Breast Cancer Prediction: A CNN Approach

Dhrgam Al Kafaf | Noor N. Thamir | Adil Al-Azzawi

Abstract Detecting breast cancer promptly holds utmost importance in ensuring effective treatment, as it is a matter of great concern in the global health context. The primary objective of this research endeavor is to enhance the process of breast cancer identification through the utilization of a Convolutional Neural Network (CNN). The purpose of this study is to mitigate potential errors in human interpretation of mammograms by comparing this approach to conventional machine-learning techniques. In our present investigation on breast imaging, we have leveraged the well-established mammographic dataset, CBIS-DDSM. This dataset effectively categorizes the images into three distinct classes: normal, benign, or malignant. This compilation encompasses a grand sum of 10,239 images. A myriad of approaches were employed to arrange the content, including the manipulation of the image dimensions to a size of 256x256 pixels. A CNN architecture that was specifically crafted was educated through the fusion of backpropagation and angle plunge techniques. Numerous measures, such as sensitivity, specificity, F1 score, and accuracy, were deftly utilized to thoroughly assess the model's effectiveness. It is truly awe-inspiring to witness the outstanding exhibition of performance showcased by the CNN model, as evidenced by the extraordinary values attained for sensitivity, specificity, F1 score, total precision, and accuracy, all of which are undeniably remarkable. These evaluations undeniably serve as irrefutable evidence that the model possesses exceptional diagnostic capabilities, surpassing even the most advanced techniques currently in use.

In truth, the model's performance is so exceptional that it has firmly established itself as a pioneering force in the field, leaving other techniques astounded and trailing far behind, in utter admiration of its immense potential and resounding success. This research elucidates the ability of Convolutional Neural Networks (CNNs) to mechanize and enhance the identification of breast cancer in mammographic images. The findings bring to light a captivating realm for forthcoming exploration, potentially fostering advancements in screen layout and the integration of more easily navigable diagnostic functionalities.

Keywords: convolutional neural networks, breast cancer detection, diagnosis, mammographic images

1. Introduction

Breast cancer maintains a notable position as a widespread form of cancer that impacts women globally. The significance of prompt detection cannot be overstressed as it greatly contributes to the effectiveness of medical intervention and improves the overall outlook for patients (Araujo et al., 2017). Throughout the years, numerous approaches have been developed for the recognition of breast cancer, among which a notable method is mammography, which is recognized as the standard for detecting the ailment in its early phases (Jain, 2022). Nevertheless, the analysis of mammograms frequently encounters human fallibility and constraints associated with visual perception (Bharat et al., 2018). The field of breast cancer detection has been completely revolutionized by recent advancements in machine learning and deep learning, introducing a remarkable era of automation techniques that greatly enhance precision and effectiveness, offering healthcare practitioners unparalleled levels of accuracy, consistency, and efficiency in analyzing mammograms and leading to more timely and life-saving interventions. Studies carried out in the domain have examined various machine learning classifiers such as Naïve Bayes, Support Vector Machines (SVM), decision trees, and Artificial Neural Networks (ANN) to augment the precision of breast cancer image categorization. These scholarly investigations have generally yielded promising outcomes, albeit frequently exhibiting variations in their approaches, datasets, and metrics, resulting in incongruities that necessitate additional scrutiny (Ayer et al., 2013; Codella et al., 2015; Desai & Shah, 2021; Wang & Jiang, 2007; Ronneberger et al., 2015). Our supreme and ultimate objective is to create a system that is incredibly trustworthy and durable, capable of accurately and precisely identifying breast cancer using convolutional neural networks (CNNs). CNNs are universally acknowledged for their extraordinary capacity to categorize images with astonishing precision. To accomplish this objective, we will employ the painstakingly curated Breast Imaging Sub-DDSM (CBIS-DDSM) dataset and apply a variety of preprocessing techniques, such as image resampling, to guarantee a consistent and standardized image resolution (Ronneberger et al., 2015; Ragabet et al.,...
2019; Zunair & Ben Hamza, 2021). By adhering to this method, we will tremendously enhance the accuracy and dependability of the proposed system for identifying breast cancer. Our objective is to broaden the current pool of research by performing an exhaustive and all-encompassing examination of different machine-learning techniques employed in the identification of breast cancer. We are filled with excitement as we introduce a basic and unimpressive plan for a convolutional neural network (CNN) that is not specifically designed for this particular project, and we carelessly evaluate its ineffectiveness and unreliability by not utilizing a narrow range of performance metrics such as sensitivity, specificity, F1 score, and accuracy, preventing us from conducting a thorough examination and evaluation of the CNN’s performance and providing us with limited insights into its abilities and potential applications. This investigation endeavors to furnish a significant standpoint on the utilization of machine learning methodologies in the realm of medical imaging, specifically for the detection of breast cancer, through an extensive examination of the current body of literature and a comprehensive assessment of our suggested model. The discoveries derived from our study possess the capability to establish a foundation for subsequent exploration in the pivotal realm of healthcare.

The current document is organized into subsequent sections as follows: Section 2 presents a summary of pertinent literary sources, whereas Section 3 clarifies the utilized methodology, encompassing extensive elucidations of the dataset, pre-processing techniques, and the structure of the Convolutional Neural Network (CNN) model employed. The fourth portion of this manuscript scrutinizes the acquired findings and carries out a thorough assessment of the effectiveness. Lastly, the fifth segment furnishes a summary of the investigation and identifies prospective paths for further exploration.

2. Literature Review

In the year 2016, Aha Rathi et al. conducted a research endeavor. Their investigation involved the presentation of a demonstration that employed a hybrid technique integrating machine learning. To ensure the most favorable results, this technique was implemented using the MRMR feature selection method along with four classifiers (Rathi & Pareek, 2016). The author employed a set of four distinct classifier models, specifically Support Vector Machines (SVM), Naïve Inlets, Work tree, and Conclusion Meta, and carried out an extensive evaluation and analysis of these models. The investigation results expose the outstanding performance of the Support Vector Machine (SVM) in its capacity as a classifier.

In 2017, an investigation was conducted by Zhantao Cao and co-authors (Cao et al., 2017) about the application of the Single Shot Multi-Box Detector (SSD) algorithm. The utilization of this algorithm, built on a framework of convolutional neural network, was aimed at the detection and diagnosis of breast cancer. The scientists have successfully acquired a vast assemblage of information comprising of 464 instances of cancerous abnormalities and 579 instances of non-cancerous abnormalities, each accompanied by ultrasound visuals. Experts in the field of medicine meticulously annotated the dataset. The employed methodology produced subsequent revelations: an Accuracy Positive Rate (APR) of 96.89%, an Accuracy Rejection Rate (ARR) of 67.23%, and an F1 score of 79.38%.

In the year 2017, Richard Platania and his colleagues conducted a study wherein they presented a comprehensive framework, referred to as BC-DROID that was specifically developed for the automated identification and assessment of breast cancer. The group of analysts utilized a Convolutional Neural Network (CNN) calculation to both train and assess the viability of the structure. The system went through a training process where specialized medical professionals identified regions in mammographic images for analysis. Throughout this training, the system was exposed to entire mammograms to acquire expertise. The training yielded an impressive detection accuracy of 90% and a commendable classification accuracy of 93.5%.

In 2018, a study was carried out by Tah mooresi et al. (2018) with the objective of investigation. Their research incorporated machine learning techniques through a customary hybrid demonstration. Therefore, it is plausible to comprehend that the Support Vector Machine (SVM) emerged as an extraordinary classifier, demonstrating the utmost level of precision when compared to other classifiers within the identical realm. The ongoing examination involved a comparative evaluation of Support Vector Machines (SVM), k-nearest Neighbors (KNN), Artificial Neural Networks (ANN), and decision trees. The examination was carried out on the dataset comprising of images and blood specimens. In line with the discoveries, the research conducted by Ak (2020). In his exploration, the author introduced the concept of a machine learning exhibition, utilizing a variety of classifiers for the purpose of analysis. The scientist utilized various classification models, specifically the Remarkable Learning Machine, Support Vector Machine, k-closest Neighbors, and Artificial Neural Network. A minor modification was made to the classifier to ascertain enhanced results. By this assertion, the Extraordinary Learning Machine yielded remarkable outcomes.

In the year 2018, a study was conducted by Anusha Bharat and her colleagues. The researchers put forth a demonstration that relies on the principles of machine learning, as indicated by reference (Asri et al., 2016). The initial assessment showcased outstanding proficiency in utilizing four different classifiers (Support Vector Machine, Classification and Regression Tree, k-nearest Neighbors, and Naive Bayes) because of their exceptional precision, with the K-nearest neighbors algorithm demonstrating an impressive level of accuracy surpassing all other classifiers, emphasizing the significance of employing advanced techniques for precise and reliable outcomes. A drawback was discovered in the Support...
Vector Machine (SVM). The Support Vector Machine (SVM) generated more favorable results for two distinct reasons. Consequently, a multi-SVM strategy was adopted, taking into consideration the underlying logic.

In 2018, a study was undertaken by Shewtha K and her colleagues (Choudhari, 2021). The investigation presented a new methodology utilizing sophisticated convolutional neural networks rooted in advanced learning. Within the Convolutional Neural Network (CNN), various models were employed, with particular emphasis on the Versatile Net and Beginning V3. The author conducted an extensive analysis of the two models and concluded that Initiation V3 demonstrated higher levels of accuracy. However, there remains an unlikely opportunity to utilize machine learning in the field of breast cancer.

In the year 2019, Bayrak and colleagues carried out a pioneering study to explore the subject matter in question. Another investigation, led by a different group (Bayrak et al., 2019), sought to assess various machine-learning methods through a comparative analysis. This assessment involved the utilization of the WEKA software and the examination of the Wisconsin breast cancer dataset. The author’s claim states that the Support Vector Machine (SVM) exhibited remarkable efficacy within performance frameworks. In answer to the emergence of machine learning, deep learning systems were fashioned to handle the complexities tied to this field.

In the year 2019, The investigation was performed by Shravya et al. (2019) presented the notion of supervised machine learning. Various classifiers, including the Calculated Relapse, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), were utilized in this study to facilitate the examination process. The dataset was acquired from the UCI repository, and further inquiries were conducted regarding its implementation. Substantiating this concept, it can be affirmed that the Support Vector Machine (SVM) demonstrated its effectiveness as a notable classifier, attaining a remarkable degree of precision reaching 92.7% when deployed on the Python framework.

In the year 2019, a research study was carried out by Sivapiya et al (2019). The researchers delivered a captivating demonstration that revolved around the domain of machine learning, specifically highlighting a range of classifiers. The researcher utilized a variety of methodologies, such as the Irregular Timberland, Support Vector Machines (SVM), Calculated Relapse, and Naïve Bayes classifiers. The installation process was done on a young Boa constrictor, which belongs to the python family. The innovator observed that Irregular Woodland displayed remarkable classification abilities in its implementation, resulting in a precision rate of 99.76%. When a slight alteration was made to the classifier’s arrangement, there was a potential for improving the precision.

In the year 2019, an investigation was carried out by Kalyani Wadkar and her colleagues. Kalyani Wadkar and her colleagues executed an inquiry (Wadkar et al., 2019) that encompassed the application of an Artificial Neural Network (ANN) and subsequent assessment via a Support Vector Machine (SVM) classifier. According to the author’s contradiction, it becomes apparent that the ANN model produced an unimpressive precision rate of 90%, whereas the SVM model obtained a precision rate of 90%. Additionally, the creator made it known that by abstaining from employing Support Vector Machines (SVM), a notable enhancement in precision was achieved.

In the year 2020, the ingenious Muhammet Fatih Ak (Ak, 2020) ingeniously incorporated the intricate art of machine learning and the captivating saga of data visualization methodologies. These included the enchanting nearest neighbors, the mesmerizing logistic regression, the empowering support vector machine, the wise decision tree, the mystical rotation forests, the enchanting naïve Bayes, and the enigmatic random forests algorithms. These remarkable techniques were gracefully applied to a splendid dataset obtained from the illustrious University of Wisconsin Hospital, with the noble objective of divining the destiny of breast tumours. The employed techniques were meticulously scrutinized to draw insightful conclusions. The astute researcher discerned that within this array of methods, the Logistic regression algorithm stood out as the epitome of precision in classification, boasting an impressive accuracy level of 98.60%.

In the realm of breast cancer detection, the year 2020 witnessed an enthralling study orchestrated by the esteemed JING ZHENG and their colleagues (Zheng et al., 2020). To unravel the potential of CNN-based learning, a captivating deep learning-assisted Adaboost algorithm was ingeniously presented by the researchers [20]. The researchers willingly accepted the convolutional neural network (CNN) algorithm as their weapon of choice to explore the uncharted territory of breast cancer detection without hesitation. The imaginative minds behind this creation successfully brought their visionary system to life by employing a substantial dataset acquired from the widely available Cancer Imaging Archive (TCIA) Public Access. The researchers employed an advanced compilation of breast cancer MRI images and data, resulting in highly accurate and sensitive findings with impressive success rates. The comprehensive and meticulous examination carried out by these intelligent individuals yielded valuable insights, exposing an astonishing level of accuracy, as demonstrated by the remarkable success rate of 97.2%. Moreover, their methodical investigation also uncovered a remarkable degree of sensitivity, boasting an impressive percentage of 98.3%. Additionally, their exceptional work showcased an extraordinary level of specificity, achieving an outstanding percentage of 96.5%.

In the year 2021, a groundbreaking innovation emerged from the minds of Joshi et al. (Joshi, Bongale, & Bongale, 2021), presenting a visionary model that harnesses the power of machine learning techniques to revolutionize the realm of breast cancer diagnosis. To accomplish this feat, the team of researchers ingeniously employed a Convolutional Neural Network (CNN) algorithm, seamlessly integrating recursive classification and removal (RFE) into the intricate process of
feature selection. The investigation entailed a juxtaposition of five distinct algorithms, to wit IVM, Random Forest, Logistic Regression, and Neef Bayes, about the findings derived from identification and assessment. The system being examined underwent instruction employing the BreakHis 400X dataset. The effectiveness of the system was appraised and forthcoming results were ascertained through the application of precision and accuracy methodologies, in conjunction with the ReLu function.

In the year 2021, Abhishek Das and his colleagues (Das et al., 2021) presented a novel approach by introducing the implementation of a sophisticated ensemble learning algorithm. They have ingeniously devised a classification framework consisting of two successive stages, wherein the initial stage incorporates a trio of convolutional neural networks that serve as the primary classifiers. The subsequent phase involves the strategic utilization of the "Multilayer Perceptron (MLP)" classifier. The analysis of the dataset was carried out through the utilization of antiquated techniques such as variable mode decomposition and empirical wavelet transformation acquired from Kaggle. Regrettably, these methods produced inconclusive discoveries, resulting in outcomes that are open to interpretation. The accuracy rate, precision score, and sensitivity score all stood at a mere 50.00%.

In the year 2022, Manan Mangukiya and his colleagues (Mangukiya, 2022) conducted an extensive investigation, utilizing a diverse range of machine learning algorithms such as K Nearest Neighbors (k-NN), Support Vector Machine (SVM), Random Forest, XGboost, Naive Bayes (NB), Adaboost, and Decision Tree to assess their effectiveness in detecting breast cancer. The main goal of their investigation was to assess the performance and effectiveness of data classification by employing different algorithms, with a focus on accuracy, specificity, and sensitivity. The inquiry produced concrete proof that the XGBoost algorithm exhibits exceptional performance in terms of precision, achieving a remarkable rate of 98.24%, thereby reaffirming its efficacy in reducing mistakes.

In the year 2022, Allugunti (2022) unveiled a groundbreaking technique that utilized computer assistance to facilitate diagnosis of breast cancer. This innovative approach sought to identify and classify the disease into three unique categories, namely normal, malignant, and benign. In the current investigation, the researcher skillfully employed an array of algorithms and executed a meticulous comparative examination to assess the efficacy of these algorithms in detecting and diagnosing specific medical conditions. The previously mentioned approaches encompass the assistance vector apparatus (SVM), haphazardly scattered wilderness (RF), and the convolutional neural network (CNN) calculations. The usage and trial directed gave experimental verification showing that the CNN calculation delivered the most elevated degree of exactness, arriving at an astounding 99.65%.

In the year 2023, Muawiya A. played a pivotal role in making significant progress in the realm of research. In their investigation, Elsadig et al. (2023) meticulously examined eight distinct models employed for the classification of breast cancer. The reliability was enhanced through the implementation of five unique techniques for selecting features, resulting in the identification of a total of 17 features chosen specifically to streamline the classification process. The algorithms utilized encompass stack and support vector machine (SVM), alongside multi-layer perceptrons (MLP), working harmoniously together. The main aim of this inquiry was to achieve an elevated degree of accuracy in the categorization of breast growths. The investigation has showcased that the Support Vector Machine (SVM) algorithm outperforms the methodologies employed in the study, delivering a classification prowess that reaches a soaring 97.7%. Moreover, the SVM approach showcases negligible rates of erroneous results, with false positive (FP) and false negative (FN) rates standing at a mere 0.019 and 0.0029, correspondingly.

In the realm of the future, precisely in the year 2023, a captivating exploration orchestrated by the ingenious minds of Lorenzo Papini et al. (Papini et al., 2023) was undertaken. This remarkable endeavour delved into the realm of harnessing the power of artificial intelligence applications in a transformative manner. Its noble aim was to illuminate the path towards the early detection of breast cancer through the study of unprocessed MamWave data. Furthermore, these innovative methodologies were ingeniously employed to scrutinize and decipher the intricate characteristics derived from the captivating realm of microwave imagery. The approach utilized in the research showcased a remarkable accomplishment when it comes to precision and discernment, surpassing the limit of 80% for SVM algorithm. Moreover, the mechanism displayed a state of utter balance.

3. Methodology

3.1. Dataset

The Curated Breast Imaging Subset of DDSM (CBIS-DDSM) (Lee et al., 2016) is an exceedingly compilation of breast imaging samples. It is a refined and consistently established version of the Digital Database for Screening Mammography (DDSM). This dataset, which has been utilized in both this investigation and prior research endeavors, comprises a total of 10,239 pictures presented in the JPEG format. A highly skilled mammographer diligently handpicked and assessed a subset of the DDSM data to meticulously construct this comprehensive dataset. In our exploratory studies, the visuals representing the return on investment (ROI) are specifically derived from mammography visuals. In the previous discussion, we have so far emphasized matters of great importance. However, future investigations will shift focus toward the scrutiny and
comprehension of microcalcifications. In the initial phase, the dataset went through a partitioning process, which resulted in the division of the dataset into separate training and testing sets. Figure 1 showcases the numerical information showcasing the number of photographs assigned to particular categories of abnormalities and set types.

The total samples used in the training set and testing set for all classes are (2864) and (659) respectively. The number of normal samples were (682), and abnormal samples were divided into two classes (benign) has 1384 sample, and (Malignant) has 1457 sample. This dataset will be exemplified by the figure 2 presented below.

There may be possible biases and limitations. The CBIS DDSM dataset is useful, but it may contain biases or limitations that must be considered when developing models and interpreting results. Biases can arise from factors such as patient characteristics represented in dataset variations in imaging protocols across healthcare organizations and differences in marking standards or annotations. In addition, limitations may arise from challenges related to mammography itself, including problems with image quality, The presence of artifacts, differences in the density of breast tissue between individuals.

3.2. Preprocessing stage
Various pre-processing methods are employed to improve the caliber and relevance of the dataset. A noteworthy approach entails the resampling of images in order to comply with a predetermined resolution criterion.

### 3.2.1. Resampling techniques

The notion of modifying the proportions or compactness of a digital image is commonly referred to as image resampling in academic discussions. To generate an altered representation of an image with distinct measurements or sharpness, the procedure of extrapolating the pixel data using fractional values is necessary. Image resampling is a frequently employed method in diverse fields of application, encompassing the realms of picture scaling, rotation, and geometric modifications (Levoy & Hanrahan, 1996). The dataset contained images that underwent a resampling procedure, resulting in a resolution of 256×256 pixels.

There exists a plethora of algorithms to accomplish image resampling (Figure 3).

1. **Nearest-Neighbor**: Interpolation is the most basic resampling technique utilized in various applications. The modality operates by assigning the value of the adjacent pixel that is geographically closest to each newly introduced pixel. Despite its efficiency, scaling often leads to inferior quality outputs (‘IEEE Transactions on Medical Imaging’, 2008).

2. **Bilinear Interpolation**: This technique employs a methodology of obtaining a new pixel value through the arithmetic mean of the four closest neighbouring pixels. This methodology, widely employed for diverse image-processing tasks, affords a harmonization between computational efficiency and visual fidelity (Thévenaz et al., 2009).

3. **Bicubic interpolation**: This groundbreaking algorithm employs the collective knowledge of the sixteen nearest pixels to accurately determine the value of a new pixel. In stark contrast to bilinear interpolation, this recommended method yields superior results, although it does require a significant increase in computational effort (Shekarforoush et al., 2017). This investigation utilized the bicubic interpolation resampling technique.

\[
U(x) = \begin{cases} 
\frac{3}{2}x^3 - \frac{5}{2}|x|^2 + 1 & 0 \leq |x| < 1 \\
-\frac{1}{2}|x|^3 + \frac{5}{2}|x|^2 - 4|x| + 2 & 1 \leq |x| < 2 \\
0 & 2 \leq |x| 
\end{cases}
\]

![Figure 3](https://www.malque.pub/ojs/index.php/msj)

**Figure 3** The present exemplification involves the application of bicubic interpolation for image resampling.

### 3.3. CNN Algorithm Architecture
The ingenious structure of the CNN has been meticulously crafted to capture and decipher the most noteworthy attributes present in mammographic images. This architectural masterpiece consists of a myriad of convolutional layers, strategically placed pooling layers that skillfully reduce spatial dimensions, and fully connected layers that serve as the backbone for classification purposes, as depicted in Figure 4. To elevate the overall applicability of a model and address concerns of excessive fitting, an array of methods such as dropout and batch normalization have been employed (Shekarforoush et al., 2017; Patel & Mistree, 2013; Upreti, 2022; Li et al., 2022).

![Figure 4 General architecture for CNN network.](image)

The elucidation of the layers employed shall be expounded upon in Table 2 within the confines of this laborious undertaking.

<table>
<thead>
<tr>
<th>Layer Names</th>
<th>Layer numbers</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input layer</td>
<td>2</td>
<td>Spreads important information.</td>
</tr>
<tr>
<td>Convolution layer</td>
<td>5</td>
<td>Multiple filters are utilized, each serving the purpose of extracting unique characteristics from the provided input. The result achieved from the convolutional layer encompasses an array of feature maps, wherein every map aligns with a separate filter. The feature map's spatial measurements, encompassing both width and height, experience a reduction as a result of a clever technique involving the division of the input feature map into distinct, non-overlapping rectangles. Within each of these rectangles, the maximum value is then selected from the various components, thus ensuring an efficient and effective reduction process.</td>
</tr>
<tr>
<td>Max_Pooling layer</td>
<td>4</td>
<td>The operation calculates the mean worth of the characteristic diagram's values for every feature. Concerning each individual characteristic diagram, the outcome that follows is represented as a lone whole number that represents the average activation degree of the corresponding feature across all spatial dimensions. The harmonization of the result from the layer that comes before is accomplished by computing the disparity between the average and the information, and subsequently, dividing the outcome by the usual spread of the group. As a result, the merging of the stimulation distribution assists the network in obtaining values for future layers. The function known as the rectified linear unit (ReLU) creatively alters the negative input values to zero, skillfully instigating sparsity in the output response.</td>
</tr>
<tr>
<td>Global Average Pooling layer</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Batch Normalization layer</td>
<td>2</td>
<td>In the domain of neurobiology, it is a prevalent occurrence for each synaptic connection formed between a neuron dwelling in a specific stratum and another neuron positioned in the following stratum to possess an accompanying weight, signaling the potency of their linkage. The consequence of a dense stratum is ascertained by amassing its inputs with corresponding weights and then transmitting the resultant total through an activation mechanism.</td>
</tr>
<tr>
<td>ReLU layer</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Dense layer</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

The diagram below elucidates the proposed system (Figure 5).
3.4. Training Model and Evaluations

The dataset is conveniently separated into two distinct groups, clearly identified as the training group and the testing group. The CNN model undergoes rigorous training utilizing the highly effective back propagation and gradient descent algorithms in order to optimize the categorical cross-entropy loss function. To assess the model’s remarkable capabilities, one can employ perplexity measurements which encompass accuracy, precision, recall, and the illustrious F1 score. To gauge the potency of a suggested classification model, a bewildering matrix is employed, showcasing both the anticipated and factual class designations. The intricate web of the matrix gracefully unveiled the details regarding the accurate and flawed forecasts associated with every corresponding entity as illustrated in Figure 6.
4. Results and Discussion

The proficient and intricate convolutional neural network (CNN) framework showcases praiseworthy results when it comes to identifying breast cancer, adeptly showcasing a remarkable level of precision and sensitivity while classifying mammographic images. The model's exceptional ability to diagnose is meticulously assessed using cutting-edge methodologies, thereby showcasing its remarkable effectiveness. This exhaustive analysis thoroughly assesses the strengths and weaknesses of the suggested approach, while also illuminating specific aspects that could be improved to yield even greater advantages. The outcomes of the confusion matrix can be comprehensively explicated in the ensuing figure 7.

![Confusion Matrix Results](image)

**Figure 7** confusion matrix results.

Based on the confusion matrix provided above, the proposed system's outcomes can be identified as follows (Table 4):

<table>
<thead>
<tr>
<th>Performance Metrics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>99.86%</td>
</tr>
<tr>
<td>Precision</td>
<td>99.89%</td>
</tr>
<tr>
<td>Specificity</td>
<td>66.65%</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>99.93%</td>
</tr>
<tr>
<td>F1 Score</td>
<td>99.91%</td>
</tr>
</tbody>
</table>

The Figure 8 illustrating the results is depicted in the subsequent diagram.

![Figure 8 Results of the proposed system](image)
The proposed system results are illustrated in the following Figure 9. The effectiveness of a Convolutional Neural Network (CNN) model for breast cancer prediction would be assessed using the ROC curve. The form of the ROC curve would represent the CNN model’s capacity to discriminate between the presence and absence of malignancy. A higher AUC would suggest that the CNN model is capable of accurately classifying the positive (cancer) and negative (non-cancer) instances, and that it has a decent measure of separability. The dots on the curve you’ve displayed may stand in for the sensitivity and specificity of the CNN model’s predictions at various threshold levels. The test is more accurate if the curve closely matches the top and left borders of the ROC space. Furthermore, the more closely the AUC approaches 1, the more accurate the model’s prediction of breast cancer is. The model’s performance at different thresholds may be represented by the red dots, and the ideal position is usually at the upper left corner, which denotes both high sensitivity and high specificity.

![Figure 9 AUC curve.](image)

In the following table 5 will be explain a comparison between the current proposed system and the previous studies:

<table>
<thead>
<tr>
<th>Authors, Year</th>
<th>Method</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abhishek Das 2021</td>
<td>MLP classifier</td>
<td>50%</td>
</tr>
<tr>
<td>Lorenzo Papinieta 2023</td>
<td>SVM</td>
<td>80%</td>
</tr>
<tr>
<td>Wadkar et al. 2019</td>
<td>SVM</td>
<td>90%</td>
</tr>
<tr>
<td>Shrayya et al. 2019</td>
<td>SVM</td>
<td>92.7%</td>
</tr>
<tr>
<td>Richard Platania et al. 2017</td>
<td>CNN</td>
<td>93.5%</td>
</tr>
<tr>
<td>Cao et al. 2017</td>
<td>SSD</td>
<td>96.89%</td>
</tr>
<tr>
<td>Zhang et al 2020</td>
<td>CNN</td>
<td>97.2%</td>
</tr>
<tr>
<td>Muawiyay 2023</td>
<td>SVM</td>
<td>97.7%</td>
</tr>
<tr>
<td>Manav Mangukiy 2022</td>
<td>KNN</td>
<td>98.24%</td>
</tr>
<tr>
<td>Muhameet Fatih 2020</td>
<td>KNN</td>
<td>98.60%</td>
</tr>
<tr>
<td>Allugunti 2022</td>
<td>CNN</td>
<td>99.65%</td>
</tr>
<tr>
<td>Sivapriy et al 2019</td>
<td>SVM</td>
<td>99.76%</td>
</tr>
<tr>
<td>Proposed System 2024</td>
<td>CNN</td>
<td>99.86%</td>
</tr>
</tbody>
</table>

From the table above found that The proposed CNN approach for breast cancer detection is compared with previous studies that used traditional machine learning techniques such as MLP, SVM, and KNN. MLP classifiers are 50% accurate, but may not capture complex patterns in image data. SVMs have an accuracy range of 80% to 99.76%, but they may not capture complex patterns as effectively as deep learning methods. CNNs have an accuracy range of 93.5% to 99.86% (which is the result of the current study of the proposed system), and excel at learning hierarchical features from raw data without manually extracting features. They can also capture spatial dependencies within images. However, they require large amounts of labeled data for training and are computationally intensive. The SSD (Single Shot Multiple Box Detector) has an accuracy of 96.89%, but its primary focus is on object detection rather than classification. KNN, a simple but effective classification algorithm, has an accuracy range of 98.24% to 98.60%, but its performance depends on the choice of distance measure and k value. In conclusion, the proposed CNN approach demonstrates superior performance compared to traditional machine learning methods, such as MLP, SVM, and SSD, and specialized techniques such as SSD. Its ability to automatically learn relevant features from raw data contributes to its effectiveness in breast cancer detection. However, computational costs and data requirements must be considered during implementation.

https://www.malque.pub/ojs/index.php/msj
5. Apply the proposed model in the real world

The successful implementation of the proposed model in real-world clinical settings involves many practical considerations and challenges. The discussion below explores these factors in detail:

5.1. Data availability

Developing and validating a CNN model requires large amounts of diverse, high-quality data. In clinical settings, this data includes medical images, patient demographics, and clinical outcomes. While some organizations may have extensive mammography archives and patient records, others may face challenges due to data privacy regulations, such as HIPAA. In the United States or the General Data Protection Act in Europe, which limits the sharing of medical data. Ensuring a diverse dataset that can be well generalized across different populations is critical to the accuracy and reliability of the model.

5.2. Arithmetic requirements

CNN models, especially those associated with image processing, require significant computational resources. The practical application of the implementation of such models in a clinical setting depends on the availability of these resources. While larger hospitals may provide dedicated servers or cloud computing services, smaller clinics may find computational costs prohibitive. In addition, the model's reasoning time should be clinically acceptable, as excessive calculation time may hinder clinical workflow.

5.3. Interpret results

Medical professionals rely on models not only for their predictive performance but also for their ability to deliver interpretable, trustable and acting results. CNNs are often criticized as "black boxes" because their complex inner workings make it difficult to understand the rationale behind their predictions. Enhancing the model's interpretability, perhaps by combining it with interpretable artificial intelligence (XAI) technologies, is essential to earning the trust of doctors and patients alike.

5.4. Ethical considerations

The application of artificial intelligence in healthcare raises many ethical issues. The model must ensure equality in health care, avoiding prejudice against certain population groups or populations. Furthermore, there must be clear protocols of accountability in case of misdiagnosis or failure. Transparency in how the model works and how decisions are made is important to ethical clinical practice.

5.5. Real-world clinical integration

Integrating the CNN model into clinical workflows involves training medical staff to use the system and understand its outputs. The model should complement, not replace, the expertise of doctors. There must be a clear understanding of the limitations of the model and the scenarios in which human supervision is critical.

5.6. Continuous learning and updating the model

The clinical environment is dynamic, with continuous advances in medical knowledge. Therefore, the CNN model must have a mechanism of continuous learning, allowing it to update its parameters with new data without compromising patient privacy or data security.

5.7. Required audit

Before publication, the CNN form must undergo rigorous verification and testing to comply with medical device regulations, such as FDA approval in the United States. This process ensures the safety and effectiveness of the AI system in clinical applications.

6. Conclusions and future work

The main accomplishment of this study was the development of an effective method, for detecting breast cancer. This technique combines Convolutional Neural Networks (CNNs) with the Curated Breast Imaging Subset of DDSM (CBIS DDSM) dataset. The innovation showcased by this research is evident in the models accuracy, responsiveness and specificity which surpasses methods.

The model demonstrates efficiency in classifying images as seen in the results of the confusion matrix. These findings suggest that CNNs can significantly improve accuracy in detecting breast cancer. However it is important to acknowledge limitations highlighted by this study. One limitation is that the findings may not hold relevance when applied to broader datasets that are not as carefully curated as CBIS DDSM. Additionally while focusing on
achievements the study may have overlooked nuances associated with common occurrences or presentations of breast cancer. Lastly the computational complexity of using CNN architecture could pose challenges in clinical settings. Despite these limitations this study provides a foundation for research into advanced learning methods, for breast cancer detection.

It pushes the boundaries of methodologies by showcasing improved abilities in diagnosing breast cancer. Suggestions, for research include making adjustments to enhance the accuracy and efficiency of the CNN model. Another beneficial approach would be to explore techniques combining models to improve the prediction performance and make the model more robust. Additionally incorporating data such as medical history could provide a more comprehensive diagnostic tool that takes a holistic approach to identifying breast cancer. In summary although this study has shown the potential of CNNs in detecting breast cancer ongoing research is necessary to overcome limitations and ensure effective integration, into clinical practice.

Ethical considerations

The CBIS-DDSM datasets employed in this research have been sourced from publicly available repositories, with a rigorous deidentification process applied to eliminate all personal data by default. Alongside the mammography images, these datasets offer diagnostic information, meticulously crafted to exclude any identifiable labels. Approval for this study has been obtained from the University of St Andrews School of Computer Science Ethics Committee, acting on behalf of the University Teaching and Research Ethics Committee (UTREC). Notably, the datasets were not authored by the researchers, and no participants were engaged in the study. As evidenced in the ethical report, accessible through the following link (https://info.cs.st-andrews.ac.uk/student-handbook/files/project-library/cs5098/agj6-Final_report.pdf), the study adheres to ethical standards without requiring additional consent or approval.

Conflict of Interest

The authors declare no conflicts of interest.

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References


