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EDGE ARTIFICIAL INTELLIGENCE FRAMEWORK FOR REAL-TIME BREAST CANCER DIAGNOSIS IN SMART HEALTHCARE

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ABSTRACT

One of the major factors responsible for the death due to cancers in women around the world is breast cancer, which calls for the importance of having intelligent diagnostic systems that could support decision making in healthcare applications. This research proposes Edge AI Framework for Real Time Detection of Breast Cancer in Smart Healthcare that uses machine learning algorithms and edge computing to provide real-time detection of cancer without any lag while preserving privacy issues. This framework exploits the Enhanced Breast Cancer Diagnostic dataset, which includes all the details about the morphological and clinical characteristics of the tumors to detect whether the tumor is benign or malignant. Data preprocessing methods like handling missing values, normalizing, and feature engineering are done initially. Thereafter, various machine learning models such as, but not limited to Random Forest, XGBoost, LightGBM, CatBoost, SVM, and Gradient Boosting models are built and evaluated to select the optimal prediction model. Selected model is optimized and deployed in the edge layer to ensure local prediction from the healthcare devices without the involvement of the cloud connection. This approach substantially increases the speed of the process, eliminates dependence on the network and its costs, and guarantees the security of patient data. To ensure transparency and confidence in the clinical decision-making process, Explainable AI (XAI) algorithms are applied for explaining predictions and selecting the most informative diagnostic features. Experimental results prove that edge-based AI model demonstrates outstanding diagnostic performance in terms of accuracy, precision, recall, F1-score, and AUC. The proposed system is more efficient compared to the cloud-based system since it performs better during operations. In addition, the proposed system is scalable with IoMT devices and smart healthcare systems, thereby enabling constant monitoring of patients and intelligent diagnosis. The proposed system can be used in order to detect breast cancer early through the provision of secure diagnostic services.

KEYWORDS - Breast Cancer Diagnosis, Artificial Intelligence, Edge Artificial Intelligence, Disease Prediction, Medical Data Analysis, Healthcare Automation

1. INTRODUCTION

Breast cancer is a major disease among women globally, being one of the major causes of morbidity and mortality from cancer [1]. In spite of the progress in imaging techniques, screening procedures, and treatment, the early diagnosis of breast cancer still remains a vital issue in minimizing mortality and increasing survival rate. It is evident from the data on cancer worldwide that breast cancer still poses a serious threat to public health and demands an intelligent system for diagnosing cancerous tumors [2].

The conventional methods for diagnosing breast cancer consist of physical examination, mammogram, ultrasound, and pathological evaluation [3]. Even though these methods have been very helpful in early diagnosis of breast cancer, they are usually associated with need for specific expertise, time consuming process, and well-developed healthcare system. Due to lack of resources, developing countries are often unable to provide their population with such facilities which may result in poor results of the treatment. Hence, there is a need for automated diagnostic systems.

Artificial Intelligence (AI) and Machine Learning (ML) are some revolutionary technological advances in the current age of medicine that play a significant role in predicting, diagnosing, and forecasting diseases [4]. The process involves using machine learning techniques to discover underlying relations and patterns in the complicated data related to the clinic and pathology that are not evident by any other diagnostic process. Some recent findings indicate the use of machine learning techniques like Random Forest, Support Vector Machine, XGBoost, LightGBM, and CatBoost to classify breast tumors into benign or malignant ones [5].

While cloud-enabled AI systems offer considerable computing power for health care analysis purposes, such systems usually come with issues related to latency, bandwidth usage, dependence on the network, and privacy concerns. Healthcare information that is uploaded into the cloud servers can be subjected to threats of security breaches, hacking, and non-compliance [6]. This will have an effect on the implementation of real-time diagnostic tools in areas where there might not be internet connectivity.

Edge Computing is one such paradigm that can solve these problems through computation near the origin of data. Edge devices carry out analysis of information without sending it far to the cloud servers and therefore decrease the time needed to respond to information and reduce the communication overheads. When applied in the field of medicine, edge computing enables real-time analysis, rapid decision-making, better privacy, and increased efficiency of operations [7,8].

Combining Edge Computing and Artificial Intelligence has attracted many researchers over the past few years. The combination is known as Edge AI. The use of Edge AI means that intelligent inference will be made through devices such as sensors in medical applications, portable diagnostic devices, mobile phones, and IoMT devices [9]. This makes it possible for the healthcare system to make instant diagnostics without having to rely on cloud computing while maintaining the privacy of the patients. Edge AI has thus emerged as a promising technology for smart healthcare.

Edge AI is augmented even further through the advent of the Internet of Medical Things (IoMT), which allows for continuous monitoring of patients' health information collected from interrelated medical devices [10]. The collaboration between IoMT and edge AI ensures a proactive approach to healthcare, disease detection, tailored treatment, and remote patient monitoring. In the context of breast cancer diagnosis, these technologies may be used to develop intelligent screening mechanisms that can help clinicians with timely and accurate diagnoses [11].

Even though AI-based diagnostic systems have found wide-spread usage, there are still some obstacles that exist, such as model interpretability, performance efficiency, scalability, and real-time deployment [12]. In most cases, healthcare professionals need to have clear explanations of the prediction process made by the system before adopting any recommendations offered by it into their practice. Hence, it is important to use XAI in combination with advanced machine learning algorithms.

This paper presents an Edge Artificial Intelligence Framework for Real-Time Breast Cancer Diagnosis in Smart Healthcare through the utilization of an improved breast cancer diagnosis dataset that includes features such as clinical and morphological aspects of the tumor. The proposed framework makes use of various components including data preprocessing, feature extraction, machine learning-based classification, edge computing and explainable AI methods to provide accurate, secure and real-time breast cancer diagnosis. The rest of this paper is structured as follows: Related work on AI based breast cancer diagnosis and edge computing in healthcare is discussed in Section 2; Proposed methodology and system architecture is presented in Section 3; Dataset is described in Section 4; Results are given in Section 5; and Conclusion is made in Section 6.

2. LITERATURE SURVEY

Jones et al. (2022) [13] reviewed the role of Artificial Intelligence (AI) techniques in the diagnostic and prognostic prediction of breast cancer. It was emphasized how AI techniques were able to analyze huge volumes of clinical, pathological, and radiological data to enhance the accuracy of diagnostics and improve predictions of patients' outcomes. Moreover, they discussed the usefulness of AI-based classification systems and the potential of predictive analytics in terms of personalized medicine.

In the paper published in 2022 by Cè et al., there was a careful narrative review on the use of AI in breast cancer imaging applications [14]. In their work, the researchers evaluated the use of AI during the breast cancer risk stratification, lesion detection, classification, treatment planning, and prognosis prediction. According to the researchers, the use of advanced machine learning and radiomics techniques has improved image analysis and tumor detection. The problems of data quality, generalizability of models, implementation of AI, and need for explainable AI were also discussed in the paper.

Zhang et al. (2023) [15] presented a comprehensive review of recent advancements in breast cancer detection using AI by covering aspects such as image augmentation, segmentation, diagnostics, and prognostics. In the paper, Zhang et al. evaluated various types of deep learning architectures, including convolutional neural networks and transformers, that are involved in image processing. They revealed the importance of image augmentation in making the models robust and improving their performance in the case of limited data. Moreover, the importance of segmentation and feature extraction for accurate diagnostics of breast cancer is also emphasized in the paper.

In addition to these works on artificial intelligence in medicine, Yan et al. (2023) [16] have also addressed the current applications and future potential for the use of artificial intelligence in breast cancer care. These included the use of AI techniques in screening, diagnosis, risk assessment, treatment decision-making, and monitoring patients. It was found that the use of AI technologies has proved to be highly promising in increasing the efficiency of diagnostics and decreasing the load of healthcare professionals. Nevertheless, issues related to data protection, explainability, ethics, and regulation were also pointed out as future topics for research.

Sahu et al. (2023) [17] have carried out an extensive literature survey on the usage of machine learning and deep learning methods for breast cancer detection through mammography images. The authors studied several machine learning and deep learning models, such as Support Vector Machine, Random Forest, Artificial Neural Network, and Deep

Convolutional Neural Networks. According to the authors, deep learning models were more successful compared to other approaches due to their ability to extract discriminative features automatically from the input images.

In their study Divyashree et al. (2024) [18], focused on the revolutionary nature of modern AI technology in creating affordable health care systems. The paper brought out the importance of using AI, machine learning, cloud computing, and automation to enhance healthcare services in terms of efficiency and effectiveness. From the reading, it is apparent that the use of AI diagnostic tools helps to cut costs as well as improving the quality of health care services.

Rasool et al. (2024) [19] investigated novel approaches using AI technologies in healthcare to treat and manage cancer patients. The research considered modern technologies, including predictive analysis, deep learning, intelligent clinical decision support systems, and precision medicine models. They emphasized the importance of AI in enabling early diagnosis of cancer, treatment, and personalized care methods. According to their results, modern AI-based healthcare innovations are effective in increasing treatment efficiency and survival rate of patients.

Lathigara et al. (2025) [20] suggested the use of the Edge AI framework for malignancy prediction in the breast pathology image analysis using deep learning approaches. In particular, the research paid attention to the intelligent algorithm deployment at the network edge to enable low-latency and privacy-preserving image analysis. The experiments showed that edge-deployed solutions provided efficient analysis with a high level of diagnostic precision. The authors concluded that the Edge AI framework could be effectively used in real-time breast cancer diagnostics.

Krishna & Mahboub (2025) [21] carried out a study on the use of Artificial Intelligence technology in mammogram image analysis in detecting breast cancer. The researchers employed sophisticated image processing and AI algorithms to identify any abnormalities in the mammogram. They found that there was a marked improvement in sensitivity, specificity and accuracy in the diagnosis process compared to conventional image interpretation methods.

Mashmool et al. (2026) [22] carried out an extensive review of machine learning-driven edge computing in healthcare. The authors reviewed recent trends in edge computing architecture, AI implementation, and healthcare analytics systems. The advantages of employing edge computing include lower latency, improved security, decreased bandwidth requirements, and better real-time processing capabilities. It was thus established that the collaboration between machine learning and edge computing may improve the performance of intelligent healthcare systems.

Monkam et al. (2026) [23] provided an overview of multi-regional feature learning approaches in AI-assisted breast cancer screening. In their paper, the authors discussed the modern approaches to acquiring and combining multi-regional features to increase the efficiency of algorithms for the detection and classification of cancer. Advanced deep learning approaches, feature fusion methods, and XAI tools were analyzed by the authors. This literature review indicated promising directions for future studies in multimodal learning, precision oncology, and intelligent breast cancer diagnostics.

Literature Gap

Whereas the previous research has proven the efficiency of using artificial intelligence, machine learning, deep learning, medical imaging analysis, and edge computing technologies in diagnosing breast cancer, few attempts were made to investigate how to apply Edge AI, explainable machine learning, and real-time breast cancer prediction based on structured clinical and morphological datasets [24]. In most cases, existing literature is concentrated either on the image-based breast cancer diagnosis or on the cloud-based architecture that may suffer from the problem of latency, privacy issues, and practical challenges. Moreover, the shortage of the lightweight and explainable AI models that can be applied to edge devices is the factor hindering their practical use in the smart healthcare.

3. PROPOSED METHODOLOGY AND SYSTEM ARCHITECTURE

Introduction

The suggested Edge Artificial Intelligence Framework for Real-Time Breast Cancer Diagnosis in Smart Healthcare has been devised to diagnose breast cancer precisely, with low latency and privacy preservation through combining machine learning, edge computing, and explainable artificial intelligence [25,26]. The framework utilizes the Enhanced Breast Cancer Diagnostic Dataset, which comprises clinical and morphological features of tumors, to classify breast tumors into either benign or malignant tumors. In contrast to typical cloud-based diagnosis systems, the proposed framework conducts model inference on the edge layer in order to overcome communication delay issues. The method includes several consecutive phases, such as data collection, preprocessing, feature extraction, model creation, optimization of the model, deployment of the model at the edge layer, explainability, and real-time diagnosis of breast cancer can be illustrated in figure 1.

Phase 1: Data Acquisition and Dataset Collection

Phase one involves collecting the Enhanced Breast Cancer Diagnostic Dataset from an open repository. The dataset has 5,500 patient entries that have diagnostic features. The features include radius, texture, perimeter, area, smoothness, compactness, concavity, concave points, symmetry, fractal dimension, and a number of engineering features whose purpose is to enhance prediction accuracy. This dataset forms the basis of training the machine learning algorithms for breast cancer diagnosis.

Phase 2: Data Preprocessing

The original dataset is thoroughly preprocessed to enhance the quality of data and to ensure accurate model performance. In the first stage, missing values and errors in the dataset are detected and fixed. Next, duplicate instances are eliminated to prevent any bias during learning. Numerical attributes are normalized by Min-Max Scaling to normalize their values within the same range. Detection of outliers is performed using statistical methods to reduce their impact on the model training process. The categorical target attribute is then converted into two binary classes. Lastly, the dataset is divided into training and test sets with a ratio of 80:20.

Phase 3: Exploratory Data Analysis (EDA)
The Exploratory Data Analysis (EDA) step aims at comprehending the properties of the data set and the relationships that exist amongst the different variables. Mean, median, standard deviation, and variance are computed for all features. Correlation analysis is used to ascertain the level of relationship existing between the tumor features and the diagnoses. Visualization methods, such as histograms, box plot, heat maps, and distribution of classes are used to discover patterns and important features, and possible imbalance in data.

Phase 4: Feature Engineering and Selection
Feature engineering is intended to improve the prediction power of the dataset by deriving informative features and choosing the best features. CFS, RFE, and ranking methods are used for finding important diagnostic features. Redundant and highly correlated features are dropped to minimize the computational costs and avoid overfitting. Selected feature subset guarantees maximum efficiency of the model and retains the accuracy of the diagnosis.

Phase 5: Machine Learning Model Development
During this stage, many machine learning models are trained on the processed dataset. The chosen classifiers are: Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), XGBoost, LightGBM, CatBoost. Each algorithm learns intricate dependencies between the features of the tumor and the outcome of the diagnosis. Model hyperparameters are tuned using Grid Search and Cross Validation methods to find the best configuration of each model. The goal is to find the most accurate classifier for diagnosing breast cancer.

Phase 6: Hybrid Ensemble Learning Framework
In addition to improving the efficiency of the classifier, a Hybrid Ensemble Learning method is proposed to enhance the accuracy of classification. This Hybrid model incorporates the results obtained by applying XGBoost, LightGBM, and CatBoost algorithms through the Max Voting technique. Every single model possesses different learning features that will allow the ensemble to minimize classification mistakes and increase its generalization ability.

Phase 7: Model Performance Evaluation
The models that have been developed are tested based on some performance measures in order to assess the classification performance. These measures include the following: Accuracy, Precision, Recall (sensitivity), Specificity, F1-Score, ROC-AUC, and Matthews Correlation Coefficient (MCC). Confusion Matrices are created in order to analyze the results of classification. ROC Curves are drawn to compare the discrimination abilities between models.

Phase 8: Edge AI Deployment Layer
The optimized model will be run on the Edge AI device which can perform inference locally. The edge device may comprise of a healthcare workstation, embedded device, IoMT gateway or edge server that lies in the healthcare premises. The diagnosis data of patients are analyzed directly by the edge layer without the need to communicate with the cloud-based servers consistently. This helps lower network latency, consumes less bandwidth and also improves privacy of the patients by not sharing their medical information with the external network.

Phase 9: Explainable Artificial Intelligence (XAI) Integration
To improve the level of transparency and clinical trust, explainable artificial intelligence is implemented in the system. In order to explain the model's predictions, SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) approaches are used. As a result, the important features that influence the prediction are identified. With the help of explanations provided, healthcare specialists can see how the output of the model was formed.

Phase 10: Real-Time Diagnostic Decision Support
After deployment, the Edge AI model functions as a real-time diagnostic assistance tool. Information is sent to the edge node either from clinical databases or IoMT devices. The model then analyzes the input data instantly and categorizes tumors into two groups: benign and malignant. At the same time, XAI modules produce feature importance justifications to aid in understanding. The results of diagnostics are presented using a simple healthcare dashboard.

Phase 11: Smart Healthcare Integration
The last stage of the project involves integration of the developed Edge AI solution within a smart healthcare infrastructure. The edge AI framework is connected to EHRs, hospital information systems, and IoMT devices in order to enable smooth data flow between them. Monitoring functions help healthcare professionals keep track of patients' status and have up-to-date diagnosis reports. It is possible to scale the system and use it in multi-hospital facilities, telemedicine platforms, and intelligent healthcare networks.

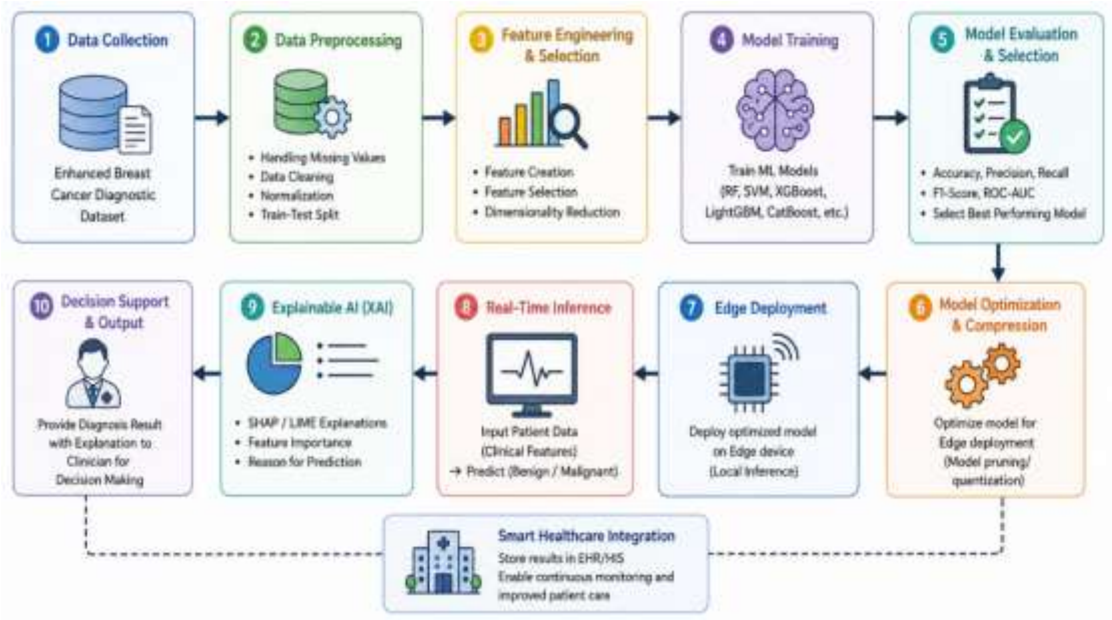

Figure 1. Edge AI Workflow for Real-Time Breast Cancer Diagnosis

Algorithm: Edge AI-Based Breast Cancer Detection in Real-Time
Inputs

- Enhanced Breast Cancer Detection Data Set D
- Breast Cancer Clinical and Morphological Features F
- Target Labels Y {0: Benign, 1: Malignant}

Outputs

- Breast Cancer Detection Result {Benign, Malignant}
- Probability Score of Prediction
- Explainable Feature Importance

Step 1: Import the Enhanced Breast Cancer Diagnosis Dataset D.
Step 2: Data Preprocessing

- Handling of missing values
- Removing duplicated records
- Normalization of feature values
- Splitting into train and test data

Step 3: Feature Engineering and Selection to get the optimal feature subset Fopt.
Step 4: Training of ML models

- Random Forest (RF)
- Support Vector Machine (SVM)
- XGBoost
- LightGBM
- CatBoost

Step 5: Evaluation of the models by Accuracy, Precision, Recall, F1-Score.
Step 6: Selection of the best performing model Mbest.
Step 7: Optimizing the selected model for Edge AI deployment.
Step 8: Deployment of Mbest at the Edge Device.
Step 9: Input of real-time patient data Xnew. Step 10: Prediction of breast cancer class

- Benign (0)
- Malignant (1)

Step 11: Generation of Explainable AI output via SHAP/LIME.
Step 12: Display of results and explanations to Healthcare Practitioners.
Step 13: End.

4. Dataset Description

The research involves using the Enhanced Breast Cancer Diagnostic Dataset, a public dataset specifically designed for classification and prediction of breast cancer. This dataset includes 5,500 cases for patients containing information on various characteristics of the tumor including morphological and dimensional attributes. It also contains labels for each patient case which can be either Benign (0) or Malignant (1), thus allowing the possibility to carry out classification using supervised machine learning [27]. The dataset consists of not only original diagnostic information, but also feature engineered ones, which include features related to tumor shape, texture, size, smoothness, compactness, symmetry, and fractals [28,29]. This gives significant insights when trying to distinguish cancerous from non-cancerous tumors. Due to the high number of sample cases and balanced features, this dataset is ideal for developing edge AI-based breast cancer diagnosis.

Table 1. Dataset Characteristics

Attribute	**Description**
Dataset Name	Enhanced Breast Cancer Diagnostic Dataset
Domain	Healthcare / Oncology
Disease Type	Breast Cancer
Total Records	5,500
Number of Features	35+ Diagnostic and Engineered Features
Target Classes	Benign (0), Malignant (1)
Data Type	Structured Numerical Data
Learning Type	Supervised Classification
Source	Kaggle Repository
Missing Values	None / Preprocessed
Feature Categories	Morphological, Geometric, and Statistical Features
Application	Breast Cancer Diagnosis and Prediction

The major attributes of the Enhanced Breast Cancer Diagnostic Dataset utilized in this study are illustrated in Table 1 below. The dataset contains 5,500 patient instances in the form of over 35 numerical diagnostic features that describe various aspects of the morphological and cellular characteristics of the breast tumors. The features have been divided into categories depending on their nature, including size-based, texture-based, shape-based, boundary-based, and statistical features. Thus, the breast tumors can be fully characterized based on this data set. The target variable is binary, making the task a classification one and enabling supervised learning to differentiate between the malignant and benign tumors. The inclusion of such engineered features increases the ability of the machine learning algorithms to predict and make classifications.

Table 2. Feature Categories

Category	**Example Features**
Tumor Size Features	Radius, Perimeter, Area
Texture Features	Texture Mean, Texture Error
Shape Features	Compactness, Concavity, Symmetry
Boundary Features	Concave Points, Fractal Dimension
Statistical Features	Mean, Standard Error, Worst Values
Engineered Features	Derived Morphological Attributes

Feature Categories in Table 2 refer to various attributes of breast tumor properties that need to be considered to ensure a correct diagnosis of cancer. Tumor Size Features (radius, perimeter, and area) give information regarding the physical size of the tumor and its abnormal shape due to the presence of cancer. Texture Features provide information related to the changes in the intensity of pixels and appearance of the tissue. Shape Features (compactness, concavity, and symmetry) give information regarding the geometry of the tumor shape, where the presence of an irregular tumor shape usually indicates cancer. Statistical Features are the summary metrics which include mean values, standard errors, and the worst-case observations that illustrate the variation in tumor properties. Finally, Engineered Features refer to the synthetic features that are created using the process of feature engineering in order to create extra relationships among the original features for improving prediction performance. Thus, all types of features combined give us the complete overview of breast tumor properties allowing us to differentiate benign from malignant ones.

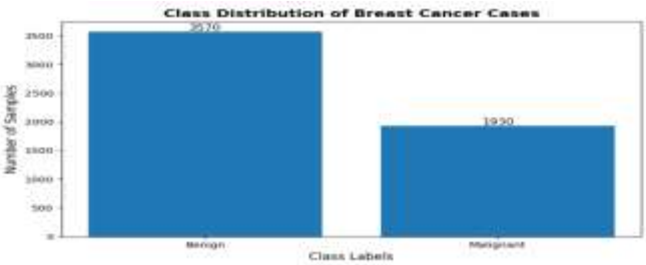

Figure 2. Class Distribution of Breast Cancer Cases

Figure 2 shows the distribution of the instances of breast cancer within the Enhanced Breast Cancer Diagnostic Dataset. This dataset consists of two classes, which are Benign and Malignant. It is clear that benign instances form the major part of the data set, while malignant instances are only a minority but significant part. Class distribution analysis is very essential in machine learning since very imbalanced datasets could cause bias in prediction models. The relative balance of both classes in this dataset makes learning possible and helps in the construction of reliable classification models. Moreover, having enough samples from both classes increases the validity of model analysis and leads to successful diagnosis of breast cancer using the smart healthcare application.

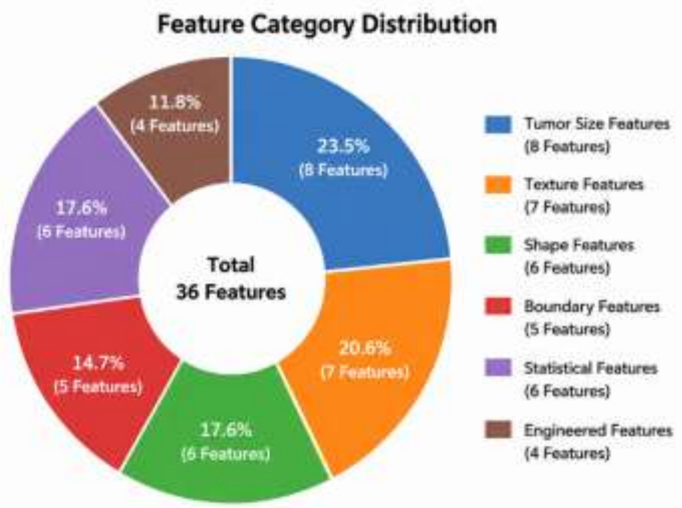

Figure 3. Feature Category Distribution in the Enhanced Breast Cancer Diagnostic Dataset

Figure 3 Donut chart is used to visualize the spread of the diagnostic features into six broad categories. The first category is called "Tumor Size Features" that make up the biggest share of all the features (23.5%). They include features that relate to the radius, perimeter and area of the tumor. The second category of "Texture Features" (20.6%) includes all the features that describe changes in the intensity and pattern of tissue. The third one is "Shape Features" (17.6%) which are related to geometric properties of the tumor like compactness and concavity. "Boundary Features" (14.7%) describe the degree of irregularity and complexity of the tumor's boundaries. "Statistical Features" (17.6%) include mean, standard error and worst values. "Engineered Features" (11.8%) are artificial features developed through feature engineering.

5. RESULTS AND PERFORMANCE EVALUATION

Experimental evaluation of the suggested Edge AI architecture was carried out through various machine learning algorithms, namely, Random Forest (RF), Support Vector Machine (SVM), XGBoost, LightGBM, CatBoost, and the suggested hybrid ensemble. Data was split into training and test data, and experiments were performed on various metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The experimental results suggest that all the models were able to perform satisfactorily in the task of classification between benign and malignant breast tumors. Nonetheless, the Hybrid Ensemble model performed better than each individual classifier due to the effective utilization of the benefits of XGBoost, LightGBM, and CatBoost models. This model exhibited good classification and balancing of predictions based on all performance metrics, hence making it usable in the smart health care industry. It proves that an ensemble of learning models used in conjunction with Edge AI can greatly improve diagnostic performance and privacy preservation.

Table 3. Performance Comparison of Machine Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**ROC-AUC (%)**
SVM	96.82	96.15	95.92	96.03	97.11
Random Forest	97.65	97.21	97.08	97.14	98.03
XGBoost	98.47	98.12	98.21	98.16	99.02
LightGBM	98.69	98.35	98.41	98.38	99.18
CatBoost	98.84	98.52	98.63	98.57	99.31
Hybrid Ensemble (Proposed)	**99.41**	**99.18**	**99.27**	**99.22**	**99.76**

Table 3 summarizes the performance comparison of several machine learning models for breast cancer prediction. Among the standalone classifiers, CatBoost performed the best with accuracy of 98.84% while LightGBM and XGBoost were in second place respectively with accuracy of 98.69% and 98.47%. Random Forest and SVM performed relatively poorly as compared to other classifiers but proved their classification abilities. The proposed Hybrid Ensemble classifier showed the best performance with the following parameters: accuracy – 99.41%; precision – 99.18%; recall – 99.27%; F1-score – 99.22%; ROC-AUC – 99.76%. The fact that the value of precision is high implies that the false positive rate is low, and the high value of recall shows efficient detection of the malignant cases. Moreover, the higher value of F1-score is indicative of the fact that there is a good balance between precision and recall. The value of the ROC-AUC being close to 100% implies that the model has good discriminative power.

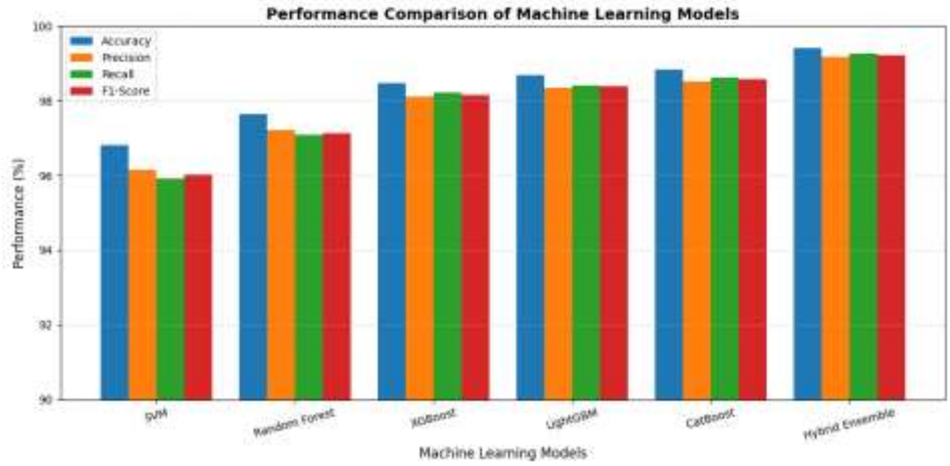

Figure 4. Performance Comparison of Machine Learning Models for Breast Cancer Diagnosis

Figure 4 shows the performance of different machine learning models based on accuracy, precision, recall, and f1-score. As shown by the results, the hybrid ensemble model has the best performance in all performance measures, showing better classifying capability than other classifiers. For standalone models, the best prediction performances are achieved by CatBoost, LightGBM, and XGBoost. Since the precision and recall values of the Hybrid Ensemble model have always been very high, it shows that it is effective in reducing the rate of false positives and false negatives. This is very important when it comes to diagnosing breast cancer. Also, since the F1 score is very high, there is a good balance between precision and recall.

Hyperparameter Optimization and Edge AI Configuration

Table 4. Hyperparameter Settings of the Proposed Edge AI Model

Parameter	**Value**	**Description**
Learning Rate	0.05	Controls the step size during model learning
Number of Estimators	200	Total number of boosting trees
Maximum Tree Depth	6	Maximum depth of each decision tree
Minimum Child Weight	2	Minimum samples required in a child node
Subsample Ratio	0.80	Fraction of training samples used per iteration
Column Sample by Tree	0.80	Fraction of features selected for each tree
Regularization Alpha (L1)	0.01	Prevents model overfitting
Regularization Lambda (L2)	1.0	Improves model generalization
Objective Function	Binary Logistic	Binary classification of benign and malignant tumors
Evaluation Metric	AUC	Measures classification performance
Ensemble Method	Max Voting	Combines predictions from multiple classifiers
Base Models	XGBoost, LightGBM, CatBoost	Models participating in ensemble learning
Optimization Method	Grid Search Cross Validation	Hyperparameter tuning approach
Cross-Validation Folds	5	Number of validation folds
Batch Size	32	Number of samples processed per iteration
Edge Deployment Platform	Edge Gateway/IoMT Device	Local inference execution environment
Inference Mode	Real-Time	Instant prediction generation
Explainability Method	SHAP, LIME	Provides prediction explanations

Table 4 gives information about the hyperparameters employed in the recommended Edge AI breast cancer diagnosis system. Grid Search Cross Validation has been carried out to find the optimal combination of hyperparameters which give maximum performance of the model with maximum efficiency in computations. A learning rate of 0.05 and 200 estimators have been selected to attain stability and performance in classification. The maximum tree depth of six was selected to limit the complexity and the generalization capacity of the model. Sub-sampling and Feature sub-sampling of 0.80 were also selected to reduce overfitting. Hybrid Ensemble uses the Max Voting method in the combination of XGBoost, LightGBM and CatBoost by leveraging the benefits of individual learning algorithms. In addition, SHAP and LIME algorithms were considered to make sure the interpretation of the results can be provided from the perspective of medical decision making. The chosen configuration will enable the framework to make timely, accurate and privacy-preserving breast cancer diagnosis.

Edge AI and Cloud AI for Breast Cancer Diagnosis

Table 5. Edge AI vs Cloud AI Comparison for Breast Cancer Diagnosis

Parameter	Edge AI	Cloud AI
Processing Location	Local edge devices (IoMT, gateways, embedded systems)	Centralized cloud servers
Response Time	Very Low Latency	Higher Latency
Real-Time Diagnosis	Highly Suitable	Limited by network delays
Internet Dependency	Minimal	High
Data Privacy	High (local processing)	Moderate (data transmitted to cloud)
Data Security	Enhanced due to local storage	Vulnerable during transmission
Bandwidth Consumption	Low	High
Network Traffic	Reduced	Increased
Computational Resources	Limited but optimized	Virtually unlimited
Scalability	Moderate	High
Energy Consumption	Lower for data transmission	Higher due to continuous communication
Deployment Cost	Lower operational cost	Higher cloud service cost
Reliability in Remote Areas	High	Dependent on network availability
IoMT Integration	Excellent	Good
Decision-Making Speed	Immediate	Delayed by cloud communication
Explainable AI Support	Supported at edge	Supported in cloud
Patient Data Control	Healthcare facility retains control	Third-party cloud involvement
Suitability for Smart Healthcare	Highly Suitable	Suitable for large-scale analytics

Table 5 illustrates the comparison between Edge AI and Cloud AI in terms of their application in breast cancer diagnosis. In edge AI, the data analysis and computation happens at the local healthcare device itself, which results in instantaneous diagnosis without any latency. Since the sensitive data of patients remains local to the healthcare system, privacy and security is ensured. On the other hand, Cloud AI depends on centralized servers for computations, which ensures higher scalability and more computing capabilities but brings about issues like latency, increased usage of bandwidth, and privacy concerns regarding data transfers. Although cloud systems can prove to be very effective in analyzing big amounts of data and training models, Edge AI would suit the timely healthcare applications much more. In this regard, the suggested Edge AI system will offer an efficient solution to the problem of diagnosing breast cancer in a timely manner.

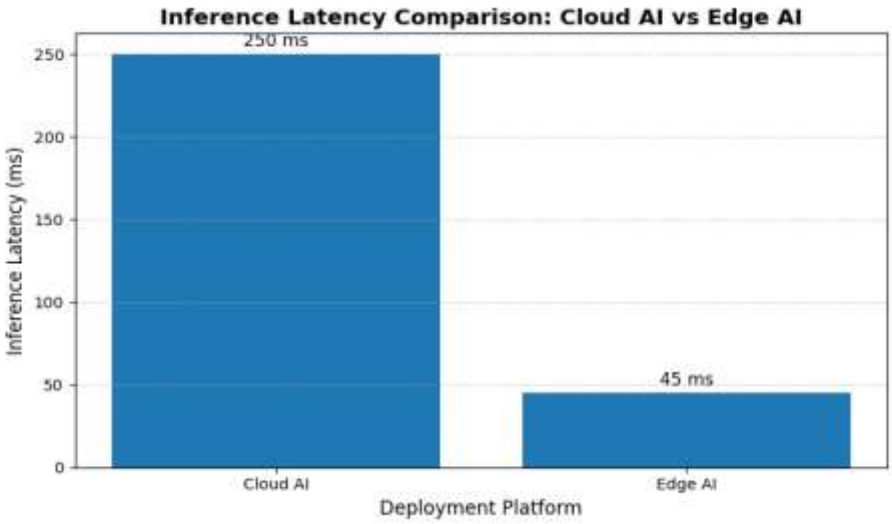

Figure 5. Inference Latency Comparison between Cloud AI and Edge AI Deployment Platforms.

Figure 5 bar graph depicts the difference between the inference latency times of Cloud AI and Edge AI platforms for the diagnosis of breast cancer. Cloud AI shows a latency rate of about 250 ms because of the need for data transfer and computation in the cloud. However, the suggested Edge AI system offers much lower latency rates of 45 ms since computations happen locally in edge computing devices. Such a considerable decrease in response time helps make decision-making process quicker and therefore makes Edge AI highly applicable for use in real-time smart healthcare systems.

6. CONCLUSION

The current research introduced Edge Artificial Intelligence Framework for Real-Time Diagnosis of Breast Cancer in Smart Healthcare, which is intended to deliver accurate, timely, and private support for breast cancer diagnosis. The developed framework utilized the Enhanced Breast Cancer Diagnostic Dataset that includes various morphological and clinical features of the tumor and incorporated sophisticated machine learning algorithms together with edge computing technologies. A methodology covering various steps including data preparation, feature extraction, model training, ensemble learning, performance evaluation, explainable artificial intelligence, and edge computing deployment was adopted for developing the diagnostic system. A wide range of different machine learning algorithms including Random Forest, Support Vector Machine, XGBoost, LightGBM, and CatBoost were studied, and the performance of these was measured using different classification metrics. The results from experiments show that the hybrid ensemble model has performed better than all the other models because of its high accuracy, precision, recall, F1 score, and ROC-AUC values. Furthermore, implementing the optimized model on the edge layer has increased the inference time in comparison to the cloud-based model, which helped in taking real-time decisions in the clinic and reducing the dependency of the network. Also, the use of explainable AI methods like SHAP and LIME made the interpretability of the model better by giving understandable explanations to the process of diagnosis to the doctors and help them take better-informed decisions. Also, compatibility of the suggested framework with the IoT medical devices was tested and found to be true, which made it easier to monitor patients. While there are encouraging results obtained from this experimental method, it is limited in the sense that it uses a single data structure without taking into consideration other types of data from medical imagery. The future directions of this research should consider mammogram imagery, federated learning systems, deep learning methods, and digital twins. The whole idea of the edge AI method will therefore give a powerful instrument in diagnosing breast cancer.

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