Application of Artificial Intelligence using Mammograms to Identify Breast Cancer

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***Abstract*—An affordable and precise way to identify breast cancer is through Mammography. It has significantly decreased mortality by detecting malignancies early and is essential for early detection. It has also increased survival rates. However, disparities in mammography access are still mostly driven by socioeconomic factors. Ongoing research aims to address these problems, improve screening methods, and raise the precision and usability of mammography. Additionally, radiologists are being assisted by computer-aided detection (CAD) and artificial intelligence (AI), which are being used to improve diagnostic accuracy. The goal of this research is to identify the best AI algorithms for breast cancer detection. We employ a range of pre-processing methods in this study, first resizing the images to see which method cleans up our data the best. After segmenting our images to locate the region of interest, we extract features using a local binary pattern. Numerous classification models have been employed, such as SVM, KNN, Random Forest, and Decision Tree. Moreover, CNN and RCN have been used for the same objective. Furthermore, it was shown that, generally speaking, neural networks outperformed classification.**

***Index Terms*—Breast Cancer, Detection, Mammograms, Artificial Intelligence, Classification, Neural Networks.**

I. INTRODUCTION

Cancer is characterized by the unregulated proliferation and spread of aberrant cells. If the spread is not halted, it may be fatal. Cancer can develop practically anywhere in the body. Breast cancer is the most common type of cancer, and if detected early enough, it is treatable. MRIs, ultrasonography, and mammograms are some of the procedures used to identify breast cancer; mammography is the most often used modality. Early detection of breast cancer makes therapy much easier, and mammography helps with that. In order to reduce false-positive mammography results and detect breast cancer early, researchers have developed artificial intelligence (AI) algorithms [1]. Robust categorization algorithms also help radiologists by lowering workload, improving decision-making, and offering a second view. One of the healthcare industry's fastest-growing segments at the moment is medical image processing. Additionally, computerized classification ensures that patients receive consistent, excellent care wherever they are by standardizing diagnosis across various healthcare facilities.The goal of this study was to evaluate an AI system's efficacy and accuracy in breast cancer screening. By applying AI algorithms and state-of-the-art imaging technologies, this study seeks to improve the early diagnosis of breast cancer through mammography. Deep learning algorithms have shown remarkable accuracy in recognizing breast cancer from mammography pictures, which could aid in early diagnosis and treatment. These models make use of convolutional neural networks to identify patterns and anomalies that the human eye would miss . The initiative aims to enhance patient outcomes and streamline screening procedures by utilizing artificial intelligence and digital mammography to facilitate radiologists' comprehension of challenging images [12] [16] [20]. Our study shows how several classification models, such as Random Forest, Decision Tree, SVM, and XGradient Boost, and neural networks, such as CNN, ANN, and RCNN, may be applied to mammography to determine if a particular image has benign or malignant cancer. In the field of breast cancer detection, categorization is essential since it influences the accuracy of the diagnosis and the subsequent course of treatment for the patient.

II. METHODOLOGY

A. Dataset

Mammograms with benign and malignant masses are included in the dataset. First, 106 mass images from the INbreast dataset, 53 mass images from the MIAS dataset, and 2188 mass images from the DDSM dataset were extracted and added to this collection. The Contributors: Ting-Yu Lin, Mei-Ling Huang. The data can be reached at "https://www.kaggle.com/datasets/tommyngx/breastcancermasses"

B. Pre-Processing Methods

1) Image Cleaning: Random errors, often known as noise, brought on by external circumstances or picture capture equipment alter images. To enhance the original image and get rid of these undesirable noises, several algorithms have been created. Computer-aided design (CAD) systems can be used to improve images through several methods, including medical image processing. Contrast Limited Adaptive Histogram Equalization (CLAHE) and other filtering methods were used to improve the mammography pictures . In order to smooth out pixel values and eliminate image noise, Mean filtering, also known as averaging, was used [2] [7]. By substituting the neighborhood median for each pixel value, Median filtering was utilized to further minimize noise in the images. Gaussian filtering involves using a Gaussian function that produces a blur effect proportionate to the distance from the central pixel. This helps to reduce noise and detail. Lastly, by reducing noise amplification and adaptively applying histogram equalization to certain areas of the image, CLAHE was utilized to enhance the contrast of the pictures and increase the distinctiveness of the features [5] [14]. These preparation steps are necessary to improve image quality and maximize the effectiveness of following classification algorithms. Using different combinations of filtering methods, we found out that Mean filtering, Gaussian Filtering and CLAHE algorithm gives the best output. Filtering images with Mean filter, Gaussian and CLAHE algorithm, we noticed it gave the highest PSNR, SNR, SSIM and SD, compared to various combinations of filtering methods [2].

2) Segmentation: The technique of segmenting an image into meaningful sections that correspond to distinct objects or structures is a crucial step in image analysis and computer vision systems [13]. Segmentation aids in providing exact information on the size, shape, and placement of certain regions, such as tumors or other anomalies, which is essential for proper diagnosis and treatment planning. It makes it possible to extract pertinent information from various image regions, which helps with medical condition analysis and classification.Segmentation improves the visibility and clarity of structures in an image by separating items from the background, which makes it simpler for medical practitioners to understand complex medical data. In our study we have implemented Binary Thresholding and Otsu Thresholding. A basic image processing method called binary thresholding segmentation turns grayscale photos into binary pictures, which are then used to isolate objects from the background [23]. Using this method, a threshold value is chosen, and pixels with values above the threshold are set to one (white), and those with values below the threshold are set to zero (black). Binary thresholding aids in the isolation of tumors or other areas of interest from surrounding tissue in medical imaging, especially in the diagnosis of breast cancer. This makes analysis and feature extraction simpler. Otsu thresholding is a sophisticated image segmentation method that figure out the ideal threshold value on its own to turn a grayscale picture into a binary image [21]. By reducing the variance in the foreground and background pixel intensities, or intra-class variance, it minimises this variation. Otsu technique is especially helpful in medical imaging for tasks like tumor detection in breast cancer since it successfully divides the image into two different classes. It improves segmentation accuracy by dynamically determining the optimal threshold, which improves region of interest separation and boosts diagnostic capabilities.

C. Feature Extraction

Identifying and isolating particular traits or qualities from raw data for additional analysis is known as feature extraction, and it is a critical stage in image processing and machine learning [18]. The amount of data that must be processed is greatly decreased by removing pertinent features, which improves computation speed and decreases the likelihood of overfitting in models. Shape, texture, intensity, and edges are examples of features that offer useful information that can be utilized to differentiate between normal and diseased tissues. This improves the diagnostic models' accuracy. By encoding an image's local spatial structure, LBP enables the capture of texture information [6]. It is very good at describing textures, which makes it applicable to a number of fields, such as face recognition and medical imaging. LBP can be used to extract texture features from mammograms for the purpose of breast cancer detection. By aiding in the differentiation of benign from malignant tissues, these characteristics can support precise diagnosis and analysis.

D. Models

1) Classification Models: - Classification models are machine learning algorithms that categorize data into predetermined classes or labels [8]. These models examine input data and estimate which category it belongs to using patterns acquired from training data.

KNN Model- A straightforward yet powerful supervised machine learning approach for classification and regression applications is the K-Nearest Neighbors (KNN) model [25]. It functions according to the idea that comparable data points should produce comparable results. One important element that establishes how many neighbors to take into account is the value of 'k'. While a big 'k' can smooth out predictions but may miss subtle patterns, a little 'k' can make the model more susceptible to noise. We observed that the KNN showed an Accuracy of "84.44".

SVM Model- Mostly used for classification, the Support Vector Machine (SVM) model is a potent supervised learning technique [22]. It is well known for being efficient in high-dimensional spaces and adaptable in many other fields. In our study, we observed that SVM gave a moderate accuracy of "85.36".

Random Forest Model- A flexible and reliable ensemble learning approach for both classification and regression applications [15] [17] . In order to function, it builds a large number of decision trees during training and outputs the mean prediction for regression or the mode of the classes for classification based on each individual tree. We saw that Random Forest gave an accuracy of "94.0035".

Decision Tree- A prominent supervised learning technique for classification tasks is the decision tree, which is renowned for its ease of use and interpretability [15] [19] . In order to create a decision tree, it splits the data recursively according to the values of the input features. The tree-building process seeks to maximize class separation or decrease prediction error. We observe that our Decision Tree gives the accuracy of ”95.412”. It was also observed that it showed high numbers of False Positive and False Negative.

X Gradient Boost- Extreme Gradient Boosting, or XGBoost, is a potent and effective machine learning technique that works especially well for classification applications [3]. It is a fast and efficient implementation of gradient boosted decision trees. XGBooster Model gave an accuracy of ”96.922”. Amongst all classification models, this model showed the least amount of false positives and false negatives.

Naive Bayes’ Model- It makes the ”naive” but frequently accurate assumption that features in a dataset are independent of one another given the class label. The classifier assumes that all features are independent given the class. It showed the least accuracy of ”70.68535”.

It was concluded that amongst all the classification models applied, Naive Baye’s showed the poorest performance, with lowest accuracy and precision whereas Decision Tree has a high accuracy but low precision, which leads to higher false outputs. On the other hand, XG Booster Model shows high accuracy and also has higher precision as it has the least false negatives and positives [11] [24]. The same can be observed in Fig.1. Evaluation Metrics of Classification Models, that shows a comparitves performance of all the models, by comparing the accuracy, precision, recall and F1 score. It can also be seen that Decision Tree and XG Boost have performances which are at par to each other.

2) Neural Network Models: Neural networks are computer models that mimic the structure and functions of the human brain [9]. They are used to solve complicated issues and look for patterns. An input layer, one or more hidden layers, and an output layer are the layers made up of interconnected nodes (neurons). Each link is given a weight, which is adjusted throughout training to lower prediction error. Neural networks are a powerful tool for tasks like speech and picture identification, natural language processing, and game play because they are excellent at detecting non-linear connections in data. Even though they are complicated, they are quite efficient and have significantly advanced artificial intelligence and machine learning.

CNN- is a deep learning model designed to interpret pictures and other structured grid data [10]. CNNs are frequently utilized for several applications such as object identification, facial recognition, and picture classification. They have revolutionized the computer vision sector. A CNN with 10 epochs was implemented. ”94.522” was the training accuracy and ”89.342” was the testing accuracy displayed by CNN. After performing Hyper- Parameter tuning on CNN, we found out that the accuracy of the model went upto ”92.692”.
RCNN- A class of models known as Region-based Convolutional Neural Networks (R-CNN) combines region suggestions with Convolutional Neural Networks (CNNs) to tackle object detection challenges [4]. By enabling more precise and effective object detection within images, the R-CNN framework has made important advancements in the field of object detection. We observed the accuracy achieved by RCNN is ”91.887”.
We find that the accuracy provided by the two neural network models is comparable to one another. In conclusion, we find that Neural Network Models outperform Classification Models in terms of accuracy and precision. Fig.2, is a visual representation of the performances of both CNN and RCNN on the basis of various evaluation metrics, we find out that both the models perform equally well.

E. Abbreviations and Acronyms

1) LBP- Local binary patterns
2) CNN- Convolutional Neural Network.
3) RCNN- Recurrent Convolutional Neural Network.
4) KNN- K-Nearest Neighbour.
5) SVM- Support Vector Machine.
6) PSNR- Peak Signal to Noise Ratio.
7) SNR- Signal to Noise Ratio.
8) SSIM- Structural Similarity Index.
9) SD- Standard Deviation.
10) CLAHE- Contrast Limited Adaptive histogram equalization
11) CAD- Computer Aided Design

III. Results and Discussions

In this study, using a dataset of mammography pictures that were classified into benign and malignant masses, we evaluated the performance of various machine learning models. XGBoost, Naive Bayes, Random Forest, Decision Tree, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) were among these models. We also developed and evaluated convolutional and recurrent neural networks (RNNs) to see how well they fared in contrast to these traditional classification models.

Our results show that neural networks, and CNNs in particular, frequently outperformed classical classification models in a number of evaluation metrics, including accuracy, precision, recall, and F1 score.

There are various reasons for this superiority:
1. Conventional models frequently use manually created features, including Local Binary Patterns (LBP), which might not be able to extract all of the fine details and patterns found in mammography pictures.
2. Neural networks, on the other hand, automatically derive hierarchical feature representations from raw pixel data, thereby improving their capacity to identify intricate structures and patterns.

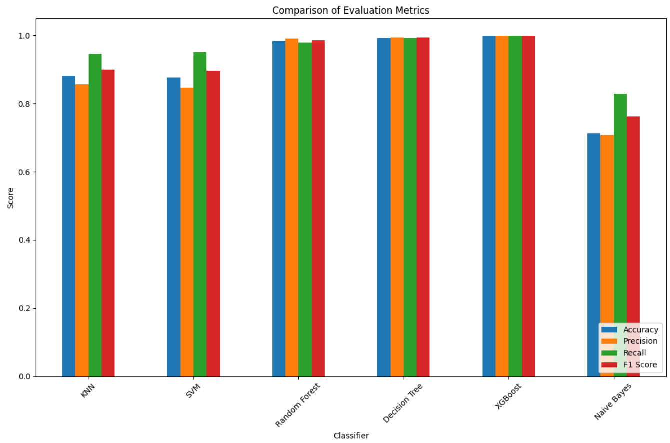

Fig. 1. Evaluation Metrics of Classification Models

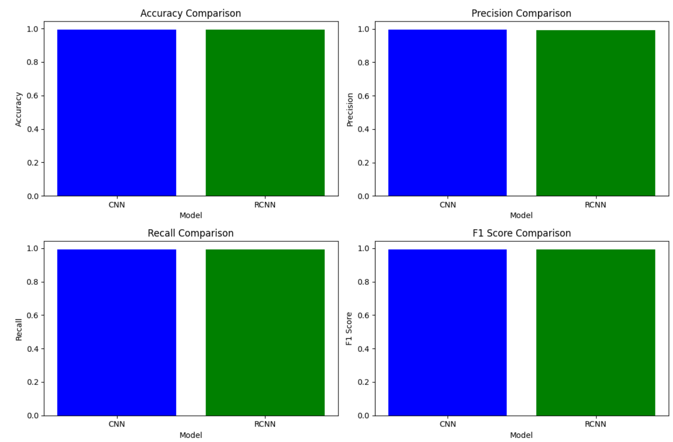

Fig. 2. Evaluation Metrics of Neural Networks

IV. Conclusion

Our observations showed us that the optimal filtering result was obtained when the CLAHE method was combined with Mean and Gaussian filtering. Our investigation led us to the conclusion that Neural Networks performed better in terms of accuracy, recall and precision when determining if a mammogram revealed benign or malignant cancer. When compared to Neural Network Models, Classification Models performed well but had greater rates of false positives and negatives. Even with the neural networks' increased accuracy, false positives and negatives couldn't be completely eliminated.

V. Future Scope

By looking at different neural network architectures and techniques, such as fine-tuning, the use of more intricate network structures like EfficientNet or Vision Transformers, and transfer learning using pre-trained models, future research can build on these findings. Furthermore, adding multi-modal data to the models like, patient demographics and medical history, may increase their predictive accuracy and clinical significance. To sum up, while traditional classification techniques continue to offer valuable insights and baseline performance, neural networks are a more accurate and efficient solution for identifying mammography pictures. Their ability to recognize complex patterns, generalize well, and handle large amounts of data efficiently makes them a useful tool in the quest to improve patient outcomes and diagnostic accuracy in medical imaging.

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