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Enhanced breast Cancer Relapse Prediction Based on Ensemble Learning Approaches

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Abstract—Predicting progression and deciding on the best follow-up techniques for breast cancer patients is difficult because the illness is diverse and characterized by varying relapse risks. Due to its prevalence, breast cancer has become the top cause of mortality among women worldwide, making diagnosis and prognosis particularly challenging areas of medical study. In addition, the fear of a cancer relapse is a major factor influencing cancer patients' quality of life. The study aims to help doctors determine the likelihood of a breast cancer relapse by applying ensemble learning techniques. In this research, artificial neural networks (ANN) and deep neural networks (DNN) ensembled with Weighted averaging, minority, and majority voting approaches have been investigated for performance enhancements on the breast cancer recurrence dataset sourced from the UCI-ML repository. The empirical analysis shows that this ensemble learning-enabled proposed novel approach shows improved accuracy, precision, sensitivity, specificity, and F1-score of 96.21%, 96.59%, 98.84%, 84.62%, and 97.41%, respectively. The findings of this study can aid doctors in making more informed treatment decisions, thereby improving patient outcomes.

Keywords- Ensemble Learning; Machine Learning; Deep Learning; Breast Cancer Disease; Relapse Prediction

I. INTRODUCTION

The mortality rate among women from breast cancer is higher than any other type of cancer, making it the second largest cause of cancer death globally due to unregulated cell division, a malignant tumor forms in the breast or surrounding tissues. The difficulty in predicting progression and choosing the best follow-up measures stems from the heterogeneity of breast cancer, which is characterized by varying relapse risks [1]. As EHRs become more commonplace, so will possibilities to put to good use the vast quantities of routinely generated electronic data. The invasive subtype of breast cancer is deadlier since it tends to invade neighboring tissues. Because of this, the liver and lungs are not the only organs that might suffer from this form of cancer [2, 3]. As the name suggests, noninvasive breast cancer is confined to the breast tissue and does not spread to other body parts. Since there is always the chance that cancer would extend outside the breast tissue region and develop into an invasive kind later, it is classified as benign but still labeled pre-cancerous [4, 5].

Breast cancer has relapsed even after years of treatment in some patients. Breast cancer recurs in over 40% of all patients. Never assume there is no chance of a recurrence; the risk is greatest in the first two to three years. If a relapse happens, it is important to remember and address certain signs. There are three distinct types of breast cancer relapse. First, there is local recurrence (LR), which occurs when the cancer returns to the same area of the breast where it was first found. The second type of recurrence is called a regional recurrence (RR), and it manifests in lymph nodes, the axilla, or the collar bone. Thirdly, distant metastasis (DM) refers to the spread of cancer to unrelated organs or tissues outside of the original site of disease. Because of their diagnostic similarities, local and regional recurrence are typically lumped together as locoregional recurrence (LLR) in the diagnostic process [6]-[8].

A. Research Gap and Motivation

Even though disease progression and patient outcomes are notoriously difficult to predict due to breast cancer's heterogeneity, the management of the disease is expected to grow more complex in the future due to promising research in novel biomarkers and new insights being developed in this field. New tools and deeper scientific understanding could help us improve our patient stratifications, leading to more individualized and tailored treatment plans. Using the massive quantity of data, machine learning (ML) and deep learning (DL) algorithms, which are strong data analysis tools, may be able to discover fresh insights and provide doctors with evidence-based ideas that can improve care and the quality of life for patients. An increase in the use of ML and DL research in the analysis of healthcare data has yielded promising results in several applications, including the detection of cardiac arrhythmias, the forecasting of diabetes mellitus, the identification of unanticipated hospital readmissions, the classification of medical images, and the forecasting of infectious diseases. In recent years, more and more ML and DL research has focused on assessing cancer prognosis and risk, including risk, survival, and recurrence. There is still much to learn about breast cancer recurrence risk factors and ML or DL algorithms despite these topics being the subject of much research. Since non-linear connections and interaction effects are prominent in cancer data, oncology has a rising trend toward employing ensemble learning along with ML and DL-based models rather than traditional statistical methods. ML is frequently used for tasks such as tumor classification, detection, and classification in oncology.

B. Objective and Contributions

In this study, the artificial neural network (ANN) and deep neural network (DNN) have been studied to see if they may be used to diagnose breast cancer relapse. In addition to traditional ANNs and DNNs, we also consider ensemble ANN methods such as weighted averaging and minority and majority voting ensemble techniques. The breast cancer relapse dataset, sourced from the UCI-ML repository, is used to analyze and assess the state-of-the-art parameters for the suggested ANN and DNN methods to attain this efficacy.

The following is a summary of the main contributions of the recent research:

- To evaluate the ANN and DNN-based breast cancer relapse classification models.
- To propose the ensemble ANN and DNN-based approaches on weighted averaging, soft and hard voting ensemble techniques.
- To achieve enhanced predictive outcomes based on this proposed ensemble learning-based novel approach.
- To help physicians make more informed treatment decisions and improve patient outcomes.

C. Paper Organization

Here is how the rest of the paper is laid out: The literature review is presented in Section 2. Methods and data for this investigation are presented in Section 3. In Section 4, you will find the recommendations. The findings are summarized in Section 5. Section 6 concludes this study and suggests further avenues for exploration.

II. Related Works

Rana et al. [9] introduced a breast cancer diagnosis and recurrence prediction model considering ML approaches on Wisconsin Prognosis Breast Cancer (WPBC) and Wisconsin Diagnostic Breast Cancer (WDBC) datasets sourced from the UCI repository and resulted in 100% training accuracy. Almuhaidib et al. [10] developed the prediction of breast cancer recurrence using the ensemble learning approaches on WPBC datasets, resulting in 76.26% accuracy. Sakri et al. [11] developed breast cancer recurrence prediction using the data mining approaches on Wisconsin Prognosis Breast Cancer datasets, resulting in 81.3% accuracy, 93.4% sensitivity, and 63.25 specificity. Chakradeo et al. [12] developed breast cancer recurrence prediction using machine learning approaches on the WPBC dataset, resulting in 97.93% accuracy, 93.36% precision, and 91% recall. Gu et al. [13] proposed explainable breast cancer recurrence prediction considering ensemble learning on the National Natural Science Foundation of China (NFSC), resulting in 91.62% accuracy, 90.28% recall, and 89.39% F1-score. Goyal et al. [14] proposed predicting breast cancer recurrence using machine learning approaches on University Medical Centre (UNC), Institute of Oncology, Ljubljana, Yugoslavia datasets. They resulted in 85.18% accuracy, 100% sensitivity, 100% specificity, 100% precision, and 100% recall. Dawangliani et al. [15] developed a prediction of breast cancer recurrence considering ensemble ML approaches on breast cancer datasets. They resulted in 82.807% accuracy, 0.828 Tp rate, 0.534 Fp rates, 81.9% precision, 82.8% recall, 82.3% F-measure, and 79.6% ROC Area. Yang et al. [16] developed breast cancer recurrence prediction considering ensemble and cost-sensitive learning approaches on the breast cancer registry from Shin Wu Ho-Su Memorial (SWHM) Hospital. They resulted in 97.3% accuracy, 97.7% sensitivity, 64% precision, 98.3% specificity, 90.7% ROC Area and 65.7% F-measure. Cohen et al. [17] proposed multimodal prediction of five-year breast cancer recurrence in women who received Neoadjuvant Chemotherapy considering machine learning and deep learning approaches on Institute Curie datasets and resulted in 57.0% specificity, 90.0% sensitivity, and 75% AUC. Gupta [18] proposed a prediction time of breast cancer tumor recurrence considering machine learning approaches on WPBC and WDBC datasets, resulting in 78.7% accuracy. Castro et al. [19] proposed to predict breast cancer Recurrence using structured and unstructured sources from economic health records considering STR, UNS, and COMB datasets and resulted in 90.0% precision, 90.7% recall, 89.7% F1-score, and 80.7% AUROC. Janik et al. [20] introduced recurrence prediction for early-stage non-small cell lung cancer patients, considering machine learning approaches on graph datasets, resulting in 76% accuracy. The reviewed state-of-the-art works are summarised in Table 1.

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TABLE I. SUMMARY OF THE CONSIDERED RELATED STATE-OF-THE-ART WORKS

Ref	Techniques Employed	Dataset(s) Employed	Findings
Rana et al. [9]	SVM, KNN, NB, LR	WDBC and WPBC	Training Acc.: 100% (WDBC and WPBC) Test Acc.: 95.68% (WDBC), 72% (WPBC)
Almuhaidib et al. [10]	RF, DT, NB	WPBC	Accuracy: 76.26%
Sakri et al. [11]	REPTree, NB, KNN	WPBC	Accuracy: 81.3%, Sensitivity: 93.4%, Specificity: 63.25
Chakradeo et al. [12]	SVM, DT	WPBC	Accuracy: 97.93%, Precision: 93.36% Recall: 91%
Gu et al. [13]	LR, KNN, SVM, DT, RF, GBDT, MLP, XGBoost	NFSC, China	Accuracy : 91.62% , Recall : 90.28% , F1-score : 89.39
Goyal et al. [14]	SMOTE, GRNN, FFBPN, SVM, DT, NB	UNC, Institute of Oncology, Ljubljana, Yugoslavia datasets	Accuracy: 85.18%, Sensitivity: 100%, Specificity: 100%, Precision: 100%, Recall: 100%
Dawangliani et al. [15]	Adaboost M1, Bagging, Stacking, Voting	Breast Cancer datasets	Accuracy: 82.807%, Tp rate: 0.828, Fp rate: 0.534, Precision: 81.9%, Recall: 82.8%, F-measure: 82.3%, AUC: 79.6%
Yang et al. [16]	Adaboost, cost-sensitive method, SMOTE	Breast Cancer Registry from SWHM Hospital	Accuracy: 97.3%, Sensitivity: 97.7%, Precision: 64%, Specificity: 98.3%, ROC Area: 90.7%, F-measure: 65.7%
Cohen et al. [17]	Clinical cohort, MRI+Clinical cohort, Holdout cohort	Institute Curie datasets	Specificity: 57.0%, Sensitivity: 90.0%, AUC: 75%
Gupta [18]	SVM, DT, and RF	WPBC and WBCD	Accuracy: 78.7%
Castro et al. [19]	LR , DT , GBT , XGB , DNN	STR, UNS, COMB datasets	Precision : 90.0% , Recall: 90.7% , F1-score : 89.7% , AUROC : 80.7%
Janik et al. [20]	RBL, GBT, LR, RF, ComplEx-N3	Graph datasets	Accuracy: 76%

III. MATERIALS AND METHODS

The methods and materials used in this research are described in detail here. The dataset, the pre-processing processes, and the various ML, DL, and EL approaches utilized can be found in the various sub-sections.

A. Dataset Description and Acquisition

The breast cancer recurrence dataset is taken from the online UCI-ML Repository for this study [21]. University Medical Centre, Institute of Oncology, Ljubljana, Yugoslavia, is the provider of this dataset. It includes 286 instances and 13 features, one of which, Class, determines whether or not the breast cancer will relapse. This data set has 201 instances of one class and 85 instances of another. Table 2 shows the attribute details along with values present in the dataset.

TABLE II. SUMMARY OF THE CONSIDERED BREAST CANCER RELAPSE DATASET

Features	Meaning	Values
Age (Start Age – End Age)	Find out how old you were when the primary tumor was found.	10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80-89, 90-99
Menopause	The age at which females finally stop having periods. In this case, the patient's menopausal status at the time of diagnosis is considered.	lt40, ge40, premeno
Tumor size (Start tumor size - End tumor size)	Specifies how big the resulting mass is. Cancerous growth is quantified in mm increments.	0-4, 5-9, 10-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59
Env Nodes (Start_env_nodes - End_env_nodes)	Identifies the total number of breast cancer-carrying auxiliary nodes after a histological test.	0-2, 3-5, 6-8, 9-11, 12-14, 15-17, 18-20, 21-23, 24-26, 27-29, 30-32, 33-35, 36-39
Node caps	Determines whether or not the tumor has spread inside the node capsule.	Yes, No
Deg-malig	Numbers 1-3 tumor histological grade, or degree of cellular similarity between tumor and healthy tissue	1, 2, 3
Breast	On the left or the right, breast cancer might develop.	Left, Right
Breast-quad	With the nipple as the pivot, the breast can be divided into four sections.	Left-up, Left-low, Right-up, Right-low, Central
Irradiation	Radiation therapy is a treatment method that uses high-energy X-rays to kill cancer cells.	Yes, No
Class [Predictive Feature]	Classification of outcomes based on patients' reports of recurrence of breast cancer symptoms.	No-recurrence-events, Recurrence-events

Since the UCI-ML Repository dataset considered in this study wasn't in the right format, classification accuracy could be low. There were blanks and duplicates in the data. The dataset also lacked parity. Therefore, the following preprocessing methods were used to prepare the dataset for classification. The data in one range is used to create a new range. Data mining is

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typically done to improve prediction and forecasting accuracy. Age, tumor size, and inv-node values are used as the minimum standard for normalization, whereas a fixed numeric value is selected for all other parameters. As a result of this nominalization process, the final dataset is nominal in form. After that, data gets turned into numbers so it can be processed further. Table 3 shows the number of instances in the dataset after pre-processing.

TABLE III. NUMBER OF INSTANCES IN THE DATASET AFTER PRE-PROCESSING

Instances	Before Pre-processing	After Pre-processing
Recurrence Events	85	81
Non-Recurrence Events	201	191
Total	286	272

B. *Artificial Neural Network (ANN)*

ANNs can understand nonlinear data by mimicking the ways in which the human brain does so. Neurons are the building blocks of ANNs, and they are arranged in layers from input to output. The behavior of the network can be learned via backpropagation by examining the connections and patterns between these units, which are analogous to biological neurons. Data is assumed to be accurate when backpropagated into a network. Component patterns are adjusted to reduce the LMSD after comparing the ANN's output with the known output. After being trained for a while, the network becomes more precise and requires less processing resources to do complex tasks. Nonlinear systems are becoming more and more like biomedical systems, making ANNs an essential computational resource for biological research. ANNs have been used for quite some time in the treatment of cancer. Our understanding of cancer's molecular characteristics has advanced thanks to recent studies. This results in more productive computational methods [22, 23].

C. *Deep Neural Network (DNN)*

DNN employs a multi-layered neural network in which each layer may be individually enabled or disabled and whose output serves as the input for the next layer. DNNs are a subset of ANNs with an increased number of hidden layers between the input and output stages of the network. A DNN can model complex and hierarchical data patterns because it is an ANN with several layers of neurons, also called hidden layers. DNNs are cutting-edge AI that has revolutionized many areas by excelling at challenging tasks on complicated, high-dimensional datasets. They play a crucial role in contemporary ML and DL applications because they can learn hierarchical representations and automatically extract features.

D. *Ensemble Learning (EL)*

The results of ML and DL can be enhanced by combining many models using ensemble learning. Employing many models together allows for the development of far more precise anticipated performance as compared to employing just one. The basic idea is to borrow a set of classifiers from a bank and put them to use in an election. In this study, we looked at three different types of ensemble methods [24, 25].

In ML, the "weighted average" or "weighted sum ensemble" technique combines the predictions from several models while giving each model's contribution a weight that is proportional to its capability. It uses the winning class by the biggest margin as a proxy for the expected output class. The voting classifier takes the mean of all the classifications it was given. To save time and effort, we may merge the data from many specialized models into a single dataset, train a single model on that dataset, and then have that model produce output predictions based on the majority vote of the models. There are two distinct voting methods: soft voting and hard voting. Soft Voting may be used for both classification and regression problems, and it combines the results of several well-tuned models trained on the same data to provide a single, unified forecast. The combined prediction result is based on the base learners' anticipated probability. Let λi be the initial prediction probability of different base learners or classifiers (Bi). The final prediction of the ensemble model can be represented by ρ, as shown in equation (1).

$$\rho = Max_i \sum_{k=1}^{B} \omega_k \lambda_k \quad (1)$$

The hard voting or majority voting concept is employed in the hard voting ensemble, which is used for classification problems. This ensemble incorporates the predictions from several trained models that are trained on the same dataset. Let ρ be the predicted class label through the hard voting technique. This predicted value can be calculated by equation (2).

$$\rho = mode\{c(a_1), c(a_2), \dots \dots, c(a_n)\} \quad (2)$$

Where c is the class for the attribute a1 of the dataset D.

IV. PROPOSED WORK

The current research employs the ANN and DNN techniques and various basic EL methods to train an approach with the Breast Cancer relapse dataset. The ANN and DNN techniques are initially applied to the pre-processed dataset to obtain the prediction result. Then, different EL approaches, such as weighted averaging and voting techniques, are applied to the pre-processed dataset. The pseudocode for the proposed model is represented in algorithm 1, and the detailed workflow of the manuscript is depicted in Fig. 1.

Algorithm 1

- Raw Breast Cancer Relapse Dataset input
- Dataset Pre-Processing
- Dataset Splitting with distribution ratio (D) as 0.2

- Initializing ANN() and DNN() to the pre-processed dataset
    - Setting the no. of input layers (I)
    - Setting the no. of hidden layers (H)=4
    - setting the optimizer = 'ADAM'
    - Setting the activation function at I='RELU'
    - Setting the activation function at H= 'RELU'
    - Setting the activation function for the output layer= 'SIGMOID'
    - Obtaining the output (O)
- Initializing EL_Approach()
    - Setting the number of epochs (E)
    - Obtaining the Initial predictions
    - Invoking Weighted_Averaging()
    - Invoking Minority_Voting()
    - Invoking Majority_Voting()
- Result comparison ANN() and DNN() among Weighted_Averaging(), Minority_Voting(), and Majority_Voting().

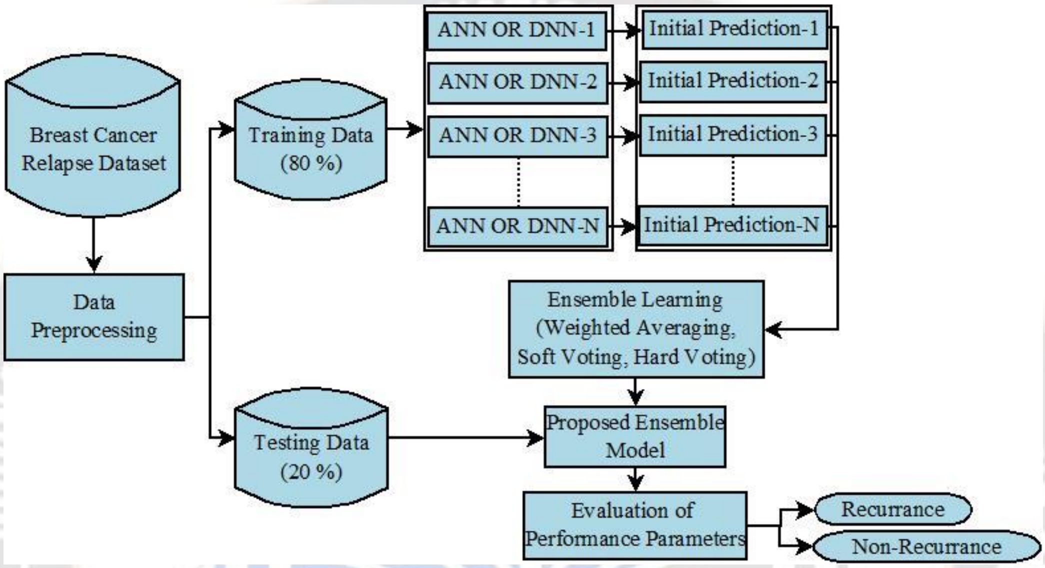

Figure 1. Proposed Ensemble-Based Model Block Diagram

V. RESULTS AND DISCUSSION

The evaluation of this proposed ensemble-based model makes several assumptions. Some preliminary studies isolate ANN and DNN. Weighted averaging, soft voting, and hard voting are the three cornerstone ensemble methods that were used to refine the prediction results. The proposed system has been tested on a workstation with 8 GB of RAM, a 500 GB SSD, a 1 TB HDD, an Intel Core i5 CPU running at 3.6GHz, and Ubuntu 20.04. Any proposed work should include substantial empirical analysis of the outcomes acquired. These metrics aim to construct a real-to-expected class confusion matrix through a systematic experimental process [26 - 28]. The confusion matrix is abbreviated as TA and TB for true positives and negatives, while FA and FB for false positives and negatives. Accuracy (Ac), Misclassification Rate (MR), Precision (PR), F1-Score (FS), False Negative Rate (FNR), False Positive Rate (FPR), Mathew's Correlation Coefficient (MCC), and Balanced Accuracy (BA), are some of the performance metrics that can be used for classification in this study, as detailed formulations are given in equations (3) – (12).

$$A_C = \frac{T_A+T_B}{T_A+T_B+F_A+F_B} \tag{3}$$

$$M_R = \frac{F_A+F_B}{T_A+T_B+F_A+F_B} \tag{4}$$

$$P_R = \frac{T_A}{T_A+F_A} \tag{5}$$

$$S_N = \frac{T_A}{T_A+F_B} \tag{6}$$

$$S_P = \frac{T_B}{T_B+F_A} \tag{7}$$

$$F_S = \frac{2\times T_A}{2\times T_A+F_B+F_B} \tag{8}$$

$$F_{NR} = \frac{F_B}{T_A+F_B} \tag{9}$$

$$F_{PR} = \frac{F_A}{T_B+F_A} \tag{10}$$

$$M_{CC} = \frac{(T_A+T_B)-(F_A+F_B)}{\sqrt{(T_A+F_A)(T_A+F_B)(T_B+F_A)(T_B+F_B)}} \tag{11}$$

$$B_A = \frac{S_N+S_P}{2} \tag{12}$$

When datasets have multiple instances, using the DL approach, ANN alone (which we named "Approach -1") makes sense. Additionally, several tests are run on ANN models that employ the weighted averaging, minority voting, and majority voting EL approaches (also called "Approach -2," "Approach-3," and "Approach-4"). DNN alone (what we've dubbed "Approach -5") is an acceptable DL approach to use when datasets have multiple instances. Weighted-averaging, minority-voting, and majority-voting EL approaches (also "Approach -6,"

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"Approach-7," and "Approach-8") are also implemented in DNN models, and these methods are subjected to several trials.

Table 2 lists the results of extensive analyses of the performance of the proposed ensemble methods. Figures 2 through 11 show the results in percentages for AC, MR, PR, SN, SP, FS, FNR, FPR, MCC, and BA, respectively in percentage. According to the observations based on the performance measurements, the model "Approach-6", i.e., DNN with weighted averaging Classifiers, as shown in Table 2 and Fig. 2, outperforms all other suggested approaches with an accuracy of 96.21%. Besides, Approach-6 with 96.59% of precisions and 97.70% of F1-scores single-handedly, as well as Approach-5 (i.e., DNN only) and Approach-6, both with 98.84% of sensitivities and Approach-6 and Approach-8 (i.e., DNN with Majority Voting), both with 84.62% of specificities also outperform other suggested ensemble approaches and is therefore "Approach-6" is considered to be the proposed ensemble approach.

TABLE IV. NUMBER OF INSTANCES IN THE DATASET AFTER PRE-PROCESSING

Approaches	AC	MR	PR	SN	SP	FS	FNR	FPR	MCC	BA
Approach-1	89.57	10.43	89.94	96.82	68.52	93.25	3.18	31.48	71.4	82.67
Approach-2	91.47	8.53	91.48	98.17	68.09	94.71	1.83	31.91	74.11	83.13
Approach-3	90.52	9.48	90.80	97.53	67.35	94.04	2.47	32.65	72.04	82.44
Approach-4	92.42	7.58	92.44	98.15	73.47	95.21	1.85	26.53	77.91	85.81
Approach-5	93.36	6.64	93.41	98.84	69.23	96.05	1.16	30.77	76.74	84.04
Approach-6	96.21	3.79	96.59	98.84	84.62	97.70	1.16	15.38	87.09	91.73
Approach-7	94.31	5.69	95.45	97.67	79.49	96.55	2.33	20.51	80.52	88.58
Approach-8	95.73	4.27	96.57	98.26	84.62	97.41	1.74	15.38	85.51	91.44

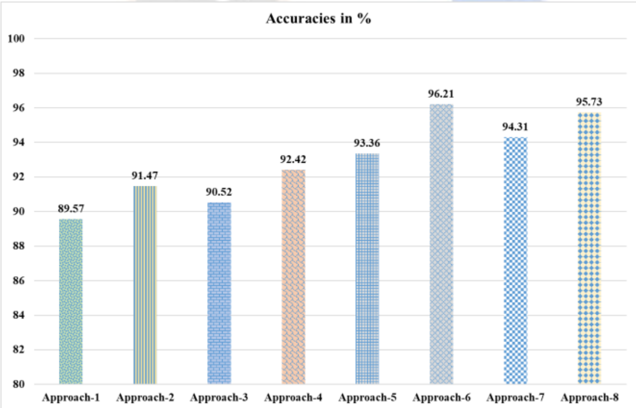

Figure 2. Measures of Accuracy in % for Various Suggested Approaches

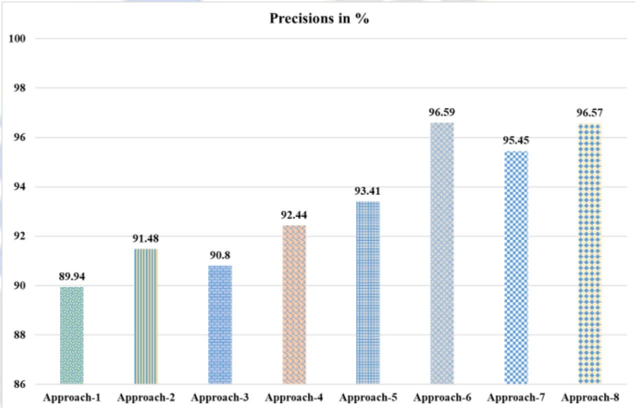

Figure 4. Measures of Precision in % for Various Suggested Approaches

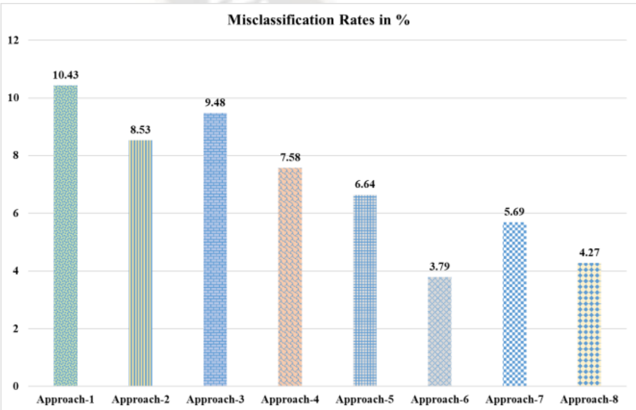

Figure 3. Measures of Misclassification Rate in % for Various Suggested Approaches

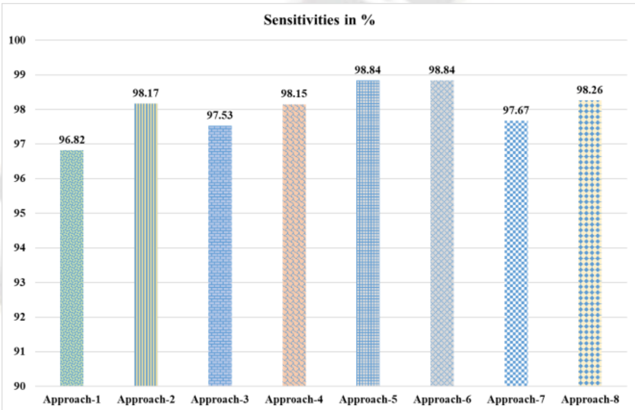

Figure 5. Measures Sensitivity in % for Various Suggested Approaches

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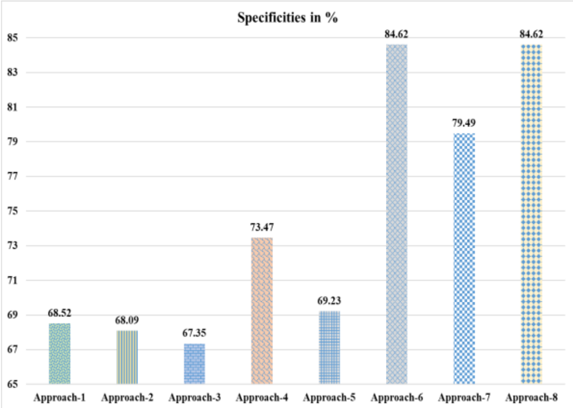


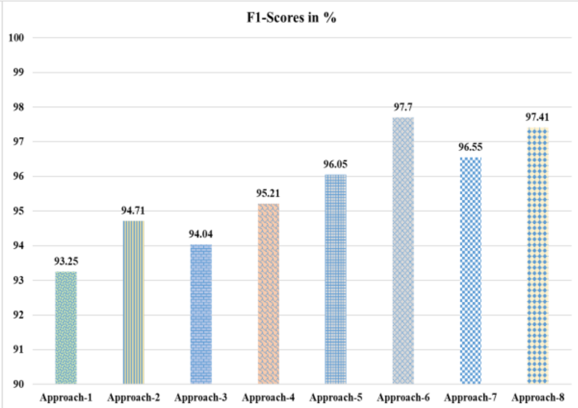
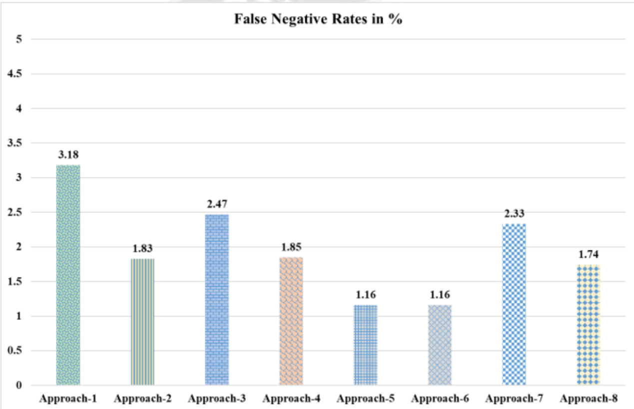


Figure 6. Measures of Specificity in % for Various Suggested Approaches

Figure 7. Measures of F1-Score in % for Various Suggested Approaches



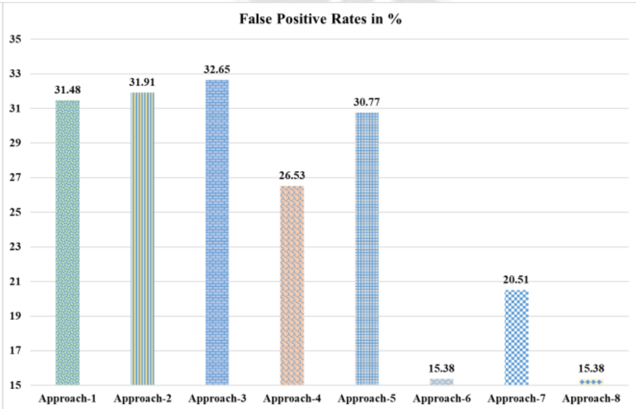
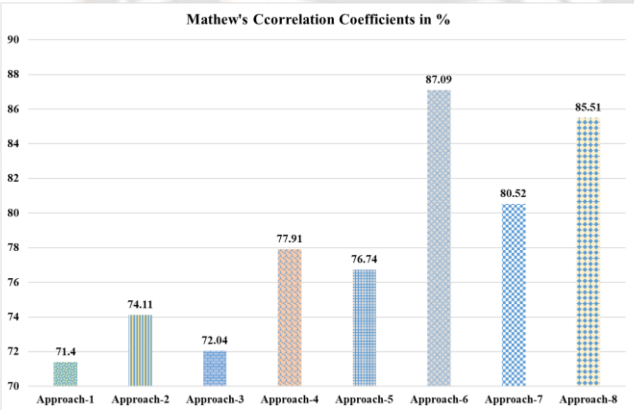


Figure 8. Measures of False Negative Rate in % for Various Suggested Approaches

Figure 9. Measures of False Positive Rate in % for Various Suggested Approaches



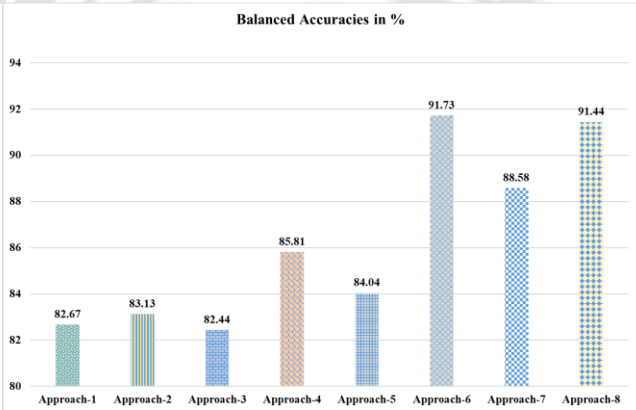


Figure 10. Measures of Mathew's Correlation Coefficient in % for Various Suggested Approaches

Figure 11. Measures of Balanced Accuracy in % for Various Suggested Approaches

To support our claim that this is a completely new and novel approach, we have compared the outcomes of utilizing this proposed ensemble work to those of other, more established works, as depicted in Table 5. Comparing the suggested work to those used in the literature, it is clear that the proposed work performs better across the board in maximum cases based on various evaluative parameters employed.

TABLE V. PERFORMANCE COMPARISON OF PROPOSED WORK IN CONTRAST TO THE EXISTING LITERATURE

Work	Comparison Parameters (in %)				
	AC	PR	SN	SP	FS
Rana et al. [9]	100% (Training), 95.68% and 72% (Test)	-	-	-	-
Almuhaidib et al. [10]	76.26	-	-	-	-
Sakri et al. [11]	81.3	-	93.4	63.25	-
Chakradeo et al. [12]	97.93	93.36	91.00	-	-
Gu et al. [13]	91.62	-	90.28	-	89.39
Goyal et al. [14]	85.18	100.0	100.0	100.0	
Dawangliani et al. [15]	82.80	81.9	82.8	-	82.3
Yang et al. [16]	97.3	64.0	97.7	98.3	65.7
Cohen et al. [17]	-	-	90.0	57.0	-
Gupta [18]	78.7	-	-	-	-
Castro et al. [19]	-	90.0	90.7	-	89.7
Janik et al. [20]	76	-	-	-	-
Proposed Ensemble-Based Model	96.21	96.59	98.84	84.62	97.70

VI. CONCLUSION AND FUTURE PLANS

The suggested ensemble-based approach is evaluated over the breast cancer relapse dataset. The ANN and DNN techniques have been applied to obtain the initial predictions for the pre-processed dataset. Then, different ensemble techniques, including the Weighted Average, minority Voting, and majority Voting techniques, are applied to the initial prediction of the base learner model ANN and DNN. The results are then compared with each other to obtain the best result. The experimental results show that the proposed ensemble model "Approach-6", i.e., DNN with weighted average Classifiers, achieves the highest accuracy (96.21%) compared to the other methods. Besides, Approach-6 with 96.59% of precisions and 97.70% of F1-scores alone, as well as Approach-5 (i.e., DNN only) and Approach-6, both with 98.84% of sensitivities and Approach-6 and Approach-8 (i.e., DNN with Majority Voting), both with 84.62% of specificities also outperform other suggested ensemble approaches.

Moreover, additional ML and DL methods can be used for other recurrent datasets, extending this work's scope. Additionally, future plans include developing a breast cancer relapse-related image-based dataset.

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