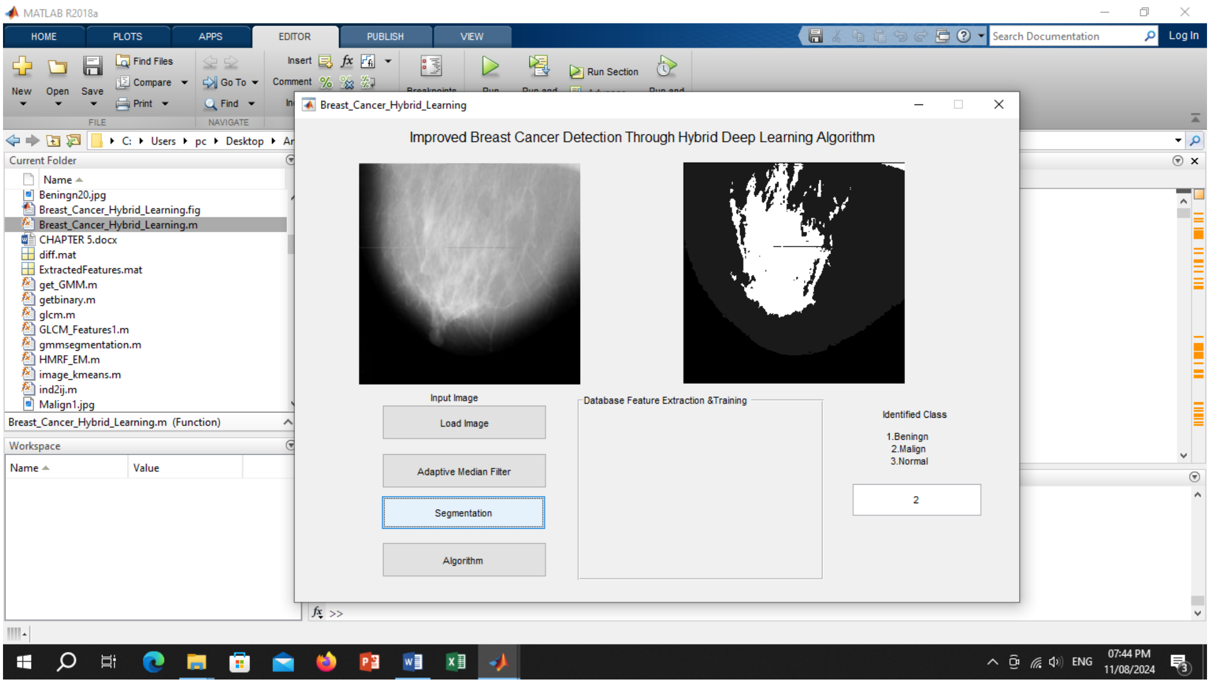

Figure 5 windows show that the improved breast cancer detection through hybrid deep learning algorithm

Figure 5 windows show that the improved breast cancer detection through hybrid deep learning algorithm for adaptive median filter segmentation and identified class 1beningn, 2 malign and 3 normal.

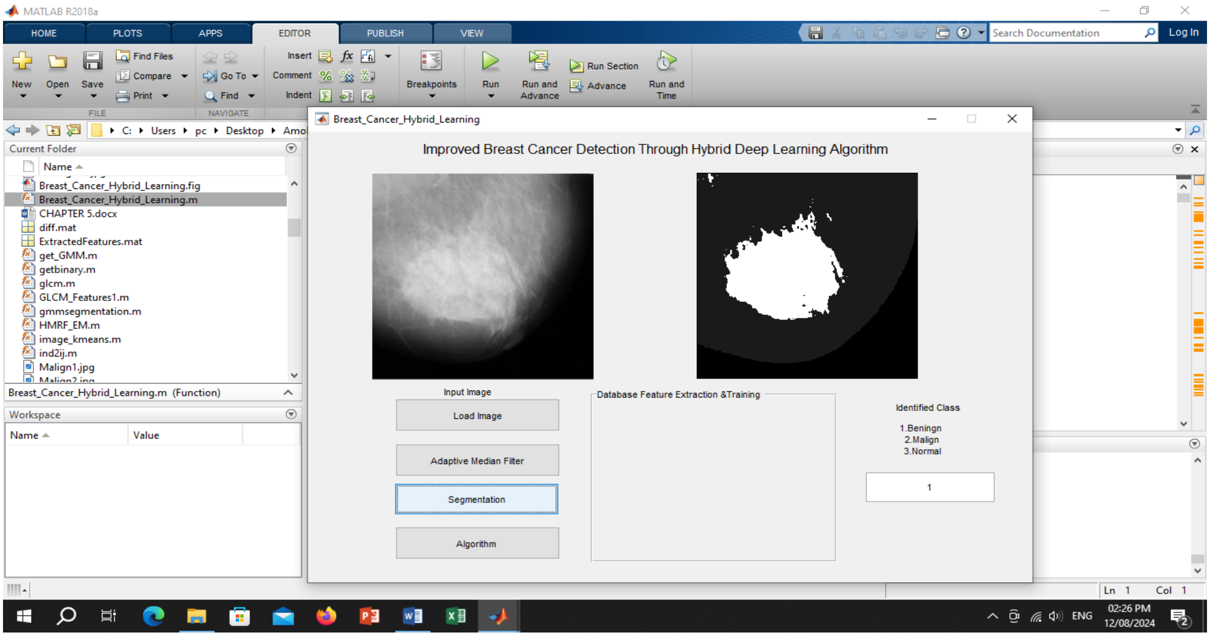

Figure 6 windows show that the improved breast cancer detection through hybrid deep learning algorithm

Figure 6 windows show that the improved breast cancer detection through hybrid deep learning algorithm for adaptive median filter segmentation and identified class 1beningn, 2 malign and 3 normal.

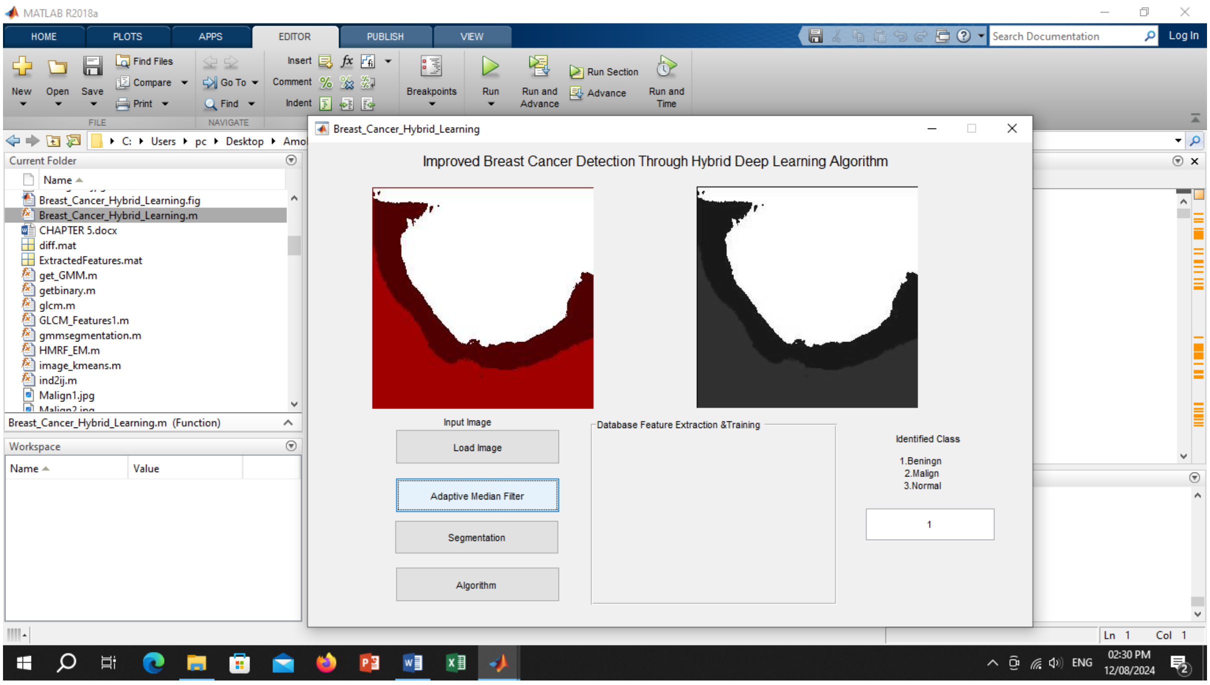

Figure 7 windows show that the improved breast cancer detection through hybrid deep learning algorithm

Figure 7 windows show that the improved breast cancer detection through hybrid deep learning algorithm for adaptive median filter segmentation and identified class 1beningn, 2 malign and 3 normal.

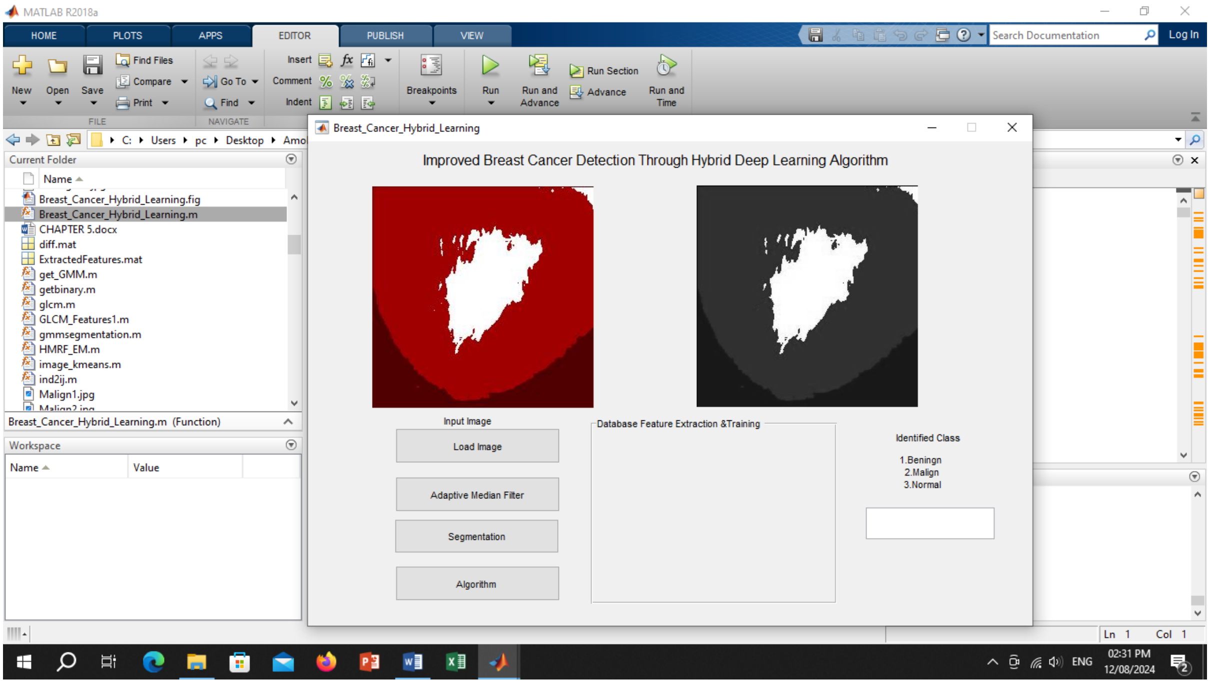

Figure 8 windows show that the improved breast cancer detection through hybrid deep learning algorithm

Figure 8 windows show that the improved breast cancer detection through hybrid deep learning algorithm for adaptive median filter segmentation and identified class 1beningn, 2 malign and 3 normal.

V. EXPERIMENT ANALYSIS

Table 1 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for Accuracy, MIAS dataset.

Method	**Accuracy**		
Proposed	98.88	98.56	99.15
CNN	97.34	98.57	98.39
Hybrid	97.64	98.46	97.87
DCNN	96.89	97.22	98.35

Table 2 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for precision, MIAS dataset.

Method	**Precision**		
Proposed	98.87	97.52	99.45
CNN	96.38	97.37	98.25
Hybrid	97.49	98.27	99.15
DCNN	96.56	97.34	98.65

Table 3 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for recall MIAS dataset.

Method	**Recall**

Proposed	98.61	97.64	98.76
CNN	97.67	96.57	97.87
Hybrid	96.35	95.99	96.51
DCNN	97.45	96.87	97.89

Table 4 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for MCC MIAS dataset.

Method	**MCC**		
Proposed	98.46	97.78	99.66
CNN	98.67	97.73	98.88
Hybrid	97.49	98.66	99.69
DCNN	96.78	97.55	98.47

Table 5 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for F1 MIAS dataset.

Method	**F1**		
Proposed	98.64	97.42	99.87
CNN	96.77	97.37	98.75
Hybrid	97.97	98.48	99.85
DCNN	96.56	97.76	98.65

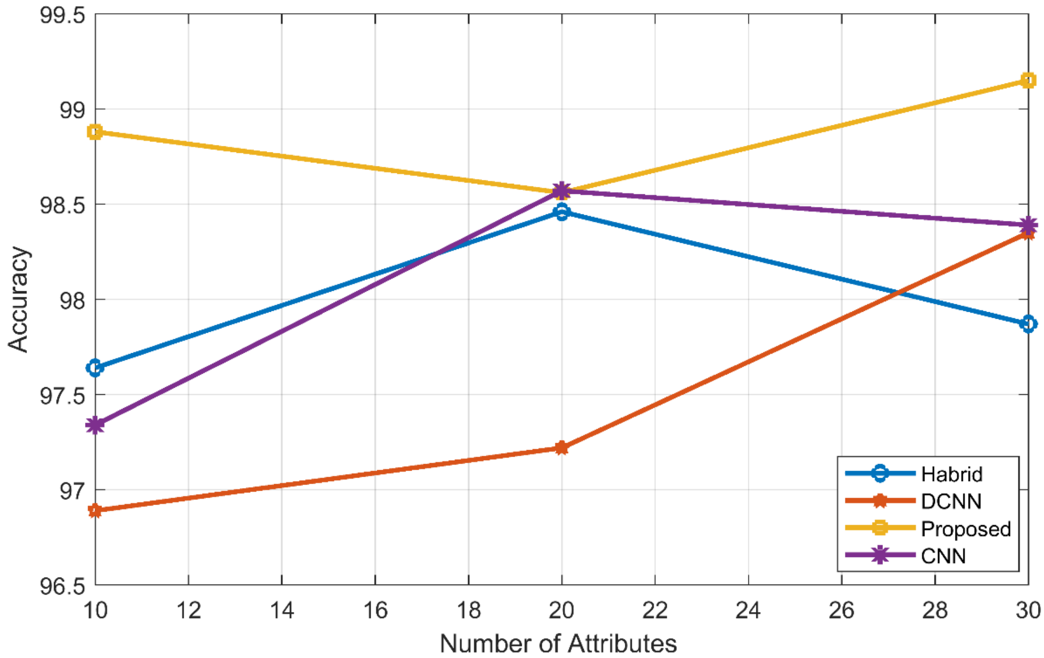

Figure: 9 Comparative performance analysis of accuracy and number of attributes using proposed, DCNN, Hybrid, and CNN, using MIAS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.15 at number of attributes 30 and the value of Hybrid is also 97.87 at number of attributes 30 and the value of CNN is 98.39 at number of attributes 30 and we see that the value of DCNN is also The number of attributes is 98.35 on 30 which is less than other methods.

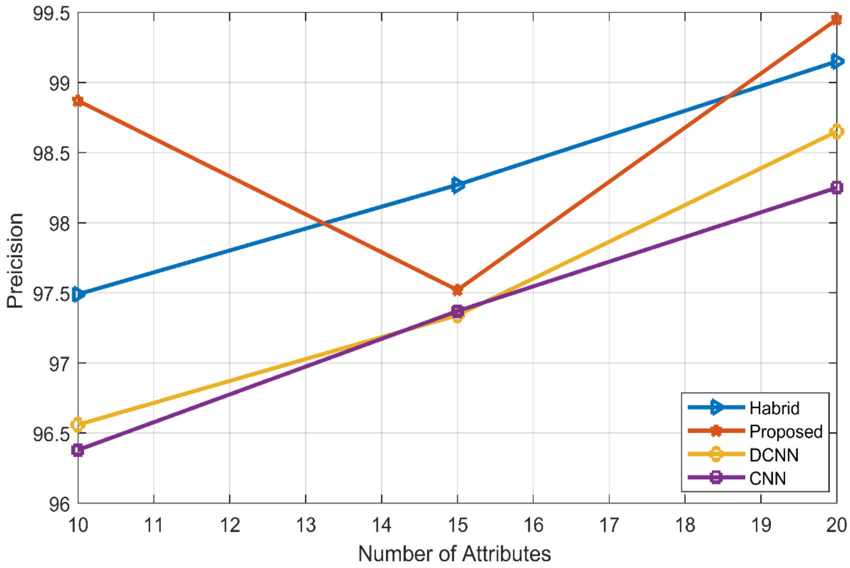

Figure: 10 Comparative performance analysis of precision and number of attributes using proposed, DCNN, Hybrid, and CNN, using MIAS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.45 at number of attributes 20 and the value of Hybrid is also 99.15 at number of attributes 20 and the value of DCNN is 98.65 at number of attributes 20 and we see that the value of CNN is also The number of attributes is 98.25 on 20 which is less than other methods.

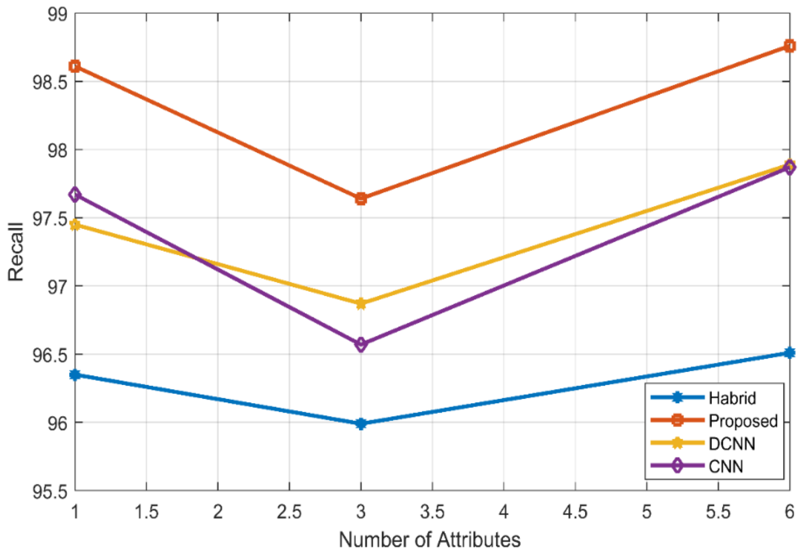

Figure: 11 Comparative performance analysis of recall and number of attributes using proposed, DCNN, Hybrid, and CNN, using MIAS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 98.76 at number of attributes 6 and the value of CNN is also 97.87 at number of attributes 6 and the value of DCNN is 97.89 at number of attributes 6 and we see that the value of Hybrid is also The number of attributes is 96.51 on 6 which is less than other methods.

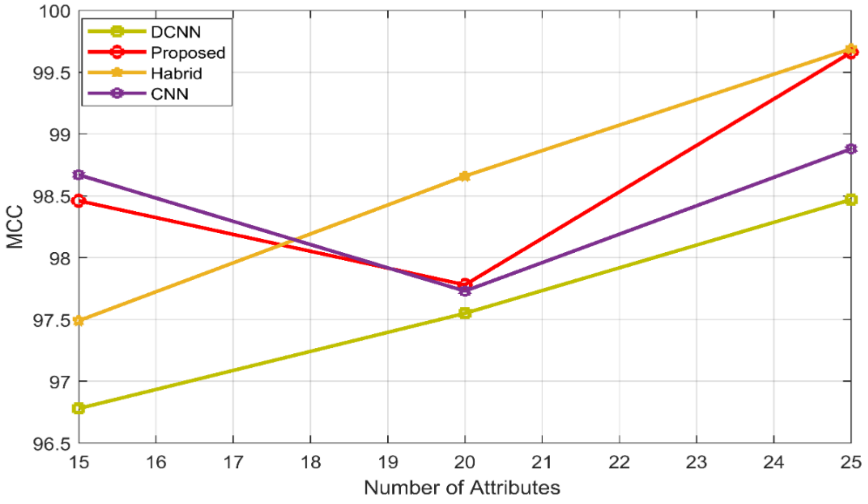

Figure: 12 Comparative performance analysis of MCC and number of attributes using proposed, DCNN, Hybrid, and CNN, using MIAS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.66 at number of attributes 25 and the value of CNN is also 98.88 at number of attributes 25 and the value of Hybrid is 99.69 at number of attributes 25 and we see that the value of DCNN is also The number of attributes is 98.47 on 25 which is less than other methods.

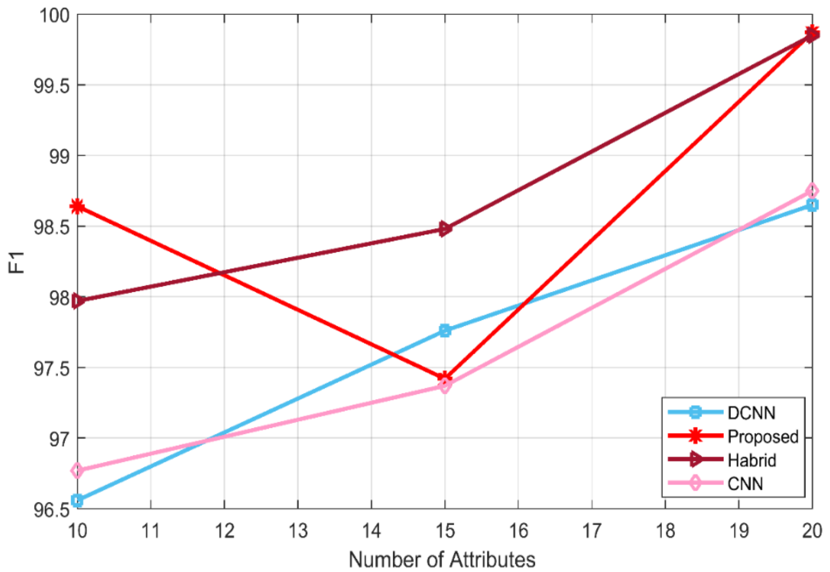

Figure: 13 Comparative performance analysis of F1 and number of attributes using proposed, DCNN, Hybrid, and CNN, using MIAS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.87 at number of attributes 20 and the value of CNN is also 98.75 at number of attributes 20 and the value of Hybrid is 99.85 at number of attributes 20 and we see that the value of DCNN is also The number of attributes is 98.65 on 20 which is less than other methods.

Table 6 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for Accuracy, CBIS dataset.

Method	**Accuracy**		
Proposed	98.87	98.55	99.57
CNN	96.45	97.78	98.61
Hybrid	97.89	96.87	97.75
DCNN	96.88	97.57	98.72

Table 7 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for precision, CBIS dataset.

Method	**Precision**		
Proposed	98.44	98.79	99.25
CNN	96.67	97.54	98.87
Hybrid	97.52	98.62	98.89
DCNN	96.78	97.46	98.84

Table 8 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for recall CBIS dataset.

Method	**Recall**		
Proposed	97.61	97.64	98.76
CNN	96.67	97.45	98.88
Hybrid	97.33	98.66	99.55
DCNN	97.35	96.89	98.85

Table 9 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for MCC CBIS dataset.

Method	**MCC**		
Proposed	98.46	98.78	99.89
CNN	96.67	97.73	98.88
Hybrid	97.44	98.69	99.79
DCNN	96.42	97.34	98.57

Table 5.4.15 Comparative result of analysis of existing with proposed, CNN, Hybrid, and DCNN using method for F1 CBIS dataset.

Method	**F1**		
Proposed	98.54	98.74	99.77
CNN	96.77	97.37	98.67
Hybrid	97.45	98.72	99.64
DCNN	96.78	97.64	98.37

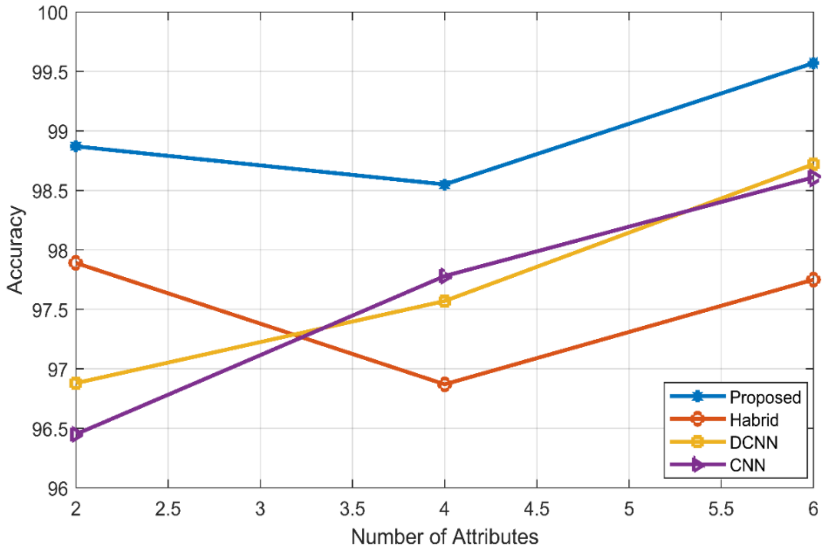

Figure: 14 Comparative performance analysis of accuracy and number of attributes using proposed, DCNN, Hybrid, and CNN, using CBIS dataset.

We observe that the proposed one is better than the other three methods, which are as follows. We see, the value of the proposed is 99.57 on the number of properties 6 and the value of CNN is also 98.61 on the number of properties 6 and we see that the value of hybrid is also 97.75 on the number of properties 6 which is less than other methods. The value of DCNN at the number of properties 20 is 98.72.

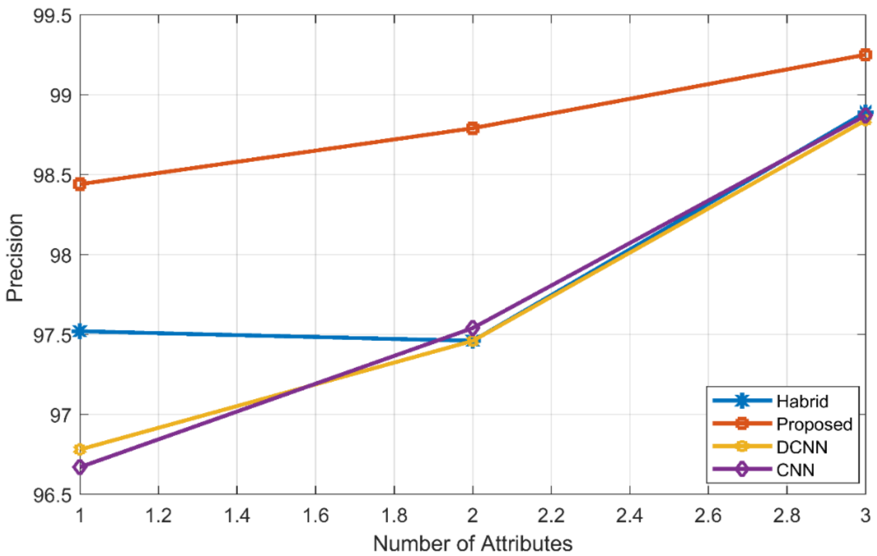

Figure: 15 Comparative performance analysis of precision and number of attributes using proposed, DCNN, Hybrid, and CNN, using CBIS dataset.

We observe that the proposed one is better than the other three methods, which are as follows. We see, the value of the proposed is 99.25 on the number of properties 3 and the value of CNN is also 98.87 on the number of properties 3 and we see that the value of DCNN is also 98.84 on the number of properties 6 which is less than other methods. The value of hybrid at the number of properties 20 is 98.89.

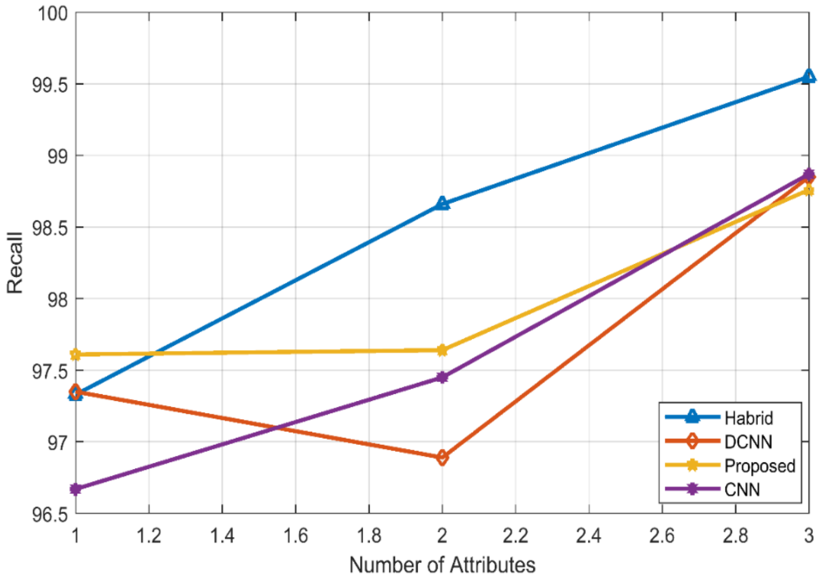

Figure: 16 Comparative performance analysis of recall and number of attributes using proposed, DCNN, Hybrid, and CNN, using CBIS dataset.

We observe that the proposed one is better than the other three methods, which are as follows. We see, the value of the proposed is 98.76 on the number of properties 3 and the value of CNN is also 98.88 on the number of properties 3 and we see that the value of DCNN is also 98.85 on the number of properties 3 which is less than other methods. The value of hybrid at the number of properties 3 is 99.55.

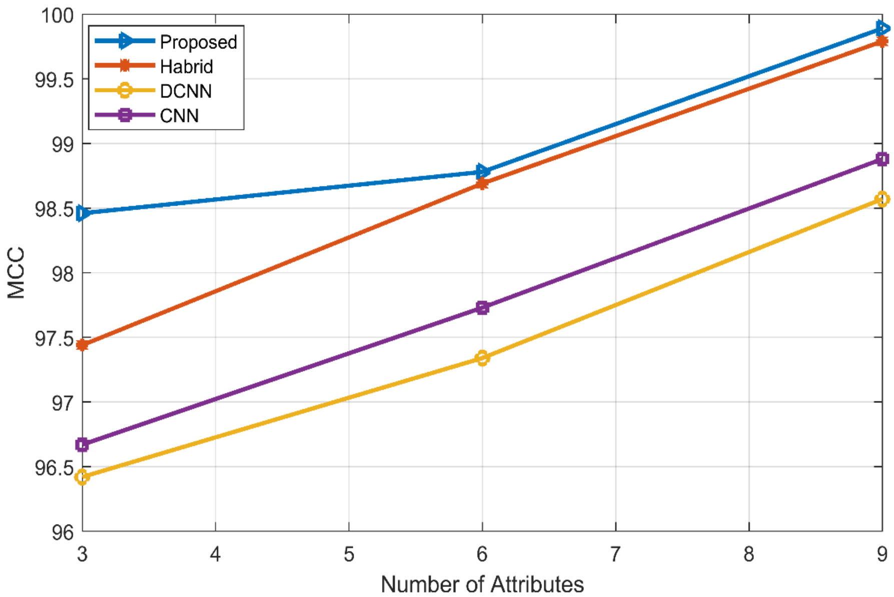

Figure: 17 Comparative performance analysis of MCC and number of attributes using proposed, DCNN, Hybrid, and CNN, using CBIS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.89 at number of attributes 9 and the value of CNN is also 98.88 at number of attributes 9 and the value of Hybrid is 99.79 at number of attributes 9 and we see that the value of DCNN is also The number of attributes is 98.57 on 9 which is less than other methods.

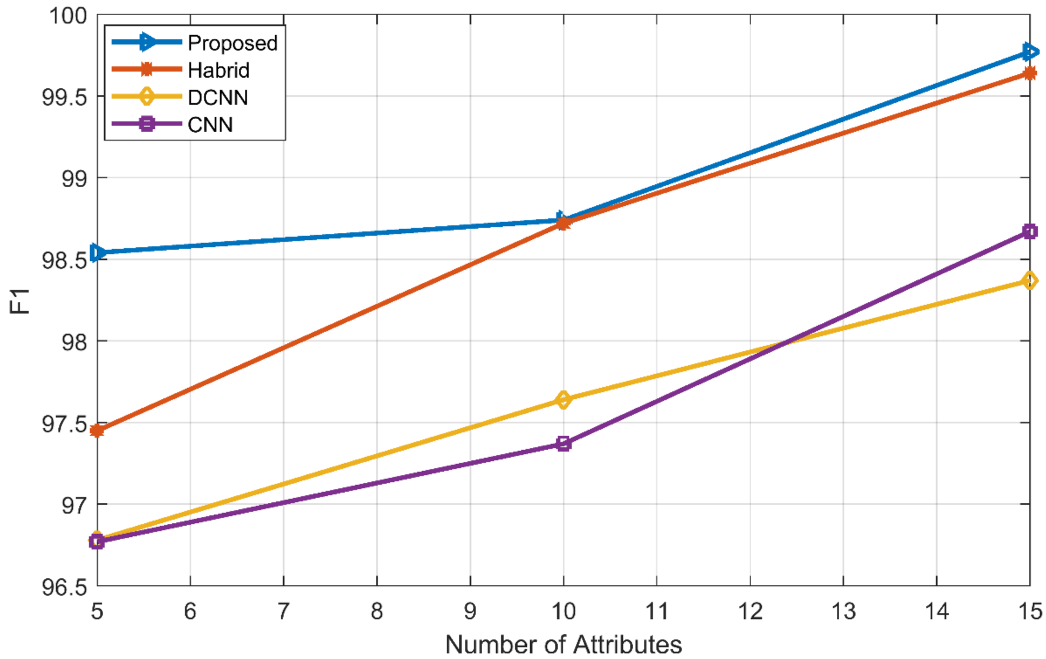

Figure: 18 Comparative performance analysis of F1 and number of attributes using proposed, DCNN, Hybrid, and CNN, using CBIS dataset.

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.77 at number of attributes 15 and the value of CNN is also 98.67 at number of attributes 15 and the value of Hybrid is 99.64 at number of attributes 15 and we see that the value of DCNN is also The number of attributes is 98.37 on 15 which is less than other methods.

VI. CONCLUSIONS

Automating breast cancer detection is crucial for improving patient care. This study proposes a Convolutional Neural Network (CNN) approach for analyzing invasive ductal carcinoma (IDC) tissue regions in whole-slide images (WSIs). The paper compares three CNN architectures, with CNN Model 3 showing the highest accuracy of 87%. This success is attributed to its five-layer structure, which is particularly effective for this task. The models were trained on a large dataset of approximately 275,000 RGB image patches (50 × 50 pixels each). The proposed CNN model outperformed traditional machine learning algorithms, demonstrating an 8% improvement in accuracy. This suggests that the model can effectively minimize human error in diagnostics and reduce the overall cost of cancer diagnosis.

However, the study relies on a secondary dataset from Kaggle, which limits its validation scope. Future research should focus on utilizing primary data to further refine results and enhance accuracy. Attention mechanisms, which are underutilized in current image classification studies, present an opportunity to improve deep learning methods. Additionally, integrating gene sequence data can provide comprehensive predictions and improve accuracy. Future work should explore gene expression data, risk assessment, recurrence prediction, and multiclass predictors, given the current focus on binary classification.

The need for large-scale, thoroughly labeled WSI datasets is evident, as these resources are essential for advancing research and improving diagnostic accuracy. The study introduces a deep learning algorithm that enhances breast cancer detection performance. Utilizing a Convolutional Neural Network (CNN) with pre-stage data processing algorithms, the method converts one-dimensional pixel data into two-dimensional modes, resulting in superior performance. The integration of a Recurrent Neural Network (RNN) as a meta classifier achieved an impressive 98.08% validation accuracy, surpassing existing methods. Future work should address hardware implementation and explore the algorithm's applicability to different breast cancer types.

A hybrid classifier combining CNN and Long Short-Term Memory (LSTM) networks is proposed. The algorithm employs a median filter for noise removal, followed by a GLCM feature extractor. This approach enhances detection of early-stage breast cancer, potentially reducing the need for chemotherapy or breast removal. Although the median filter provides effective noise removal, it may blur image details. The algorithm, simulated in MATLAB, is compared with existing methods like CNN, MLP, ELM, and ensemble classifiers. Future work will extend the model to cover all breast cancer categories.

VII. SUGGESTION FOR FUTURE WORK

The proposed algorithm shows high accuracy in early-stage breast cancer detection, which is vital for improving patient outcomes. Key performance metrics—accuracy, sensitivity, and specificity—demonstrate the algorithm's effectiveness in distinguishing between cancerous and non-cancerous tissues. Future work should focus on several areas:

1. **Real-Time Analysis**: Develop methods for real-time analysis of breast cancer behaviors.
2. **VLSI Fabrication**: Implement the proposed algorithm with VLSI (Very-Large-Scale Integration) technology to improve hardware efficiency.
3. **Complexity Reduction**: Address the increased complexity of the algorithm to reduce processing time for more efficient operation.
4. **Biomedical Engineering Applications**: Explore applications of the research in various areas of biomedical engineering.

These steps aim to enhance the algorithm's performance, applicability, and integration into clinical practice.

REFERENCES

[1] S. P. Bingulac, “On the compatibility of adaptive controllers (Published Conference Proceedings style),” in *Proc. 4th Annu. Allerton Conf. Circuits and Systems Theory*, New York, 1994, pp. 8–16.

[2] Alfifi, Mona, Mohamad Shady Alrahhal, Samir Bataineh, and Mohammad Mezher. "Enhanced artificial intelligence system for diagnosing and predicting breast cancer using deep learning." (2020).

[3] Sheth, Deepa, and Maryellen L. Giger. "Artificial intelligence in the interpretation of breast cancer on MRI." Journal of Magnetic Resonance Imaging 51, no. 5 (2020): 1310-1324.

[4] Prakash, Sidharth S., and K. Visakha. "Breast cancer malignancy prediction using deep learning neural networks." In 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), pp. 88-92. IEEE, 2020.

[5] Pacilè, Serena, January Lopez, Pauline Chone, Thomas Bertinotti, Jean Marie Grouin, and Pierre Fillard. "Improving breast cancer detection accuracy of mammography with the concurrent use of an artificial intelligence tool." Radiology: Artificial Intelligence 2, no. 6 (2020): e190208.

[6] Sechopoulos, Ioannis, and Ritse M. Mann. "Stand-alone artificial intelligence-The future of breast cancer screening?." The Breast 49 (2020): 254-260.

[7] Ibrahim, Asmaa, Paul Gamble, Ronnachai Jaroensri, Mohammed M. Abdelsamea, Craig H. Mermel, Po-Hsuan Cameron Chen, and Emad A. Rakha. "Artificial intelligence in digital breast pathology: techniques and applications." The Breast 49 (2020): 267-273.

[8] Mahmood, Tahir, Muhammad Arsalan, Muhammad Owais, Min Beom Lee, and Kang Ryoung Park. "Artificial intelligence-based mitosis detection in breast cancer histopathology images using faster R-CNN and deep CNNs." Journal of clinical medicine 9, no. 3 (2020): 749.

[9] Lee, Christoph I., Nehmat Houssami, Joann G. Elmore, and Diana SM Buist. "Pathways to breast cancer screening artificial intelligence algorithm validation." The Breast 52 (2020): 146-149.

[10] Amkrane, Yassine, Mohammed El Adoui, and Mohammed Benjelloun. "Towards breast cancer response prediction using artificial intelligence and radiomics." In 2020 5th International Conference on Cloud Computing and Artificial Intelligence: Technologies and Applications (CloudTech), pp. 1-5. IEEE, 2020.

[11] Kakileti, Siva Teja, Himanshu J. Madhu, Geetha Manjunath, Leonard Wee, Andre Dekker, and Sudhakar Sampangi. "Personalized risk prediction for breast cancer pre-screening using artificial intelligence and thermal

radiomics." Artificial Intelligence in Medicine 105 (2020): 101854.

[12] Bhor HN, Kalla M. TRUST-based features for detecting the intruders in the Internet of Things network using deep learning. Computational Intelligence. 2022; 38(2): 438–462.

[13] Pinjarkar, V. U. ., Pinjarkar, U. S. ., Bhor, H. N. ., Mahajan, Y. V. ., Patil, V. R. ., Rajput, S. D. ., Kothari, P. ., Ghori, D. ., & Bhabad, H. P. . (2023). Student Engagement Monitoring in Online Learning Environment. International Journal of Intelligent Systems and Applications in Engineering, 12(1), 292–298.

[14] Bhole, V. ., Bhor, H. N. ., Terdale, J. V. ., Pinjarkar, V. ., Malvankar, R. ., & Zade, N. . (2023). Machine Learning Approach for Intelligent and Sustainable Smart Healthcare in Cloud-Centric IoT. International Journal of Intelligent Systems and Applications in Engineering, 11(10s), 36–48.

[15] Terdale, J. V. ., Bhole, V. ., Bhor, H. N. ., Parati, N. ., Zade, N. ., & Pande, S. P. . (2023). Machine Learning Algorithm for Early Detection and Analysis of Brain Tumors Using MRI Images. International Journal on Recent and Innovation Trends in Computing and Communication, 11(5s), 403–415.

[16] H. N. Bhor and M. Kalla, "An Intrusion Detection in Internet of Things: A Systematic Study," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020, pp. 939-944, doi: 10.1109/ICOSEC49089.2020.9215365.

[17] Dembrower, Karin, Erik Wåhlin, Yue Liu, Mattie Salim, Kevin Smith, Peter Lindholm, Martin Eklund, and Fredrik Strand. "Effect of artificial intelligence-based triaging of breast cancer screening mammograms on cancer detection and radiologist workload: a retrospective simulation study." The Lancet Digital Health 2, no. 9 (2020): e468-e474.

[18] Saputra, Raka Hendra, and Budi Prasetyo. "Improve the accuracy of c4. 5 algorithm using particle swarm optimization (pso) feature selection and bagging technique in breast cancer diagnosis." Journal of Soft Computing Exploration 1, no. 1 (2020): 47-55.

[19] Suh, Yong Joon, Jaewon Jung, and Bum-Joo Cho. "Automated breast cancer detection in digital mammograms of various densities via deep learning." Journal of personalized medicine 10, no. 4 (2020): 211.

[20] Agustian, Fajar, and Muhammad Dzil Ikram Lubis. "Particle swarm optimization feature selection for breast cancer prediction." In 2020 8th International Conference on Cyber and IT Service Management (CITSM), pp. 1-6. IEEE, 2020.

[21] Zhao, Zhen, Yong Pi, Lisha Jiang, Yongzhao Xiang, Jianan Wei, Pei Yang, Wenjie Zhang et al. "Deep neural network based artificial intelligence assisted diagnosis of bone scintigraphy for cancer bone metastasis." Scientific reports 10, no. 1 (2020): 17046.

[22] Adachi, Mio, Tomoyuki Fujioka, Mio Mori, Kazunori Kubota, Yuka Kikuchi, Wu Xiaotong, Jun Oyama et al. "Detection and diagnosis of breast cancer using artificial intelligence based assessment of maximum intensity projection dynamic contrast-enhanced magnetic resonance images." Diagnostics 10, no. 5 (2020): 330.

[23] Islam, Md Milon, Md Rezwanul Haque, Hasib Iqbal, Md Munirul Hasan, Mahmudul Hasan, and Muhammad Nomani Kabir. "Breast cancer prediction: a comparative study using machine learning techniques." SN Computer Science 1 (2020): 1-14.

[24] Hall, Karl, Victor Chang, and Paul Mitchell. "Machine Learning Techniques for Breast Cancer Detection." In COMPLEXIS, pp. 116-122. 2022.

[25] Sawant, S., Soni, P., Somavanshi, A., Bhor, H.N. (2024). Enhancing Medical Education Through Augmented Reality. Lecture Notes in Networks and Systems, vol 878. Springer. https://doi.org/10.1007/978-981-99-9489-2_16.

[26] Zhou, Li-Qiang, Xing-Long Wu, Shu-Yan Huang, Ge-Ge Wu, Hua-Rong Ye, Qi Wei, Ling-Yun Bao et al. "Lymph node metastasis prediction from primary breast cancer US images using deep learning." Radiology 294, no. 1 (2020): 19-28.