

Deep Learning-Based Automated Breast Cancer Detection Using CNN and MRI Images

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ABSTRACT

In order to produce better results, transfer learning with the use of pretrained models like ResNet and VGG16 is utilized. These models are optimized using breast cancer data to acquire deep informative features that can be successfully classified. Alternatively, a different CNN architecture can be adopted so that it can suit the specifics of the dataset. In order to facilitate the comprehensive investigation, the effectiveness of the model is considered through such standard classification metrics as accuracy, precision, recall, and F1-score. With the help of the developed system, it is possible to develop an efficient clinical decision support tool by incorporating the generated system in web or mobile application. The technology can enable medical professionals to diagnose early and save lives of breast cancer victims through early treatment and intervention.

Keywords: Deep learning, machine learning, neural networks, breast cancer, convolutional neural networks (CNN), Cancer, medical imaging, disease.

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1. Introduction

Medical imaging plays an important role in the modern healthcare system by the detection of breast cancer. Traditional methods of diagnosis require the use of qualified radiologists which is a tedious and error prone procedure. Cancer classification through images has been shown to have an outstanding potential through deep learning techniques, namely the Convolutional Neural Networks (CNNs). The proposed study will enhance the effectiveness of early detection and diagnosis by developing a CNN-based model trained on datasets associated with breast cancer.

Breast cancer is a very serious medical issue, and the early diagnosis of this condition increases the chances of survival tremendously. Radiologists are involved with conventional diagnostic process which may be cumbersome and subject to human error. Convolutional Neural Networks (CNNs) are employed here to develop an automated system that is capable of detecting malignant and benign breast cancer images. The system is able to interpret medical images using deep learning methods to extract valuable information as well as enhance the accuracy of diagnoses. By

preprocessing, data augmentation, and optimization, the system will offer an effective and reliable tool to help the physicians in the early detection of breast cancer. The most appropriate to be used in medical image applications would be the Convolutional Neural Networks (CNNs) as they are better at categorizing images. The study will develop a CNN-based model that is effective in recognizing benign or cancerous images (breast cancer images). The proposed solution will incorporate machine learning to make the breast cancer diagnosis more effective and accurate in the long run to enable medical practitioners to make higher-quality decisions. Additionally, the manual process of extracting features is also eliminated because of the natural ability of Convolutional Neural Networks (CNNs) to learn hierarchical features directly on raw image data. CNNs are able to identify patterns in a medical image, unlike the traditional machine learning methods that require manually generated features, which enhances the accuracy of the diagnosis. We can enhance the early cancer detection and ensure timely intervention by reducing false-positive and false-negative levels with a deep learning-based detection system. The application of

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this type of AI technologies to the healthcare system would considerably reduce the workload of radiologists and offer available and scalable diagnostic solutions. Major Characteristics of CNN-based breast cancer tumor detection and classification based on MRI images. The possibility to analyze a number of MRI sequences to enhance the accuracy of the diagnosis is one of the main characteristics of CNN-based methods. Research has indicated that information on various MRI sequences of T1-weighted, T2-weighted, and dynamiccontrast-enhanced (DCE) MRI can be combined to provide better detection and classification of breast tumors. The accuracy of breast cancer detection and classification has been enhanced tremendously due to the development of advanced CNN architectures. Indicatively, it has been demonstrated that CNNs using dilated multi-scale residual blocks are effective in extracting features in different regions of an image, and they are able to detect breast cancer with an accuracy of 98.57%.

2. Study Design

Zhiyong Yang, 2023 in "The Comparison of the Deep Learning Networks by using both the mask R-CNN and ResNet50 Classification to detect and diagnose breast cancer on the MRI images). The article measures the performance of combined deep learning in breast MRI, namely, the use of Mask R-CNN to identify the suspicious location and ResNet50 to estimate the probability of malignancy. It has a high sensitivity (96.1% in Dataset-1, 81.1% in Dataset-2) and moderate specificity (78.1% and 80.6% respectively). False positives are also found in the study that is attributed to benign lesions, vessels, and asymmetric enhancements and it is proposed that more algorithms can be used to refine the study. Farag H. Alhsnony in 2024, Lamia Sellami, in advancement of breast cancer detection using CNN: A comparison of MIAS and DDSM Datasets. The paper is based on a Convolutional Neural Network (CNN) system based on mammography images helping to identify breast cancer. The accuracy of the model on MIAS and DDSM is 94.23 and 95.53, respectively. Although it does not directly cover the MRI images and literature review, it shows the usefulness of CNNs as classifiers of either tumor as normal, benign, or malignant and the fact that it can also help advance the current practice of early detection of breast cancer by using advanced medical imaging technologies.

3. Methodology

To extract characteristics of photos of breast cancer efficiently, the architecture employs several convolutional and pooling layers in order to down sample the feature maps. The dropout layers are used in order to overcome overfitting and make sure that the model is functioning properly when applied to new data.

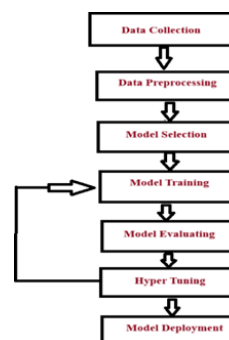


Fig. 1. Flow Chart

By using the final fully connected layers and using the right activation function (sigmoid in the case of binary predictions), the model can make predictions that are accurate. The architecture also has a serious process of hyperparameter tuning to improve performance, varying variables of the architecture include; kernel size, the number of filters, the learning rate, and the choice of optimizer. A balance of the complexity of the model is provided to ensure high accuracy and computational efficiency. Besides, batch normalization is utilized to enhance convergence and stabilize training. Another element that cannot be ignored in the methodology is feature visualization that assists in explaining how the model makes its predictions. Other methods like Grad-CAM (Gradient-weighted Class Activation Mapping) enhance visibility and trustworthiness because they show the element of the image that influences the judgment of the model. Gather medical imaging evidence (e.g. CT scans, MRI, ultrasound) related to breast disease. Add healthy and diseased breast samples datasets and label them as such Take into consideration the public medical datasets or hospital-provided datasets. Split the data to training (80) and testing (10) subset. This is a confusion matrix of a CNN model that is trained to predict breast cancer as either "Negative" (no cancer) or Positive (cancer present) with the use of MRI images. The confusion matrix gives a summary of performance of classification..

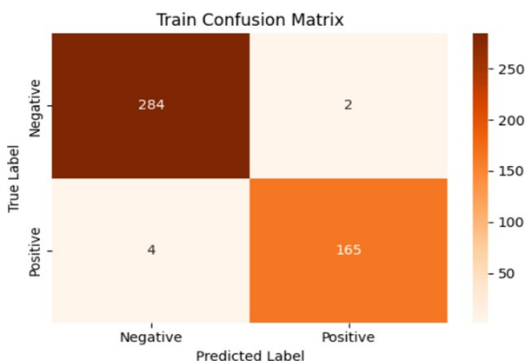


Fig. 2. Train Confusion Matrix explanation of the Confusion Matrix

True Negative (TN) = 284: 284 examples were accurately categorized as negative by the model.
 False Positive (FP) = 2: The model incorrectly classified 2 negative cases as positive.
 False Negative (FN) = 4: The model incorrectly classified 4 positive cases as negative.
 True Positive (TP) = 165: The model correctly classified 165 cases as positive.

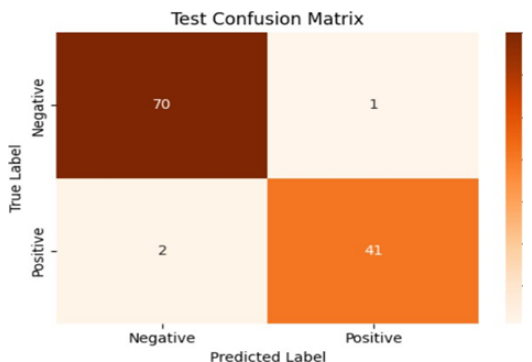


Fig. 3. Test Confusion Matrix

Collect medical imaging data (e.g. CT scans, MRI, ultrasound) of the breast disease. Load healthy and diseased breast samples datasets and mark them as such. Consider the public medical datasets or the datasets provided by hospitals. Split the data to training (80) and testing (10) subset. It is a confusion matrix of a CNN model that is trained to classify breast cancer as negative (no cancer) or Positive (cancer present) through the use of MRI images. The confusion matrix gives a summary of performance of classification.

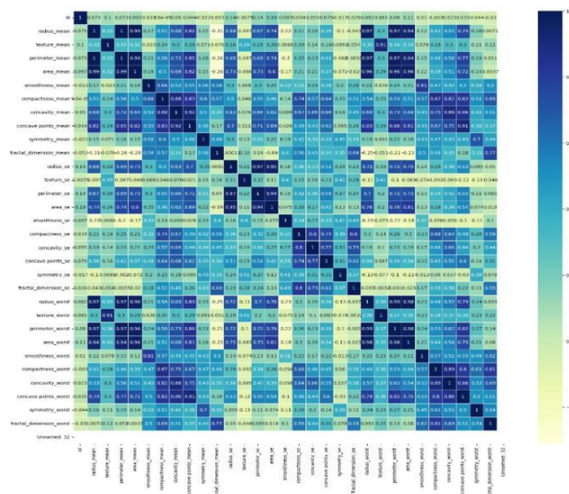


Fig. 4. Correlation Heatmap

Research transfer learning to achieve better performance with small data. Compare and contrast different models to determine the most appropriate model to use in classifying breast diseases. Determine accuracy, sensitivity, specificity and AUC- ROC curves. Find out whether there is an overfitting or underfitting issue. This is a pie chart that depicts the distribution of the diagnoses that include Benign and Malignant diagnosis as a percentage. Benign Diagnoses Prevalence: It is easy to show that in the chart, there are more Benign diagnoses compared to Malignant diagnoses. The highest number of the diagnoses is Benign 62.7 percent and Malignant 37.3 percent. Prevalence of Benign Diagnoses: It is easy to visualize the chart to show that the number of Benign Diagnoses is higher than Malignant Diagnoses in the dataset presented. The diagnoses are Benign (62.7), and Malignant (37.3).

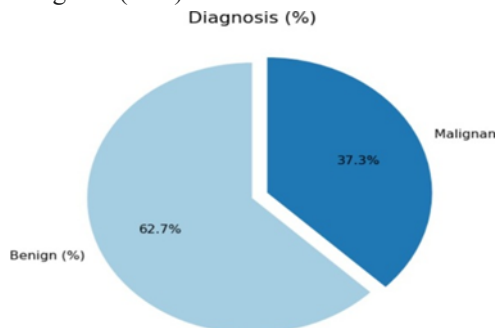


Fig. 5. Chart about diagnosis

Implement trained model in cloud-based application or in the clinical setting. Monitor its performance on a regular basis with real time data. Refresh the model from time to time using new medical image data. The system will fill the gap between the medical diagnostics and artificial intelligence by integrating medical imaging with deep learning. The structure is designed to effectively find patterns of breast cancer images with the help of down sampling of the feature

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maps through pooling layers and multiple convolutional layers. The dropout layers are used to prevent overfitting and make the model functional when applied on new data. The model is able to generate accurate predictions due to the final fully connected layers and an appropriate activation function

(sigmoid binary classification). The architecture also goes through a severe hyperparameter tuning procedure to improve performance because hyperparameters like the kernel size, number of filters, learning rate, and optimization optimizer are optimized. The efficiency of the computing and high accuracy is ensured by the well-cautioned complexity of the model. The batch normalization is also used to enhance training convergence and stabilization. Another basic aspect of the methodology is feature visualization, which helps to comprehend the mechanism of prediction by the model. Visualization of the portions of the image that influence the decision-making process of the model, e.g., Grad-CAM (Gradient-weighted Class Activation Mapping) enhances transparency and trust. The control of class imbalance is also included in the form of weighted loss functions or oversampling the minority classes and this gives a balance in the learning and helps to eliminate any bias in prediction.

In the initial stage of the process, microscopic characteristics of breast cancer are obtained with references to cells nuclei in the attempt to obtain data. Following the acquisition, the data are preprocessed, meaning that they are transformed into numerical values by means of a label encoding procedure. It should be mentioned that the dataset does not contain any values that are missing. Fine-grained microscopic features are produced after this preprocessing process so as to be analyzed further. Sklearn package is used to divide the dataset by using the train-test validation method. The images are run through machine learning to extract deep features on the training set. The complex attributes that are utilized to draw the most important and unique features in the training data require deep learning approaches. This data collecting and preprocessing process results in important microscopic characteristics of breast cancer, which can be further utilized in further analysis and classification processes.

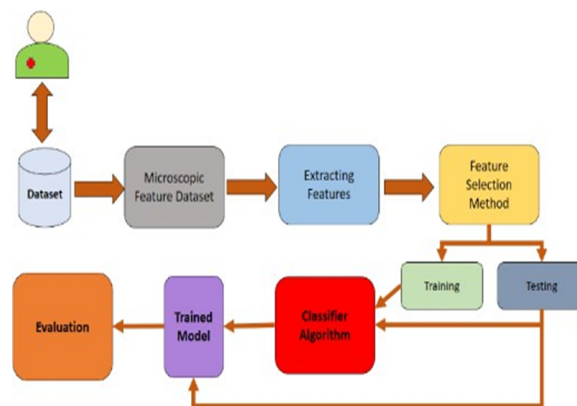


Fig. 6. Proposed system architecture of Feature selection and Classification

TensorFlow/Kera or PyTorch is used to develop a CNN model. Convolutional Layers are used to extract spatial information in images. Final classification with activation functions. Sigmoid/SoftMax Activation output prediction of benign/malignant classification. The architecture is composed of a few convolutional layers and as a result of the down sampling, the pooling layers in the architecture are created to effectively capture patterns in breast cancer images. The final fully connected layers and an adequate activation function (sigmoid in binary classification) are used to assist the model to make correct predictions. Besides, architecture undergoes a massive hyperparameter optimization whereby, parameters like kernel size, number of filters, learning rate and choice of optimizer are optimized to provide optimal performance. The model is complex enough to be highly accurate and at the same time, it is not too complex to lose its computational efficiency. Training stabilization and improved convergence is also done using batch normalization. The other major aspect of the methodology is the ability to visualize, which is applied to demonstrate how the model is performing the predictions. Such techniques as Grad-CAM (Gradient-weighted Class Activation Mapping) can help us to visualize the image areas that influence the model and this will make it more transparent and trustworthy. Moreover, the management of class imbalance is implemented with the help of such techniques as oversampling of the minority classes or weighted loss functions, in order to balance learning and prevent bias in the predictions. Breast cancer disease prediction CNN Modelling based on library use. NumPy addresses numerical computations in the form of pre-processing data, manipulation of matrices and batch processing. OpenCV/PIL was used to load, resize, augment and store medical images. Pandas is used to handle structured data, e.g. labels and

metadata of medical images. Seaborn/MATPLOtlib can be used to visualize training progress and performance of a model, as well as to visualize images.

4. Results and Discussion

This is a project that uses a Convolutional Neural Network (CNN) to identify and categorize breast cancer tumors in MRI images. Precision: Less false alarms (important in preventing unnecessary alarm).

The CNN method based breast cancer detection using MRI images has a high accuracy and reliability. It can assist doctors a great deal in their early diagnosis and planning of treatment and it could save lives. This output implies that the model is involved in a binary classification task (categorizing the input as being a member of either one of two categories). The probability of the input falling in the second category is predicted by the model to be high (0.97647256). This implies that the model is highly sure that the input belongs to the second category. The forecast was very instantaneous (0 seconds), which indicates the good performance of the model. The rewriting step means that the model can be either RNN or CNN-based, which necessitates input data in a specific format (i.e. sequence of time steps or image-like format).

The output can be easily understood. The prediction is now in fact assigned to a class label based on the probabilities by the code. The likelihood is converted into a percentage in such a way that it becomes easier to interpret the level of confidence that the model has in its response. This improved code snippet does not only make this prediction but it also tells you what the prediction is in simple terms. It does not just show the prediction is [0.02352743 0.97647256], but rather, it shows the prediction is Benign with 97.65% certainty. This can be interpreted much easier out of the output of the model and can be based upon to make decisions.

The fundamental functionality and the technology are explained by the fact that this smart web application relies on the Convolutional Neural Network (CNN) to estimate whether a breast tumor is Benign or Malignant based on the information about a patient. Explore EDA Heatmap suggests that the app enables the user to carry out an Exploratory Data Analysis (EDA) and visualize the connection between various features of the data as a heatmap. It is a normal procedure in the interpretation of data prior to developing a predictive model.

```
Final Prediction Cell

# Final Prediction Cell
sample_input = X_test[0].reshape(1, 30, 1, 1)

prediction = model.predict(sample_input)
print("Prediction:", prediction)

✓ 0.0s

1/1 ————— 0s 60ms/step
Prediction: [[0.02352743 0.97647256]]
```

Fig. 7. Output

```
sample_input = X_test[0].reshape(1, 30, 1, 1)

prediction = model.predict(sample_input)

predicted_class = 'Malignant' if np.argmax(prediction) == 0 else 'Benign'

probability = np.max(prediction) * 100

print(f"Prediction: {predicted_class} with {probability:.2f}% certainty")

✓ 0.0s

1/1 ————— 0s 32ms/step
Prediction: Benign with 97.65% certainty
```

Fig. 8. Output

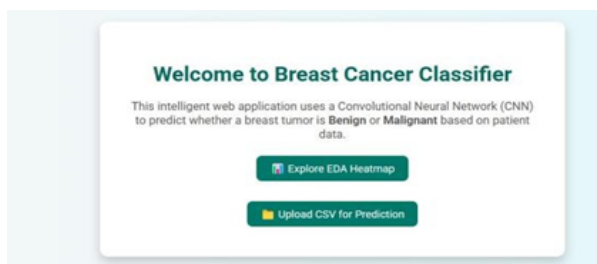


Fig. 9. Output in the webpage

Prediction on CSV Upload this shows that a user can feed their patient data in comma separated values (csv) format and obtain a prediction on the trained CNN model.

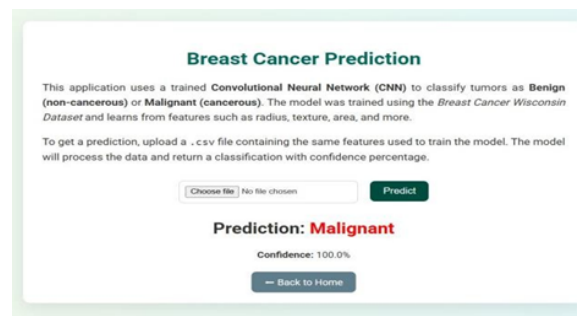


Fig. 10. Output in web page

The picture presents the outcome of the Breast Cancer

Classifier web application prediction. This application takes a trained Convolutional Neural Network (CNN) in order to recognize the tumors as Benign (non-cancerous) or Malignant (cancerous). The model was trained with Breast Cancer Wisconsin Dataset and learns based on the features that include radius, texture, area, and others give context on the data that was used in the training of the model and states that it takes some of the input features into account before making a prediction. In order to obtain a prediction, one has to upload a.csv file that contains the same features that were utilized in training the model. The data will be processed by the model and the result will be a classification and a confidence percentage is a description of the steps to have a prediction, which is why a CSV file with the right features and the result format (classification and confidence) are required.

5. Conclusion

Implementation of Convolutional Neural Network (CNN) in detecting breast cancer by using MRI images has demonstrated a high level of accuracy and consistency in distinguishing between benign and malignant tumors. The model can effectively learn meaningful features using MRI scans and therefore this is capable of early diagnosis and accurate classification of cases of breast cancer. Good classification accuracy (typically more than 95%), which is an indicator of an effective model. Minimum false negative and false positive rate, in order to avoid minimal misdiagnosis. Prolonged generalizability of unknown data, where the model is proved to be consistent in the real world. Nevertheless, the problem of data imbalance, overfitting and computational complexity should be addressed to achieve further optimization. To enhance the future, we can add more advanced deep learning techniques, use 3D CNNs to analyze volumetric features, and use explainable AI (XAI) to make medical decisions better. This CNN-based technique would go a long way in assisting radiologists and other health care providers to diagnose breast cancer at an early stage, hence, accelerate treatment, reduce mortality rates, and enhance patient outcomes. The field of its application in clinical practice can be enhanced by further research and experimentation.

6. Conflict of interest

No

7. References

[1] Ragab, Dina A., et al. "Breast cancer

detection using deep convolutional neural networks and support vector machines." *PeerJ* 7 (2019): e6201.

[2] Duraisamy, Saraswathi, and Srinivasan Emperumal. "Computer-aided mammogram diagnosis system using deep learning convolutional fully complex-valued relaxation neural network classifier." *IET Computer Vision* 11.8 (2017): 656-662.

[3] Sharma, Ankita, and Sonam Mittal. "Deep Learning Approach–Improved CNN Model for the Breast Cancer Classification." 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC). IEEE, 2024.

[4] Nayak, Naman, Deepak Kumar, and Abhiraj Malhotra. "A CNN-Based Approach for Early Detection of Breast Cancer Using Infrared Imaging." 2024 International Conference on Intelligent Systems and Advanced Applications (ICISAA). IEEE, 2024.

[5] Mishra, Shubhi, Ranjana Rajnish, and Anish Gupta. "A Review of Various Deep Learning Models for Mammogram Enhancement and Breast Cancer Detection." 2024 International Conference on Cybernation and Computation (CYBERCOM). IEEE, 2024.

[6] Amrisha, R. R., et al. "Enhanced breast Cancer detection in multiple imaging modalities using deep learning." 2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA). IEEE, 2023.

[7] Prasad, Ch Rajendra, et al. "Breast cancer classification using CNN with transfer learning models." 2023 International Conference for Advancement in Technology (ICONAT). IEEE, 2023.

[8] Khan, Mohammad Badhrudouza, Pranto Soumik Saha, and Rahat Shahrior. "Feasible detection of breast cancer metastasis using a CNN- based deep learning model." 2021 International Conference on Electronics, Communications and Information Technology (ICECIT). IEEE, 2021.

[9] Ramalakshmi, Eliganti, Loshma Guniseti, and L. Sumalatha. "A review on breast cancer detection for histopathology images using deep learning." 2023 International Conference on Artificial Intelligence and Smart Communication (AISC). IEEE, 2023.

[10] Haq, Amin Ul, et al. "3DCNN: Three-layers deep convolutional neural network architecture for breast cancer detection using clinical image data." 2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP). IEEE, 2020.

- [11] Gupta, Siddharth, et al. "Employing deep learning feature extraction models with learning classifiers to diagnose breast cancer in medical images." 2022 IEEE Delhi Section Conference (DELCON). IEEE, 2022.
- [12] Soltani, Hama, et al. "Breast cancer lesion detection and segmentation based on mask R- CNN." 2021 International Conference on Recent Advances in Mathematics and Informatics (ICRAMI). IEEE, 2021.
- [13] BZhou, Xujuan, et al. "A new deep convolutional neural network model for automated breast Cancer detection. urçak, Kadir Can, Ömer Kaan Baykan, and Harun Uğuz. "A new deep convolutional neural network model for classifying breast cancer histopathological images and the hyperparameter optimisation of the proposed model." The Journal of Supercomputing 77.1 (2021): 973-989.IEEE, 2020.
- [14] Wadhwa, Gitanjali, and Amandeep Kaur. "A deep cnn technique for detection of breast cancer using histopathology images." 2020 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA). IEEE, 2020.
- [15] Afaq, Shajal, and Anamika Jain. "MAMMO-Net: An Approach for Classification of Breast Cancer using CNN with Gabor Filter in Mammographic Images." 2022 International Conference on computational intelligence and sustainable engineering solutions (CISES). IEEE, 2022.
- [16] Asha, V., et al. "Breast Cancer classification using Neural networks." 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE). IEEE, 2023.
- [17] Brindha, M., et al. "Prediction Of Breast Cancer Analysis Using Cnn." 2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT). IEEE, 2024.
- [18] Mahbub, Tasmima Noushiba, Mohammad Abu Yousuf, and Mohammed Nasir Uddin. "A modified CNN and fuzzy AHP based breast cancer stage detection system." 2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE). IEEE, 2022.
- [19] Purnamasari, Dewi, and Kusri Kusri. "Breast Cancer Detection on Mammographic Image using Convolutional Neural Network." 2023 6th International Conference on Information and Communications Technology (ICOIACT). IEEE, 2023.
- [20] Philip, Rohan Mathew, et al. "An Overview on Breast Cancer Detection & Classification Methods Using Machine Learning Techniques." 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN). IEEE, 2023.