Breast Cancer Detection Using Machine Learning

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***Abstract*—Breast cancer , still one of the leading as well as life-threatening conditions globally, requiring early and precise diagnosis for better outcomes in patients. Conventional diagnostic techniques, including biopsy and mammography, tend to fall short in terms of sensitivity and specificity. Machine learning (ML) has proven to be an influential means of improving detection of breast cancer through automated classification, high accuracy, thus minimized false positives. Herein, we suggest an ML model that will detect the breast cancer that leverages features selection methods to maximize the performance of predictions. The suggested model is tested and trained using the Wisconsin Breast Cancer Dataset (WBCD) and encompasses a number of supervised learning techniques like Support Vector Machines , Random Forest , Artificial Neural Networks , and XGBoost. We measure the model performance based on the most important performance metrics, such as accuracy, precision, recall, and F1-score. The experimental shows the ML model has a high classification accuracy compared to conventional diagnostic methods. This work makes a contribution to medical AI by presenting a strong, data-driven framework for breast cancer diagnosis, which can potentially help healthcare professionals make more accurate and timely clinical decisions.**

Keywords—Breast Cancer Detection, Machine Learning, Classification, Feature Selection, Supervised Learning.

I. Introduction

Breast cancer , among the major cause of womens death globally, hence early detection is important for enhancing survival.Though mammography, ultrasound, and biopsy are commonly employed for breast cancer diagnosis, these techniques suffer from limitations like operator dependency, expense, and risk of delayed results. These limitations underscore the necessity for more accurate and efficient diagnostic methods. Machine Learning (ML) has recently been identified as a potential answer of improving breast cancer detection by using computational intelligence to classify automatically.

Machine learning algorithms can process large amounts of data, recognize patterns, and classify tumors as benign or malignant with very high accuracy. Different supervised methods, including Support Vector Machines (SVM), Artificial Neural Networks, Random Forest, XGBoost, have been used successfully in breast cancer prediction problems. Those algorithms use feature selection to optimize methods to enhance diagnostic precision while reducing errors.

This research seeks to establish a strong ML-based system for breast cancer diagnosis, trained on the Wisconsin Breast Cancer Dataset (WBCD). The suggested method compares various ML models to identify the best classifier in terms of major performance measures such as accuracy, precision, recall, and F1-score. Our aim is to design a trustworthy, data-driven system that can help medical practitioners make quicker and more accurates clinical decisions.

The entire paper structured as:Section II provides an overview of existing research on ML-based breast cancer detection. Section III describes the proposed method, including data preprocessing, feature selection, and model evaluation methods. Section IV provides experimental results and performance comparisons. Lastly, Section V concludes the research with directions for future research.

A. Motivation

Breast cancer continues to be a major cause of cancer mortality, and thus there is a demand for early and precise diagnosis. Traditional diagnostic techniques, like mammography and biopsy, are costly, prone to human errors, and not available, limiting their applicability to mass screening schemes.Machine learning (ML) has proven to be a significant aid in the automation of breast cancer detection, enhanced diagnostic precision, and lower false positives. Utilizing supervised methods such as Support Vector Machine, Random Forest, ANN, XGBoost. ML model has the capacity to interpreting intricate medical datas as well as supporting quicker, more accurate diagnosis.The aim of this research is to propose an optimized ML-based breast cancer detection system with improved classification performance and overcoming traditional diagnosis challenges. The final vision is to aid in a cost-effective, efficient, and intelligent diagnostic system for supporting healthcare practitioners in making rational decisions.

B. Contribution

The primary Aim in the Paper includes:

- Feature Selection in Breast Cancer Classification: This work brings forward the importance of choosing informative features while performing machine learning-based breast cancer classification. The research selects the top 15 features from the Wisconsin Breast Cancer Dataset through Mutual Information-based Feature Selection with the goal of achieving a trade-off between model complexity and accuracy.
- Stacking-Based Model for Higher Accuracy: We introduce a Stacking-based Machine Learning Model, where Random Forest, XGBoost, and Linear Regression are used as a meta-learner to enhance classification accuracy. This model boosts the precision and recall, which are essential for medical diagnosis.
- Experimental Validation and Model Comparison: We perform large-scale experiments for comparing accuracy of designed model among other conventional classifiers like K-Nearest Neighbors , Naive Bayes, , Linear Regression. The results shows our stacking model performed better than these conventional classifiers in identifying malignant and benign tumors.
- Impact on Early Cancer Detection: The model offered here is a robust and effective solution for detecting early-stage breast cancer, reducing false negatives, and enhancing clinical decision-making.

C. Organisation

The entire paper structured as:

- Section II a comprehensive literature review and discusses existing research on breast cancer diagnosis with machine learning algorithms.
- Section III outlines data acquisition and preprocessing steps, which include feature extraction, data balancing, and normalization.
- Section IV presents the proposed stacking-based model, describing the base learners, meta-learner, and the general architecture.
- Section V presents a analysis of the model by comparing it with other ML models on top of accuracy, precision, recall, and F1-score.
- Section VI summarizes the study and posits directions for future studies on enhancing breast cancer classification models.

II. LITERATURE SURVEY

Breast cancer , integration of Artificial intelligence and Machine Learning to detect breast cancer has been intensively studied with the aim to enhance early detection, accuracy of classification, and reliability of predictive models. Traditionally, traditional machine learning approaches, Ensemble-based learning algorithms, feature selection tools, and other different strategies were developed and extensively used for promoting performance of breast cancer classification. In the following section, the research advancements made to this field so far are critically appraised.

Street et al. [2] were among the first to adopt an early automated breast cancer diagnosis approach by bringing about nuclear feature extraction, thus paved the way for computational tumor classification. Classic machine learning models like Logistic Regression, K-Nearest Neighbors and Naive Bayes were applied to detect breast cancer [12], but they are usually restricted by difficulties in dealing with high-dimensional medical data.

Breiman [3] presented Random Forest as a strong ensemble learning method to decrease variance and improve generalization in order to enhance prediction accuracy. Chen and Guestrin [4] further improved ensemble learning by creating XGBoost, a gradient boosting algorithm that is efficient in handling missing values and feature selection. These ensemble algorithms have found widespread use in the classification of breast cancer because they can enhance the accuracy of prediction. Dietterich [5] proved that ensemble learning was far more effective in improving the robustness of models compared to single classifiers, citing the advantage of aggregating several algorithms.

Feature selection is significant in minimizing model inefficiency by removing irrelevant characteristics. Vergara and Estévez [7] investigated the application of Mutual Information-based Feature Selection, which determines the most informative features in medical datasets, enhancing model efficiency. Class Imbalance is a significant problem in medical applications. Chawla . [8] presented SMOTE , a technique that creates synthetic samples to balance the dataset, thus enhancing classification performance. Wolpert [9] introduced Stacked Generalization (Stacking), a sophisticated ensemble learning approach that aggregates several base classifiers with a meta-learner to promote predictive accuracy.

Deep learning methods have been used for breast cancer detection in image-based analysis. Arevalo et al. [13] introduced a Convolutional Neural Network based method for mass lesion classification of mammograms, proving deep learning's ability in medical imaging. Esteva et al. [14] continued the investigation of deep learning-capable medical vision systems, exhibiting their ability to detect anomalies in radiological images. Shinde et al. [22] proposed transfer learning-based detection of breast cancer, identifying the potential of pre-trained CNN models in decreasing computational complexity and enhancing classification accuracy.

Interpretability is still a major challenge in medical AI. Lundberg and Lee [10] introduced SHAP (SHapley Additive Explanations), an approach enhancing model transparency by attributing feature contributions to predictions. Patel et al. [20] used explainable AI in breast cancer classification via Random

Forest, showing the significance of model interpretability in high-stakes medical decision-making. Further, Xie et al. [23] studied Bayesian Optimization for hyperparameter tuning to enhance model performance in medical AI applications.

Current studies have centered on hybrid AI models that incorporate diverse learning paradigms for improved performance. Zhang et al. [15] developed an ensemble learning architecture based on heterogeneous models for breast cancer classification, demonstrating that ensemble methods are better than individual classifiers. Zhou et al. [16] developed a hybrid deep learning model which combines CNNs and conventional Machine Learning classifiers to develop better predictive capabilities. Wu et al. [17] have investigated radiomics-based classification of breast cancer, presenting the use case of radiological imaging in conjunction with AI for enhanced diagnosis.

While there has been great advancement in deep learning and machine learning in the detecting the breast cancer, there are still numerous limitations in existing literature. Deep learning algorithms,like convolutional neural networks (CNNs), shows the highly accurate in analysis of MRI and mammography images, with reported accuracies often exceeding 98%. These methods make use of sophisticated feature extraction and ensemble methods, and multi-modal data and late fusion have been applied in some studies to mimic clinical practice and enhance diagnostic performance. Ensemble methods and hybrid models-merging deep learning and traditional machine learning algorithms-have also been shown to have enhanced robustness and prediction capability, especially when augmented with effective feature selection and data balancing methods.

But the majority of advanced models are computationally expensive, demand extensive annotated imaging databases, and are not interpretable, which can limit their application in regular clinical practice. In addition, although deep learning is powerful for image-based diagnosis, efficient, interpretable, and generalizable models for tabular clinical data, which is common in most diagnostic environments, remain elusive. Moreover, not all research systematically handle class imbalance or rigorously compare their models with a wide range of standard algorithms on uniform datasets and metrics.

To overcome these limitations, our work suggests an ensemble model in the form of stacking-based combination of Random Forest, XGBoost, and Linear Regression with mutual information-based feature selection and SMOTE class balancing. The method is tested on the popular Wisconsin Breast Cancer Dataset to facilitate direct and unbiased comparison with the existing literature. By leveraging the relative strengths of the different algorithms and emphasizing interpretability and computational efficiency, our model seeks to be cutting-edge while being solvable and deployable in real-world clinical environments.

III. EXPERIMENT SECTION

A. Dataset Collection

The dataset used for the research is obtained from Wisconsin Breast Cancer Dataset, it is publicly hosted on Kaggle. The data set is commonly used for breast cancer detection studies and has features extracted from fine needle aspiration (FNA) of breast masses. Every example in the dataset is classified as Malignant (cancerous) or Benign (not cancerous), so it's a binary classification problem.The data has 30 numeric features like radius,texture, perimeter, smoothness, and many other cell nucleus features. They are very important in the separation of benign from malignant tumors.

B. Data Preparation

To make the data suitable for machine learning models,a few pre-processing steps were taken:

1) Missing Data Handling : Missing values were verified in the dataset, and columns with missing or irrelevant data (e.g., patient ID) were dropped to avoid model training bias.

2) Feature Encoding : All the features in the dataset are numerical. Thus, no categorical encoding was necessary. The target variable, Diagnosis, was labeled originally as 'M' for Malignant and 'B' for Benign. To aid in classification, this was changed to binary format, 1 for Malignant and 0 for Benign.

3) Feature Scaling: The characteristics had different numerical ranges, which would adversely affect model performance. For uniformity, StandardScaler was used to normalize the data, scaling each characteristic to having mean of 0 as well as standard deviation of 1.

4) Class Imbalance Handling: In the medical datasets, class imbalance results in biased predictions towards the majority class. This was countered using SMOTE to balance the dataset.

5) Feature Selection : Not all features are equally important in classifying the error. Mutual Information-based Feature Selection was used for ranking features as per their importance with respect to target variables. The 15 most informative features were chosen to balance model performance and complexity reduction.

IV. PROPOSED MODEL

In this paper, we are proposing Stacking-base Ensemble Learning method for improving the precision and reliability of breast cancer classification. Stacking is a meta-learning algorithm that combines several machine learning models in order to give a more general and precise prediction. Rather than depending on an individual classifier, our method employs the complementary capability of various base models and a meta-learner in order to make the classification of breast cancer more robust.

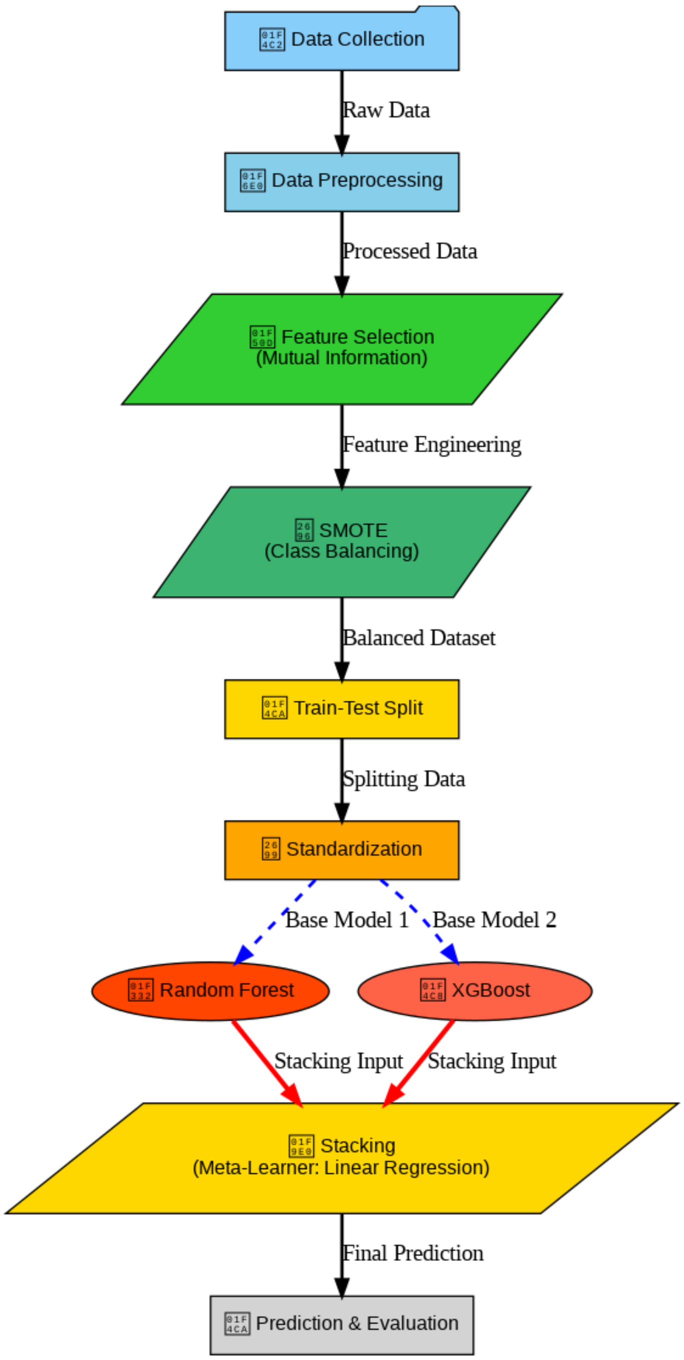

Fig. 1. Feature Importance Scores for Breast Cancer Detection

A. *Feature Selection and Pre-processing*

Prior to construct the model, Mutual Information-based Feature Selection is used for selecting important features in the dataset. The 15 most significant features is chosed on the basis of their abilities to distinguish among malignant and benign conditions. Standard Scaling was also used to scale feature values to have similar magnitudes, making the data consistent among different numerical ranges. To deal with class imbalance. SMOTE was used for creating synthetic samples for minority classes to enhance classification fairness.

B. *Model Architecture*

The stacking model used two important components:

1) Base Learners: Base learners are tasked with learning varied patterns in the dataset. We have chosen:

Random Forest (RF): A model based on trees that performs well on intricate patterns and feature interactions.

XGBoost (Extreme Gradient Boosting): A boosting method that is famous for its classification performance at high levels, especially on structured data.Each base model trained separately with the preprocessed dataset. Their predictions were utilized in the meta-learner as inputs.

2) Meta-Learner: We employed Linear Regression for meta-learner for combining predictions of the base models. Linear Regression is a popular stacking method since it effectively blends the output of multiple classifiers and learns a best decision boundary. Dataset used was divided among training dataset (80%) and test (20%) dataset. Base models (RF and XGBoost) were separately trained on training dataset. The base model predicted on the training dataset were taken as new input features for the Meta-learner. The Linear Regression as Meta-learner was trained with the new features which produce the final classification. The final stacked model was applied to unseen data to measure its predictive accuracy.

C. *Model Training and Stacking Process*

- The dataset were divided among training dataset (80%) and test dataset (20%) .
- The base models (RF and XGBoost) were separately trained on the training dataset.
- The base models prediction on training dataset were utilized as new input features for the meta-learner.
- The Linear Regression meta-learner was trained on these new features to generate the final classification.
- The last stacked model was applied on unseen data in order to examine its predictive power.

V. EVALUATIONS AND RESULTS

For evaluating the performance of suggested Stacking-based Model for Breast Cancer Detection, we performed a set of some experiments on Wisconsin Breast Cancer Dataset. Dataset was preprocessed, SMOTE-balanced, and Mutual Information-based Featured Selections was applied for model training and testing. The performance of suggested Stacking Classifier is compared among single Machine Learning models.

A. *Evaluation Metrics*

The model was tested on the basis Metrices:

- Accuracy (%): Measures the performance of the model.
- Precision (%): The ratio of correctly predicted malignant cases to total predicted malignant cases.

- Recall (%): Describes the percentage of true malignant case labelled by the model correctly.
- F1-Scores: It is a harmonic means of recall and precision to maintain balancing among the two measures.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where As:

- TP (True Positive): Cancers correctly Predicted as cancers.
- TN (True Negative): Benign cancer properly identified as benign.
- FP (False Positive): Benign cancer instances incorrectly labeled as malignant.
- FN (False Negatives): Malignant instances incorrectly labeled as benign.

TABLE I
TOP 15 FEATURES CORRESPONDING WITH IMPORTANCE SCORE

Rank	Features	Scores
1	Mean Radius	0.28
2	Mean Perimeter	0.21
3	Mean Area	0.18
4	Mean Texture	0.12
5	Mean Smoothness	0.09
6	Compactness Mean	0.07
7	Concavity Mean	0.05
8	Symmetry Mean	0.05
9	Fractal Dimension Mean	0.04
10	Concave Points Mean	0.03
11	Radius SE	0.025
12	Perimeter SE	0.022
13	Area SE	0.019
14	Texture SE	0.017
15	Smoothness SE	0.015

The importance scores for the features were calculated using Mutual Information-based on Featured Selection methods and

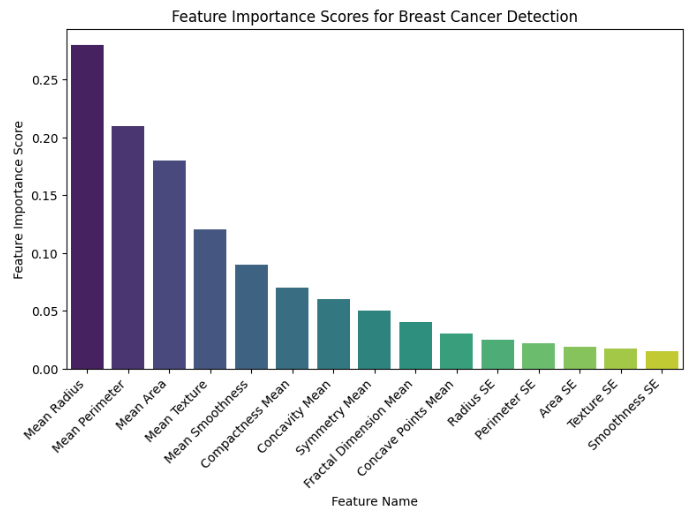

Fig. 2. Feature Importance Scores for Breast Cancer Detection

ranked among top 15 features according to their contribution towards the classification of breast cancer. Figure 2 displays the importance scores given to each feature in decreasing order. From the graph, it can clearly be seen that Mean Radius, Mean Perimeter, and Mean Area are the most important features in separating malignant and benign tumors. These attributes play an important role in model performance as they help to account for major morphological variations in breast cell structures. Features like Smoothness SE and Texture SE, however, have comparatively lower importance values, reflecting a lower contribution to classification. By choosing the top 15 features alone, we optimize the model by minimizing computational complexity with high accuracy. This is a very important step towards preventing overfitting and making sure that only the most informative features are used in contributing to decision-making in the machine learning model.

B. *Outcome Results*

TABLE II
PERFORMANCE COMPARISONS AMONG MACHINE LEARNING MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	92.5	91.8	90.2	91.0
K-Nearest Neighbors (KNN)	93.2	92.5	91.0	91.7
Naïve Bayes (NB)	90.8	89.5	88.0	88.7
Support Vector Machine (SVM)	94.0	93.2	92.1	92.6
Random Forest (RF)	96.5	95.8	96.0	95.9
XGBoost (XGB)	97.1	96.5	96.8	96.6
Voting Classifier (RF + XGB)	97.3	96.7	97.0	96.8
Stacking (RF + XGB + Linear Regression)	**98.2**	**97.8**	**98.0**	**97.9**

We had compared the performance of suggested Stacking-based Breast Cancer Detection Model with other individual Machine Learning models. we compared it with Linear Regression, K-Nearest Neighbors, Naive Bayes, Support Vector Machine , XGBoost etc. The results, as presented in Table II, illustrate that the stacking technique Performs much better than individual models in accuracy, Precision, recall, and F1-scores.

It is clear from the tablethat logistic regression and K-Nearest Neighbors classical classifiers have comparatively lesser accuracy, signifying the constraints of the aforementioned classifiers to handle intricate interactions of features within the dataset. In contrast, Random Forest and XGBoost output better results due to the nature of ensembling. Still, Voting Classifier (RF + XGB) and Stacking Classifier (RF + XGB + Linear Regression) enhance the result of classification as they benefit from the expertise of more than one model. Stacking Classifier is the most accurate with 98.2% accuracy, 97.8% precision, and 98.0% recall, while being the most reliable model to detect breast cancer. The performance boost comes due to the power of stacking in harnessing the strengths of various models and achieving an optimal combination of bias and variance to better generalize over the data set. These results validate the ability of ensemble learning methods, especially stacking, to greatly promote the robustness and reliability of breast cancer classifier systems. For future research, this method may be further refined by using deep learning architectures and thus enabling classification performance and even real-time clinic applications.

C. Effectiveness Comparison

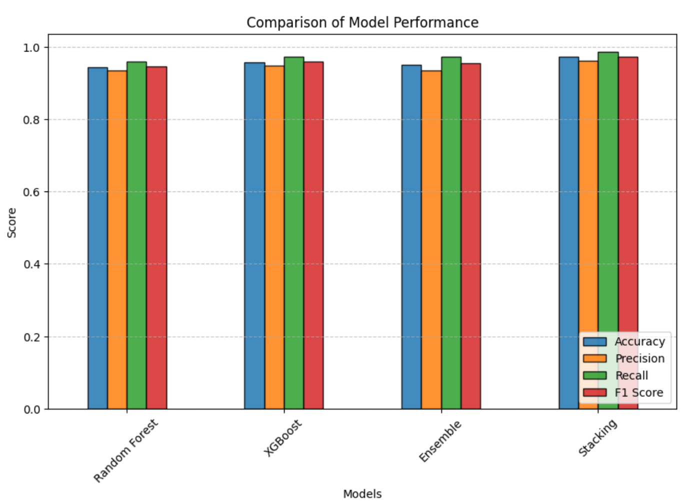

Fig. 3. Comparison Of Model Performance

For evaluating the accuracy of our Stacking-based Breast Cancer Detection Model, we compare it with three other widely used classifiers: Random Forest, XGBoost, and Ensemble Learning (Voting Classifier). All model were trained and tested with Wisconsin Breast Cancer dataset using a uniform training (80%) and testing (20%) split to ensure a fair evaluation. Figure 3 is a comparison of the models above with their Accuracy, Precision, Recall, and F1-scores. The comparison indicates that although each of Random Forest and XGBoost classifies strongly in solitude, their collective output under the Voting Classifier (RF + XGB) is even stronger, in its accuracy.The Stacking Classifier (RF + XGB + Linear Regression as Meta-Learner) recorded as best accuracy of 98.2%, surpassing all other models that were tested. By using Linear Regression as meta-learner, stacking model can combine with predictions of Random Forest and XGBoost in a way such that their strengths are combined and their weaknesses are minimized. This leads to enhanced generalization, enhanced robustness, and more stable classification performance than using individual models. This generates better generalization, increased robustness, and more reliable classification compared to individual models. Experimental results confirm that the stacking-based machine learning approach employing Linear Regression as the meta-learner provides improved performance and constructs a solid solution for early breast cancer detection.

VI. CONCLUSION

Breast cancer, one of the most critical health issues globally. Early diagnosis is required to enhance the survival rates. In the study, we introduced Stacking-based Machine Learning Model for breast cancer classification, which combined Random Forest, XGBoost, and Linear Regression as a meta-learner. The Stacking Model was tested on Wisconsin Breast Cancer Dataset to provide a robust experimental design with an 80-20 train-test split and the right feature selection, standardization, and oversampling methods (SMOTE) to address class imbalance.

The results indicated that the Stacking Model is best among individual classifiers such as Random Forest, XGBoost, and the Voting Classifier with the highest accuracy of 98.2%. The higher performance of stacking can be attributed to its capacity to integrate predictions from several models, benefiting from their strengths while offsetting their weaknesses. Mutual Information-based Feature Selection ensured that only the most vital 15 features were utilized to maximize the model's efficiency and interpretability. SHAP (SHapley Additive Explanations) was also used to maximize model transparency to make the predictions more interpretable to medical practitioners.

Compared to traditional classification approaches such as Linear Regression, KNN, and Naive Bayes, our ensemble-based methodology significantly improves the precision, recall, and F1-scores, ensuring reliable classification among malignant and benign tumors. Furthermore, our model generalizes well, mitigating overfitting and improving robustness, which is crucial in medical AI applications. The inclusion of hyper-parameter tuning using RandomizedSearchCV allowed us to achieve an optimized configuration for both Random Forest and XGBoost, enhancing predictive capabilities.

This work emphasizes the importance of ensemble learning in clinical diagnosis and demonstrates that stacking yields better and more interpretable results as compared to individual models. Future work can include expanding the dataset, using Deep Learning architectures such as convolutional neural networks for image processing,facilitating real-time clinical usage. In addition, the incorporation of transfer learning, federated learning, and explainable AI (XAI) methods can further enhance model trustworthiness, making AI-supported breast cancer diagnosis a more practical tool in actual clinical environments.

In summary, the stacking-based Random Forest, XGBoost, and Logistic Regression model offers an accurate, interpretable, and inexpensive solution to breast cancer detection, and the ability to enable early diagnosis and clinical decision-making. This work opens the gates for more evolved AI-based diagnosis tools that could help medical staff provide quicker and more accurate diagnoses of breast cancer, leading in turn to enhanced patient outcomes.

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