

Evaluation of AI-Driven Models for Breast Cancer Detection: An In-Depth Comparative Study of Algorithms

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Abstract

One of the most serious illnesses that affects a lot of individuals worldwide is breast cancer. Even though scientists from all over the world have put out a number of diagnostic approaches for the identification of breast cancer, these approaches still need to be improved in order to guarantee precise and effective identification of this illness. As mentioned above, the feasibility of these algorithms is tested on the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. A number of classifiers presented in the paper include CNN, RF, NB, MLP, and SVM, and their accuracy, precision, and recall, as well as F1 scores, were compared. CNN turned out to be more accurate than SVM, RF, NB, and MLP among the models, with a higher accuracy of 98.5%, precision of 99%, and F1 score of 99.9%. And recall of 99.9%. CNN outperformed SVM, RF, NB, and MLP among the models, achieving 98.5% accuracy, 99% precision, 99.9% recall, and 99.9% F1-score. The results highlight CNN as the most effective model for breast cancer detection, offering robust and reliable classification for early diagnosis. This study contributes valuable insights into AI applications in medical diagnostics, particularly in enhancing the accuracy of breast cancer detection.

Keywords: Breast Cancer, Diagnosis, Healthcare Systems, Mammography, Risk Factors, Artificial Intelligence.

1. INTRODUCTION

One of the world's most hazardous illnesses for both men and women is cancer. Among the most frequent malignancies is Breast cancer is today the most common type of disease affecting women and the leading cause of disease burden. WHO's World Cancer report suggests that if breast cancer is detected early then survival is possible up to 80 percent. [1][2]. About 1.7 million new cases of breast cancer are diagnosed annually, while 500000 women die from the disease every year; these figures might rise in the future. Breast cancer development is influenced by a number of factors, including breast density[3], medical history, age at first pregnancy, breastfeeding, alcohol usage, and others[4]. While some factors have a significant influence, others have a little one. While there are no controllable factors like being a woman or growing older, maintaining a healthy lifestyle can help reduce our chance of breast cancer [5].

Three methods are employed in the diagnosis of breast cancer: physical examination, mammography, and biopsy. The most popular of these diagnostic techniques is mammography. However, the examinations need to be interpreted by qualified radiologists. One drawback, though, is that various radiologists interpret the same mammography differently, leading to numerous interpretations. [6][7]. Furthermore, mammograms have an accuracy rate of 65% to 78%. When a tumour is identified by mammography To ascertain whether breast cancer is malignant, a biopsy is performed. It is important to note that although biopsy has an accuracy rate of about 100%, it is expensive, time-consuming, unpleasant, and invasive[8][9]. It may be difficult for medical practitioners these issues make it difficult to tell if a malignancy is benign or aggressive. These qualities are the reason It is possible to diagnose using machine learning techniques [10][11].

In the last few years, primary conventional AI approaches have found their application mostly in the area of early detection of breast cancer. Machine learning can be defined as a subset of AI [12]. Some of the state-of-the-art DL algorithms ML[13] employed in medical systems are primarily for the identification of breast cancer [14][15]. The precision of a patient's diagnosis used to rely on the doctor's skill. Years of observing a patient's symptoms have given a doctor this level of experience. But you can't rely on the accuracy. Data collection and storage are now easier because of advancements in computer methods[16][17]. Therefore, intelligent healthcare systems are a vital and dependable field. By using precise and significant standards, these systems can assist doctors in diagnosing patients[18]. Furthermore, these developments can assist people in planning for their future medical needs. In this sense, healthcare workers' challenging physical labour may be managed by machine learning techniques [19][20][21].

A. Motivation and Contribution of the Study

The motivation behind this study is the rising prevalence of breast cancer, which is a leading cause of feminised cancer mortality in the entire female population of the global community. This is why timely diagnosis and diagnosis accuracy are so important towards the survival of patients as well as the recovery of their conditions. Despite their effectiveness, traditional diagnostic techniques frequently have accuracy and scalability issues, underscoring the need for more sophisticated, data-driven strategies. By using AI-driven algorithms for machine learning to improve breast cancer detection and classification, this work aims to overcome these issues, offering a more efficient, reliable, and scalable solution. The main contribution of this study is listed below:

- Collect As a tool for breast cancer detection, the Wisconsin Diagnostic Breast Cancer database.
- Use of Z-score for standardising features and handling skewed data.
- Application of edge detection and texture analysis for relevant feature identification.
- Apply AI models like CNN, Random Forest, Naive Bayes, and MLP, using SVM to identify breast cancer.
- Analysis based on precision, accuracyF1-score and recall for better classification insights.
- An assessment of adaptability Using machine learning methods to effectively identify breast cancer.

B. Structure of the paper

The paper's structure is as follows: The research methodology for this study is presented in **Section III**, whereas **Section II** covers the background study on breast cancer detection. The results of the experiment and an evaluation of model's accuracy are provided in **Section IV**. Findings and recommendations for further research are presented in **Section V**.

- Artificial Intelligence (AI) has fundamentally transformed the landscape of cybersecurity, offering
- advanced capabilities that significantly enhance threat detection and response. By leveraging
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2. LITERATURE REVIEW

The study looks at the corpus of studies on the categorisation and identification of breast cancer in this area. The majority of the examined publications concentrated on classification methods. A few reviews are:

This study, Koç et al., (2024) the present work, the Wisconsin breast cancer detection data set is employed and Four machine learning techniques including Support Vector Machine (SVM), Decision Tree, Gaussian Naïve Bayes (NB), and K-Nearest Neighbors (KNN) are used. Finally, the best platform overall was the SVM as the model delivered an accuracy rate of an astonishing 96.7%. The formulate the research, Python was used as the programming language, equipped with the Scikit-learn package in Visual Studio Code [22].

This research, Tinao, Rodriguez and Calibara, (2024) uses eight breast cancer characteristics found in a research by Rabiël et al. (2022). Anonymised data gathered from a sample of 112 women chosen through random sampling makes up the dataset used in this investigation. According to the analysis, the best performing model is the K-nearest neighbours model with accuracy of 0.8696. This shows that 86.96% of the examples are successfully classified by the model [23].

This study, Rovshenov and Peker, (2022) to classify the features of images on benign and aggressive breast cancer. Random Forest, Support Vector Machine, Artificial Neural Network were employed to categories features extracted from photographs. The Wisconsin Breast Cancer data was used in the experiments. As evaluated in experiments, the Artificial Neural Network method provided 99% of the optimal performances. Experimental evidence suggests that the categorisation approach can classify breast cancer at an early stage [24].

This study, Neelima et al., (2023) determines how machine learning works for fuzzy based breast cancer detection. For the Wisconsin (Diagnostic) Data Set, the current study presents two machine learning methods as follows: The Support Vector Machine (SVM) and Decision Tree (DT). The fuzzy-based SVM and DT classification algorithm accurately diagnose

breast cancer diseases with specificities of 97.8%, recalls of 96.5%, accuracies of 98.2%, and precision of 97.6% [25].

The paper, Anklesaria et al., (2022) For feature selection, adopt the Random Forest Feature Importance Method and to apply several machine learning (ML) algorithms accompanied by hyperparameter tuning, they include; SVM, Logistic Regression, KNN, DT, RF, ANN, NB. These models were developed using the Wisconsin Diagnostic Breast Cancer (WDBC) Dataset. However, the most suitable algorithm to fit this dataset was the Support Vector Machine Algorithm as identified by the research work with a accuracy of 95.8%. The second-best algorithm was KNN with accuracy of 95.3% [26].

This study, Sharma, Singh and Bhardwaj, (2022) compared the current advanced artificial intelligence, especially the machine learning approach frequently applied in cancer diagnosis of which breast cancer was also included using the Wisconsin dataset on the disease. The current study has comparatively and

statistically analysed and mapped the ML methodologies employed in classification like NB, KNN, LR, RF, SVM, XG, and DT for determining the accuracy in terms of recall, precision, F1 score and percentage accuracy). Further, these categorisation techniques was visualised using the ROC Curve as done below. Therefore, this research concludes that the XGboost model is 98.24 % accurate, and the SVM model is 96.49 % accurate [27].

In this paper, Telsang and Hegde, (2020) Examine the accuracy of some algorithms of learning methods for breast cancer detection performance measures, including accuracy and the area under the receiver operating characteristic curve (AUC). For modelling we are using Wisconsin Dataset of Breast Cancer abbreviated as WDBC. This study found that the SVM model has 96.25% accuracy and an AUC of 99.4 was identified. Furthermore, the mathematical models of these algorithms might be changed to improve the breast cancer prognosis [28].

The comparative analysis of background study based on their findings, limitations, and future work are provided in Table I.

TABLE 1: COMPARATIVE ANALYSIS OF MACHINE LEARNING APPROACHES FOR BREAST CANCER DETECTION.

Author	Source	Methodology	Findings	limitation	Future work
Koç et al.,	Wisconsin Diagnostic Breast Cancer (WDBC) Dataset	Applied SVM, Decision Tree, Gaussian Naive Bayes, and KNN to classify breast cancer using confusion matrix, accuracy, and precision.	SVM outperformed other models with 96.7% accuracy.	Limited to basic ML models without advanced hyperparameter tuning or feature engineering.	Explore deep learning models and feature engineering to improve accuracy.
Tinao, Rodriguez and Calibara,	Custom dataset of 112 anonymised women	Used KNN to classify breast cancer cases. Investigated relationships between life events, family problems, and breast cancer incidence.	KNN achieved 86.96% accuracy. Family history and life stress were significant factors.	The small dataset size (112 participants) limits generalizability.	Increase sample size and incorporate other machine learning models for comparison.
Rovshenov and Peker,	Wisconsin Breast Cancer Dataset	Utilised Artificial Neural Networks, SVM, and Random Forest for classification. Evaluated the models based on accuracy.	ANN achieved the highest accuracy at 99%, outperforming SVM and Random Forest.	Focused only on accuracy without considering other metrics like precision or recall.	Incorporate more metrics and explore different image feature extraction techniques.
Neelima et al.,	Wisconsin (Diagnostic) Data Set	Combined SVM and Decision Tree models using fuzzy logic for enhanced breast cancer detection. Assessed using accuracy, precision, recall, and specificity.	Fuzzy-based SVM and Decision Tree reached 98.2% accuracy, 97.6% precision.	Limited application of fuzzy logic to only two ML models.	Extend fuzzy-based approach to other models and explore more complex datasets.
Anklesaria et al.,	Wisconsin Diagnostic Breast Cancer (WDBC) Dataset	Applied SVM, Logistic Regression, KNN, Decision Tree, Random Forest, ANN, and Naive Bayes. Used Random Forest feature importance for feature selection. Balanced dataset using undersampling and SMOTE.	SVM achieved 95.8% accuracy, followed by KNN with 95.3%. Undersampling outperformed SMOTE.	Focused primarily on accuracy without emphasising the trade-offs in recall and precision for imbalanced datasets.	Use different balancing techniques and tune hyperparameters for better generalisation.
Sharma, Singh and Bhardwaj,	Wisconsin Breast Cancer Dataset	Compare Naive Bayes, KNN, Logistic Regression, Random Forest, SVM,	XGBoost achieved the highest accuracy	Limited focus on interpretability of	Explore model interpretability techniques like

		XGBoost, and Decision Tree using metrics such as accuracy, recall, precision, F1 score, and ROC curves.	at 98.24%, followed by SVM at 96.49%.	models such as XGBoost.	SHAP or LIME for more transparency.
Telsang and Hegde,	Wisconsin Dataset of Breast Cancer (WDBC)	Compared different ML algorithms using accuracy and area under the ROC curve (AUC) for breast cancer prediction.	SVM achieved 96.25% accuracy and an AUC of 99.4%.	Algorithms and specific methodologies were not fully detailed, leading to incomplete reproducibility.	Provide detailed algorithms and investigate modifications to increase accuracy further.

3. Methodology

The aim of this research is to assess the role of Artificial Intelligence in increasing the potential of screening breast cancer. The subsequent stages of the research design are described in the context of the flowchart provided in Figure 1 below. The approach is first applied to the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. First, the cleaned data in the current study was preprocessed, whereby some of the generally employed methods included data outlier elimination, noisy data elimination, and data handling of missing values. After that, to find the most pertinent features for model training, feature extraction methods such as edge detection and texture analysis were used, followed by feature selection. Next, Z-score normalisation was performed to standardise the dataset. Then, the preprocessed data was divided into two sets: Overall, the data was split into 20% for testing and 80% for training. Finally, the effectiveness of the following classification models was compared: CNN, SVM, MLP, RF, and NB. As for the assessment of each model, accuracy, precision, recall, and F1-score were used.

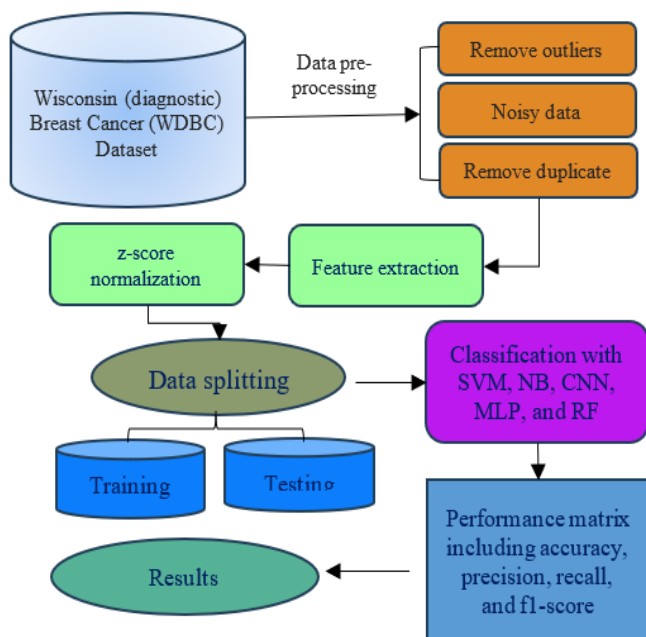


Figure 1: Flowchart for breast cancer detection.

The overall steps of the flowchart for breast cancer detection are provided below:

A. Data Collection

This study Kaggle was used to collect the Wisconsin (diagnostic) Breast Cancer (WDBC) Dataset, which was used in this investigation. It includes a total of 569 instances of Breast Cancer in Wisconsin, with a distribution of 212 malignant

(37.26%) and 357 benign (62.74%) cases, classified into two categories: malignant and benign. The exploratory data analysis is a tool for visualising the insight of the dataset. Some of visualisation are as follows:

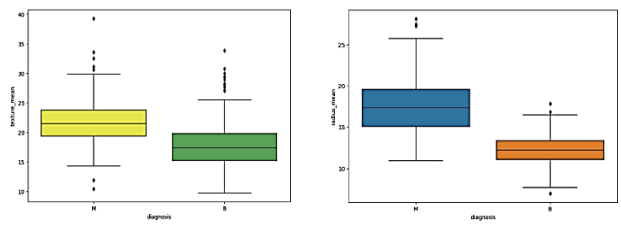


Figure 2: Box plot for radius mean, and texture mean.

The box plots compare the distributions of radius mean, and texture means for classes B and M, showing that class B generally has lower median values for both features compared to class M, represented in Figure 2. The interquartile ranges (IQRs) are similar for "radius mean" but slightly tighter for texture mean in class B. Outliers are present in both classes, with class M having more outliers in the lower range for radius mean and class B having more outliers in the higher range for texture mean. Despite differences, the distributions overlap, suggesting some class overlap in these features.

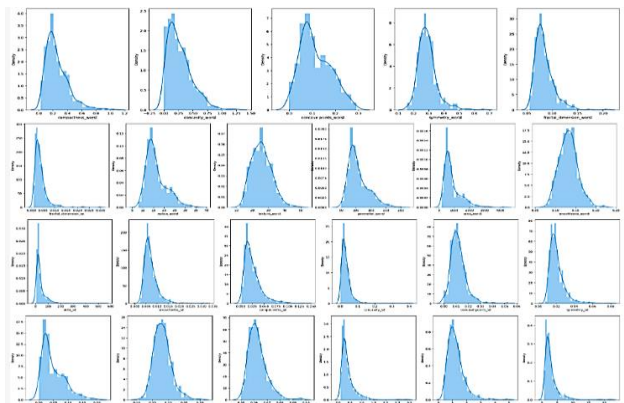


Figure 3: Distribution of numerical features.

The grid of histograms and density plots for 30 numerical features reveals diverse distributions, with many skewed, some exhibiting outliers and a few showing multimodal characteristics are present in Figure 3. Right-skewed features include compactness_worst and concave points_worst, while left-skewed features include fractal_dimension_mean. Although some distributions approximate a normal shape, many deviate significantly. Understanding these distributions is essential for preprocessing, as skewed features may require transformations, and outliers need careful handling to prevent affecting model predictions.

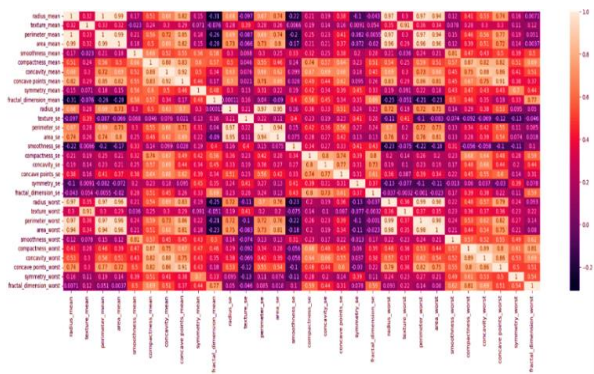


Figure 4: Heatmap matrix for selected features.

Figure 4 shows the heatmap that illustrates the correlation between various features, with blue indicating negative correlations and red indicating positive correlations. Strong positive correlations are shown by darker red squares, while strong negative correlations appear as darker blue squares. The diagonal line represents self-correlation (always 1), and the heatmap is symmetrical around this line. Many features exhibit weak correlations, indicated by lighter colours, highlighting the relationships among features for further analysis.

A. Data Preprocessing

The initial data samples are acquired with a variety of attributes and values, often containing a wide range of issues such as outliers, noisy data, duplicates, missing values, and skewed data. To address these issues, preprocessing of the data is necessary. The data cleaning process involves eliminating or reducing missing data and noisy information[29]. This can be achieved by deleting tuples, inputting missing values, and replacing numerical values with the mean attribute or the attribute mean of the corresponding class. The following pre-processing steps are listed below:

- **Remove outliers:** Outliers can skew results and lead to inaccurate models, so it's crucial to analyse the dataset for these anomalies and remove them to ensure the integrity of the analysis.[30]
- **Noisy data:** Random mistakes or deviations in measured variables are referred to as noisy data. This may be caused by a number of things, including data input problems or malfunctioning sensors[31].
- **Remove duplicates:** In any machine learning project, identifying and handling outliers is essential. [32]. However, eliminating or deleting outliers is not always necessary.

B. Feature Extraction

After preprocessing, feature extraction is the subsequent step, where relevant features significant for breast cancer detection are identified and extracted from the pre-processed images. Techniques for feature extraction may include edge detection [33], texture analysis, or shape analysis. The most relevant characteristics that might increase the precision of the machine learning model are selected using feature selection techniques after feature extraction.

C. Z-score normalisation

One of the most effective and popular normalisation techniques is z-score normalisation. [34]. Data normalisation was done

using the Z-score, which is the distance between the standard deviation (s) and the average (\bar{x}), as indicated by Equation (1).

$$z_i = \frac{x_i - \bar{x}}{s} \quad (1)$$

Where x_i is the i -th variable value, and Z_i is the i -th Z-score. The scale function in the R package is used in this study to calculate the Z-score.

D. Data Splitting

The preprocessed data, in turn, elaborates a training dataset as well as a testing dataset. Training set that contains 80% data is used in modeling, while the testing set with 20% data, is used in model evaluation.

E. Classification with CNN model

CNNs are regarded as deep learning's foundational architecture. A pooling layer and one or more consecutive convolution layers make up the convolutional neural network's architecture[35][36]. A completely linked layer and a classification layer, respectively, are added to these layers. In this investigation, the CNN model put forward by [37][4]. This model's architecture is a minor modification of Collobert's CNN design. [38][39]. The layers for convolution, subsampling, complete connectivity, and classification layer of the Important features are extracted from the input data using the CNN architecture shown in Figure 5. The input data categories are established using these properties.

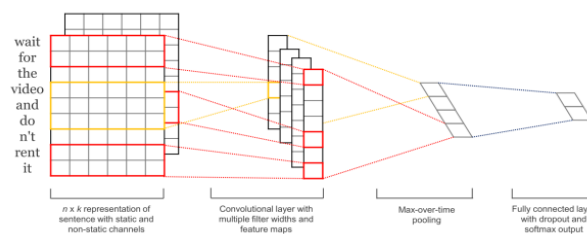


Figure 5: Model architecture of CNN.

Each of the n inputs in the input layer is represented as a dense vector with k dimensions[40][40]. Thus, a $d \times k$ dimensional feature map represents the input x . Let the i -th word in the input phrase be represented by the word vector in k dimensions $x_i \in \mathbb{R}^k$. The symbol for An n -length sentence is (2).

$$x_{1:n} = x_1 \oplus x_2 \oplus \dots \oplus x_n \quad (2)$$

where the operator for concatenation is \oplus . In order to create a new feature, a convolution operation applies the $w \in \mathbb{R}^{hk}$ filter on a window of h words. For instance, a new property c_{ii} feature is created as follows (3) utilising a window $x_{i:i+h-1}$ words.

$$C_i = f(w \cdot x_{i:i+h-1} + b) \quad (3)$$

In Eq. (3), $b \in \mathbb{R}^f$ is a non-linear function, like the hyperbolic tangent, and is a bias term. Using this convolution filter on every possible word window inside the sentence $x_{1:h}, x_{2:h+1}, \dots, x_{n-h+1:n}$ creates a feature map. Eq. (4) is used to construct this feature map:

$$c = [c_1, c_2, \dots, c_{n-h+1}] \quad (4)$$

Here $c \in \mathbb{R}^{n-h+1}$. The feature map is then subjected to a max-over-time pooling process to get the maximum values that

correspond to the filters. In feature maps, this procedure aims to capture the most noticeable characteristics[41]. With the use of several filters and varied window widths, the model seeks to identify various traits [36][42]. The last layer, which is a completely linked layer, receives the outputs of the layer that has these characteristics. The probability distribution on the labels is constructed using a fully connected SoftMax layer.

F. Performance Metrics

A collection of assessment measures, sometimes referred to as performance metrics, were utilised to assess how well phishing email detection performed[43][44]. A two by two contingency table known as the confusion matrix is used to compare the actual and expected performance of the developed model. Five assessment measures were used to evaluate the resulting models[45]: The evaluation measures used include accuracy, precision, recall, and F1-score. The models are initially evaluated by confusion matrices using the following metrics: correct positively classified instance: true positive (TP), incorrectly classified instance as positive: false positive (FP), correct negatively classified instance: true negative (TN), and incorrectly as negative: false negative (FN):

G. True positive (TP): Both models and the observation's actual class suggest that it will be benign.

H. True negative (TN): The observation's actual class is cancerous, and models indicate that it will be as well.

I. False positive (FP): Although models mistakenly anticipate it as benign, the observation's true class is malignant.

J. False negative (FN): Models mistakenly anticipate the data as malignant when, in fact, it belongs to the benign class.

Accuracy: Accuracy is the percentage of labels that a classifier properly predicts out of all the labels. It is stated as follows (5):

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN} \quad (5)$$

Precision: Another name for precision is classifier exactness. Another way to think of precision is as the ratio of TPs to FPs. The representation of it is (6):

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

Recall: Recall is also known as sensitivity, and It is the total number of all positive examples divided by all the correct classifications of the positive cases. It is shown in (7):

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

F1-score: The measure derived from the accuracy and recall scores, which is basically the ratio of the sum of the two multiplied by two to the sum of the square of the two, is called the F measure or F1 score. The accuracy or recall number that is less will always be closer to the F measure. The following is a definition of the F1 score (8):

$$F1 = \frac{2*(precision*recall)}{precision+recall} \quad (8)$$

These matrices are also used for comparison of model performance.

4. Result & Discussion

This section looks at the outcomes of the several categorisation methods used in this investigation. In order to diagnose breast cancer effectively, our study employed AI approaches. These methods are RF, NB, MLP, SVM, and CNN. The WDBC Dataset was used to assess how well AI systems performed. The models' results were compared using metrics such as F1 score, recall, accuracy, and precision.

TABLE 2: CNN MODEL PERFORMANCE ON WISCONSIN (DIAGNOSTIC) BREAST CANCER DATASET.

Matrix	Convolution neural network
Accuracy	98.5
precision	99
Recall	99.9
F1-score	99.9

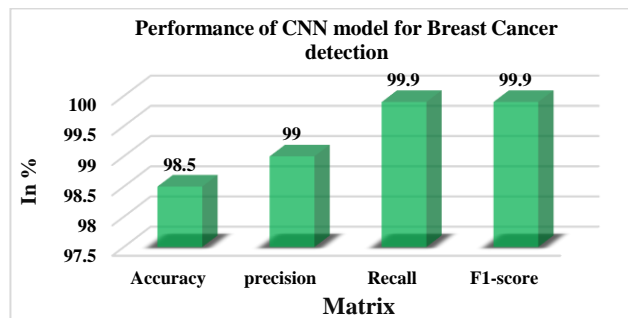


Figure 6: CNN model Performance on WDBC data.

The following Table II and Figure 6 show the Bar graph for CNN model performance. The CNN achieves 98.5% accuracy, 99% precision, and 99.9% recall, demonstrating exceptional performance characteristics. The F1-score, which is also 99.9% and exhibits a strong balance between accuracy and recall, demonstrates the model's effectiveness in accurately recognising instances with minimal false positives and negatives. These findings demonstrate CNN's resilience and dependability in categorisation tasks.

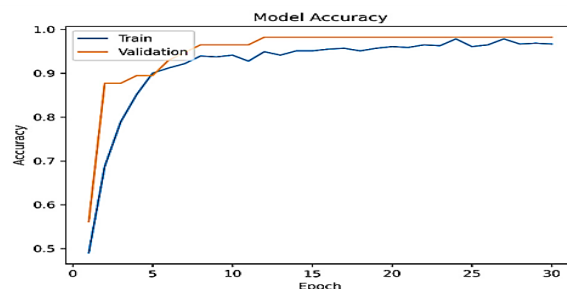


Figure 7: Accuracy graph of Training and Validation for CNN.

Figure 7 reveals the accuracy of a CNN model during the training and validation phases. As the plot of training accuracy (blue line) gradually rises up, the situation of validation accuracy (orange line) can either constantly rise up or stabilise and even decline, which reflects the problem of over-learning. A increasing discrepancy between training and validation accuracy indicates overfitting, which happens when a model exhibits strong performance on training data but struggles to generalise to fresh data.

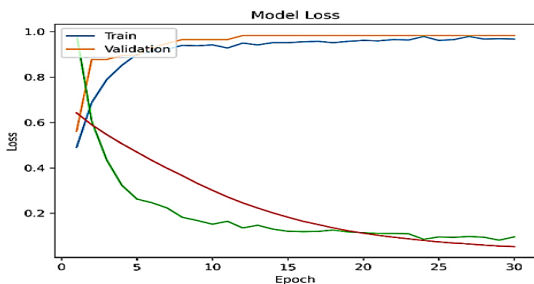


Figure 8: Loss graph of Training and Validation for CNN.

The CNN model fails during validation and training, as seen in Figure 8. The blue line represents the training loss, which lowers as the model learns. On the other hand, the orange line represents validation loss, which initially follows a similar pattern but may plateau or even climb, which indicates overfitting. A lower validation loss signifies better model performance, and managing overfitting can improve generalisation to unseen data.

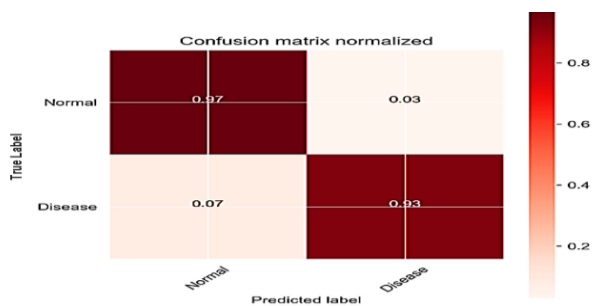


Figure 9: Confusion matrix of CNN model.

Figure 9 displays the CNN model's classification performance as a confusion matrix, with rows denoting real labels and columns denoting predicted labels. Diagonal cells indicate correct predictions, where the model correctly identified 97% of Normal cases and 93% of Disease cases. Three percent of "Normal" cases were incorrectly identified as disease, while seven percent of disease cases were incorrectly classified as normal, according to off-diagonal cells, which stand for mistakes. The model performs well overall, especially for the "Normal" class, although additional measures like recall, accuracy, and F1-score would provide a more thorough assessment.

TABLE 3: COMPARATIVE ANALYSIS FOR BREAST CANCER DETECTION BETWEEN MODELS' PERFORMANCE.

Matrix	RF[46]	NB[47]	MLP[48]	SVM[10]	CN N
Accuracy	94.7	94.5	92	95.61	98.5
precision	97	89	97	97.14	99
Recall	95.5	86	81	95.77	99.9
F1-score	95.5	86.4	88	96.45	99.9

The comparison of model performance is presented in Table III above. In this comparison, CNN exhibited the highest accuracy at 98.5%, surpassing other algorithms such as SVM at 95.61%, RF at 94.7%, NB at 94.5%, and MLP at 92%. Notably, the CNN also achieved exceptional precision and recall scores of 99% and 99.9%, respectively, indicating its robustness in minimising

false positives and maximising true positive detections. In comparison, RF and SVM also performed well, with RF achieving a precision of 97% and a recall of 95.5%, while SVM had a slightly lower recall of 95.77%. Although MLP showed a decent precision of 97%, its lower recall of 81% suggests potential challenges in identifying all positive cases. Overall, CNN stands out as the most effective model for breast cancer detection, demonstrating superior performance across all metrics.

5. Conclusion & Future Work

Breast cancer is a lethal disease. Cancer occurs because of the unwanted growth of cells. Globally breast cancer (BC) is increasing rapidly. BC is the most widespread tumour and is among the foremost reason for cancer-related deaths in females. Presently, the most effective strategies for managing and treating this disease involve breast scanning for early detection. This research highlights the substantial potential of AI-driven models, particularly Convolutional Neural Networks (CNN), in enhancing breast cancer detection. The CNN model performed the best out of all the classification algorithms that were assessed, with 98.5% accuracy, 99% precision, 99.9% recall, and a 99.9% F1 score. These remarkable figures show how reliable CNN is at correctly identifying cases of breast cancer while reducing FP and FN. The results of this study highlight the vital role that cutting-edge machine learning methods play in medical diagnostics, which can greatly improve patient outcomes by detecting breast cancer earlier and with more accuracy. Implementing such AI models in clinical practice could lead to transformative improvements in diagnostic accuracy and efficiency. So that can develop a reliable system for finding breast cancer early, future studies should concentrate on improving these models, investigating their use in various clinical contexts, and combining them with additional diagnostic instruments.

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