International Journal of Advanced Multidisciplinary Research
ISSN: 2393-8870
www.ijarm.com
(A Peer Reviewed, Referred, Indexed and Open Access Journal)
DOI: 10.22192/ijamr Volume 11, Issue 3 -2024

Research Article

DOI: http://dx.doi.org/10.22192/ijamr.2024.11.03.010

AI-based breast cancer classification using cloud computing and secure data handling

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Abstract

Breast cancer has ever since kept the status of anepidemic, as it takes innumerable women in its wake year after year. This thus entails the need to raise awareness toward early detection to save human lives. Here, early detection becomes a sine qua non, for subjective and traditional methods of diagnosis in breast cancer are highly labor-dependent and, hence, an AI-based automated classification is needed to address these complications. The present work proposes an AI-based

Keywords

PCA (Principal Component Analysis), Feedforward Neural Network (FNN), AES Encryption, Data Security.

classification model for breast cancer in a cloud-computing environment such as Google Cloud and GCP to enhance accuracy, minimize human error, and maintain data in compliance with HIPAA and GDPR. This methodology will initially involve the preprocessing phase, which includes data cleaning for feature selection, application of PCA for feature selection, and classification using a feed-forward neural network, which is supported for model creation.Data related to transmission and storage will be kept secure through AES encryption and its applicability in cloud computing.The model under consideration gives an accuracy of 94%, a precision of 80%, a recall of 67%, and an F1 Score of 83%. Thus, the ROC has a good incentive for performance with an AUCof 0.96, which can improve recall to reduce false positives. With all these in mind, AI-cloud-supported secure data would become a boon for breast cancer detection. Therefore, this refines the pathway for rapid and inexpensive but still dampened facilitation across the doctor networks.

1. Introduction

An optimal application of artificial intelligence has been developed for AI-Based Classification of Breast Cancer Using Cloud Computing and Secure Data Handling, which specifies improvement in precision and efficiency of breast cancer detection through artificial intelligence (AI) techniques [1]. The futuristic vision behind the investigation is the complete automation of the classification of breast cancer as malignant or benign using various machine learning and deep learning algorithms with the use of Breast Cancer Wisconsin Dataset, which provides multiple important (pertaining) features such as radius, texture, and smoothness calculated from computerized images of breast cancer biopsy samples [2]. The model training and testing are going to be hosted on cloud computing platforms such as Google Cloud or AWS, therefore making it less scalable and requiring a lot of computational power, as models need to be trained on very large datasets and consume considerable resources [3]. Some other factors contributing to cloud computing would include model training & deployment, and experiences related to storing data securely and safely [4]. Here, secure data handling has been defined and introduced as an implementation regarding sensitive patient data under relevant laws such as the HIPAA and GDPR privacy regulations [5]. The methods include techniques such as AES encryption, which secure data at rest and during transit, as well as the safety of sensitive health information from the very start through to the very end [6]. Furthermore, this is enforced with Multi-factor Access Control and Role-Based Access Control (RBAC) as a way of restricting unauthorized access to the data and models, making it possible for only authorized personnel to interact with the system [7]. Therefore, this becomes the effective, scalable, and secure approach in breast cancer classification through AI, cloud computing, and secure data handling [8]. Its contribution towards diagnostic weightage has increased, and human error has been reduced, thereby increasing decision support in healthcare [9]. Besides, through real-time prediction, the healthcare professionals are empowered to make quick and sure decisions [10].

The aforementioned methodology is an AI-based classification for breast cancer detection, and the data regarding activities for using breast cancer datasets while incorporating the concept of Principal Component Analysis (PCA) techniques for feature extraction and dimensionality reduction [11]. Initial data pre-processing steps included cleansing, normalization, and missing value treatment, progressing along with storage and transfer of data to a secure place with AES encryption to maintain the privacy of information according to HIPAA and GDPR [12]. Such classifiers could be feedforward neural networks that would optimize via binary cross-entropy loss and Adam or SGD [13]. All information is monitored regularly by the system about the performance and security of the model, and could yield live prediction with retraining when required for efficient breast cancer detection [14]. Another limitation could be owing to some model overfitting despite PCA dimensionality reduction applied on high dimensions [15]. Unbearable categorization of benign tumors can be a cause for concern as part of the imbalance of the dataset [16]. AES encryption, for example, provides security for data storage and/or data transmission, yet it is going to consume additional computing resources [17]. Hence, in general, it could lack the generalizability of datasets and real-life medical data that are drastically different from the training set [18]. The high dimensionality of datasets remains a challenge in classification tasks, especially when working with complex biological data like breast cancer images [19]. Overfitting in machine learning models is another common issue when applying AI techniques on high-dimensional data, especially without proper cross-validation [20]. The role of data augmentation and regularization techniques in addressing the overfitting issue has been proposed in many studies [21]. Another concern is the bias that can arise from imbalanced datasets, which may lead to the misclassification of benign and malignant samples [22]. Secure data transfer methods using modern encryption standards are continuously evolving to stay ahead of potential cybersecurity threats in cloud computing [23]. Despite the high performance achieved by these AI systems, the trade-off between computational resources and security still presents challenges for scalability [24]. Finally, the integration of AI-based breast cancer detection systems in clinical settings requires the validation of models through rigorous testing with diverse datasets to ensure their generalizability and reliability in real-world scenarios [25].

The contribution of the paper is below:

- Develop an optimal AI-based classification of malignant versus benign tumors can be further improved by means of considering performance arguments related to computational applications like machine learning and deep learning for breast cancer classifications in terms of definability in the cloud and data handling security.
- Utilize the breast cancer Wisconsin dataset describes radius, texture, and smoothness computed from computerized images of breast cancer biopsy samples, which were used afterward for training and testing a model.
- Implementing these high-dimensional data sets can be sufficiently dealt with by principal component analysis (PCA) under feature extraction and dimension reduction concepts, which help to boost the model performance.
- Apply to the security of its storage and communication will be ensured through AES encryption and HIPAA, Patient sensitive information protection against unauthorized access, as well as GDPR, in addition to multi-factor access control (MFA) and role-based access control.

2. Literature survey

Applied communication technology is transforming life sciences through enabling the interconnection and sharing of data from many intelligent objects and various detectors [26]. In particular, the awareness about platforms for processing and managing IoT data is on the rise [27]. Some benefits that AI would accord to medical science relate to automating processes, making inquiries, and conducting analysis drills within large patient databases [28].A cloud computing-based framework for classification of breast tumor images is presented in this research, wherein it combines the AlexNet architecture and GLCM texture features with an ensemble multi-kernel SVM (MK-SVM) [29]. This system is to enhance the breast cancer detection, especially for any remote patient with no medical facilities, with an attained accuracy of 96.26% on the MIAS dataset [30]. This research produces ABCanDroid, an app for Android integrated with a cloud system, implementing transfer learning on a ResNet101 model to enhance efficiency and early diagnosis of noninvasive breast cancer, producing a very impressive accuracy of 99.58% [31].

The research emphasized the potential that breast cancer diagnosis holds for these deep learning algorithms and is geared toward providing both healthcare systems and society with an improvement [32]. More obstacles are posed to the colliding institutions on data privacy and variable transparency of the algorithms [33]. Accordingly, the paper proposes some solutions to fasten the responsible and ethical incorporation of AI and cloud technologies into oncology [34].In this paper, we have provided a comprehensive description of the role of artificial intelligence and machine learning applications in the various stages of breast cancer detection and history making, from data acquisition, through features extraction and machine learning, and eventually history through the possible AI algorithms like Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Fuzzy Logic [35]. So far, fuzzy logic is said to have shown more accuracy and robustness against dirty data than any other artificial intelligence technique in this study [36]. Deep transfer learning and fog computing are used to operate an independent breast cancer diagnostic system relying on mammography images from the Cancer Imaging Archive [37].

The research proposes a CAD system for breast cancer classification through machine learning algorithms to improve the system performance [38]. Having 13 features and 5 classifiers adopted into the study, the LightGBM classifier results in the highest accuracy [39]. There is a federated learning approach for breast cancer classification as per the research, and anywhere patient privacy is maintained to add accuracy to diagnosis [40]. The system mainly works for transfer learning feature extraction, SMOTE data processing, and a FeAvg-CNN + MobileNet classifier, giving it superiority in classification over any existing system [41].An automated breast cancer diagnostic system was established under federated learning and deep learning paradigms to offer better classification from histopathological images [42]. Five stages decided: obtaining the image, encrypting the image, transmitting the encrypted image, decrypting the image, and finally, classifying the disease with the convolutional capsule twin attention network [43]. This study puts forth a Medical IoT-based diagnostic system that correctly classifies breast cancer cases into malignant and benign types using hyperparameter-optimized neural networks by making use of ANN and CNN techniques [44]. The framework for breast cancer classification on ultrasound images based on deep learning with feature fusion towards early detection for mortality reduction [45]. An augmented dataset yields high accuracy by the proposed method and thus outperforms current state-of-the-art methods by applying a chain of optimized processes like data augmentation, transfer learning, and feature selection.

3. Problem statement

Breast cancer is a particular type of disease that stands first on the list in cases occurring among women in the world. Evidence-based early detection methods would spare costs; therefore, different manual or imaging techniques, almost all of them cumbersome and give false-positive results, should be ruled out for breast cancer detection [46]. The automation of accuracy and scaling health systems in the diagnosis of breast cancer is an urgent necessity. Clouds and AI underpinnings are discussed in the paper regarding their classification and role in breast cancer diagnosis [47]. Dating back to this kind of system, several significant improvements or countless enhancements could be made in great applicability to different aspects like data cleansing, normalization of data, dimension reduction, and PCA, which would effectively make the modeling for the particular problem of breast cancer a very valid one and more so in the case of the Breast Cancer Wisconsin Dataset where it'll apply radius, texture, and smoothness as recognized features for the Feedforward Neural Network to classify tumors-from malignancy versus benign[48]. Under the secure access environment provided by multi-factor authentication (MFA), sensitive health data transfer using AES encryption is further protected in terms of privacy and integrity, being able to meet both HIPAA and GDPR requirements[49].

The real-time monitoring and training of cloud infrastructure, deployment, and performance updates further enhance the capacity of the infrastructure in terms of scalability and flexibility [50]. In that respect, these features are proposed to vastly improve the breast cancer detection process, further automated at a very large scale with high diagnostic accuracy while optimizing the workflow in healthcare.

4. Proposed methodology

This method involves the collection of data during which the breast cancer dataset is prepared for classification. Some of the features include radius, texture, and smoothness. After the cleaning and pre-processing have been done with removing missing values and outlier data, the next step will be normalizing the data and preparing it for feature extraction and training for a machine learning model through scaling the features and checking for consistency. Principal Component Analysis (PCA) is a feature extraction adopted here. This reduces dimension while fairly well preserving data. The application of PCA eliminates from the model perspective irrelevant parameters, making it important for both performance enhancement and complexity reduction. Upon completion of all pre-processing and feature extraction, the data is connected to a cloud computing infrastructure that can keep the chi stock to process for scalability and flexibility. Such platforms as AWS, Google Cloud, or Azure do fulfil resource requirements in data storage, model training, and deployment. The data is stored and transferred via AES encryption, the best-known protocol for encryption, which should therefore assure maintenance of standards for data privacy. For this purpose, HIPAA and GDPR are the applicable security standards. Furthermore, strong access control and MFA ensure that a significant amount of unauthorized access to data and models has been kept at bay. Base classification missions are accomplished via feedforward neural network types, significantly reducing the binary classification distinction between malignant and benign tumours. The features that have passed through both pre-processed data and PCA extraction are then trained to learn the respective networks with their sigmoid activation function to predict malignancy or non-malignancy. The loss function that is used is a binary cross-entropy, and optimizers, Adam or SGD, are used to minimize loss in training. Evaluation of the model occurs after training with the performance parameters such as accuracy, precision, recall, and F1 measure. Similar to other data sources, when used for testing, will demonstrate the relevance of the model in what is termed generalizability and prediction-wide accuracy. The deployed system, therefore, should also continuously monitor itself for a trend of real-time model performance and notify for model retraining whenever accuracy shows a significant loss or there is a change set of patterns within the data. Thus, this methodology offers a full-fledged AI-enabled system to detect breast cancer, while at the same time facilitating very efficient management of data along with excellent prediction, and all of this is coupled with very high security for the sensitive health information of patients.

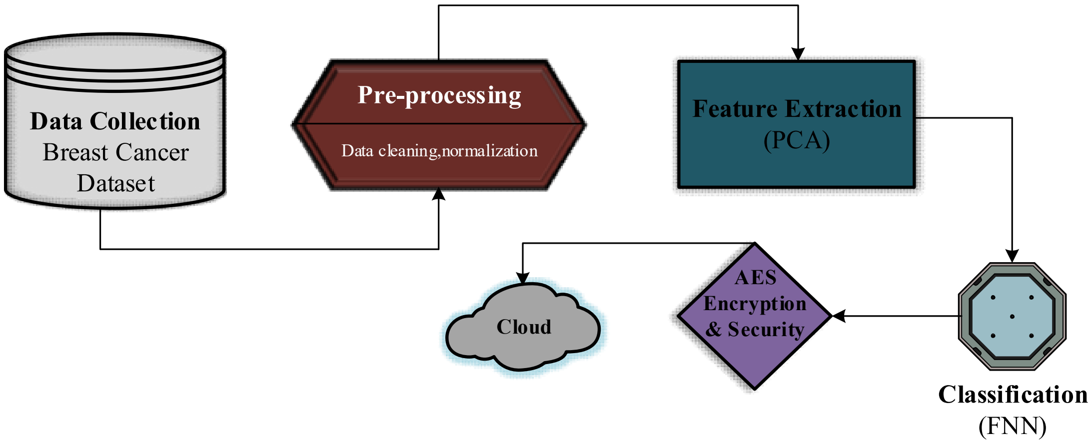

Figure 1: Overall architecture of the proposed method

4.1 Data collection

The Breast Cancer Wisconsin Diagnostic Dataset is simply a dump of some breast cancer sample data suitable for a few simple classification algorithms. The dataset comprises 30 defined features for each kind of tumour according to cellular and tumour properties. Any person can download the dataset, and there are a lot of applications in healthcare-related areas, especially in breast cancer testing. While these datasets are structured in a supervised way, some cleaning and normalisation will have to be performed to locate outliers or missing values. This will then provide a way to build an AI classification model for tumours to relieve the subjective burden on evaluation, thereby facilitating early diagnosis and personalised treatment.

4.2 Pre-processing

The pre-processing phase in the workflow includes many transformations of the dataset to be certain that it is clean, standardised, and set for feature extraction and model training. The reason for the importance of pre-processing is that it provides a way of counteracting noise, resolving inconsistencies, and finally formatting data in a way of maximizes model performance. The main pre-processing steps common to the Breast Cancer Dataset include data cleaning and normalisation.

Data cleaning

- **Data-cleaning therapy:** Missing values, duplicate observations, and outliers in data usually influence the accuracy of the results.
- **Handling missing values:** Treating missing data is accomplished using many methods. Out of these methods, mean imputation (replacing missing values with the mean of the feature) is one of the most common methods.

Formula: For a feature with missing values, mean imputation can be expressed as:

$$x_i^{\text{imputed}} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (1)$$

where n is the total number of instances available for xi, has been substituted with the mean over the feature across instances where xi has not been missing.

Removing Outliers: Sometimes, the Z-score method can indicate which values would be outliers. Such a feature is considered an outlier if the Z-score exceeds the threshold, which is generally taken at about ±3. The Z-score for the feature x_i is calculated as

$$Z = \frac{x_i - \mu}{\sigma} \qquad (2)$$

This means that μ is the mean, while σ is the standard deviation of the property. One of the most typical practices is to exclude extreme values from the dataset where the Z-scores go beyond a certain cut-off threshold.

Normalization

Objective: Normalizes or standardizes features so that they approach one another on a similar scale. This is extremely important for a number of algorithms that derive their feed data scale, such as SVM and FNN.

Action Min-Max: The method rescales the data to some fixed ranges, which usually can be, but is not limited to, [0, 1]. Thus, for the feature xi, the formula of Min-Max scaling is given by:

$$x_i^{\text{scaled}} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \qquad (3)$$

where $\min(x)$ and $\max(x)$ indicate the minimum and maximum value taken by feature x in the whole dataset.

Z-Score Normalization:

Z-score normalization (standardization), another method, rescales the feature to a mean of zero and a variance of one. For any feature xii, Z-score normalization would be expressed as follows:

$$x_i^{\text{normalized}} = \frac{x_i - \mu}{\sigma} \qquad (4)$$

The term means μ, indicating the average, and σ, the term referring to the standard deviation of the feature.

4.3 Feature extraction

In the Feature Extraction phase, the aim with this step is to convert the raw data into observable features that could be used for model training. The importance of this stage step significantly enhances the measure of performance and efficiency when it comes to machine learning models because it helps reduce the complexity of the data adequately yet maintains its important characteristics. In this specific workflow, Principal Component Analysis (PCA) is used as the principal method of feature extraction. PCA is a well-renowned method of dimensionality reduction which identifies those directions, which are principal components, along which the data vary the most. The method consists of estimating the covariance matrix of the data and then computing its eigenvectors and eigenvalues. The eigenvectors correspond to the directions of maximal variance in the data whereas the eigenvalues represent the amount of variance in that direction. PCA lowers the number of features by projecting on those eigenvectors corresponding to the largest eigenvalues while preserving the major varieties that account for most of the variance in the dataset.One key formula defines the covariant matrix or covariance matrix of the datasets, and this is one of the most important formulas in principal component analysis (PCA)-formulated feature extraction.

Covariance Matrix Formula:

$$C = \frac{1}{n} X^T X \qquad (5)$$

Where X is the data matrix of size n×m, X^T is the transpose of the matrix X, C is the covariance matrix of size m×m.

A row in X is a sample, while a column in X is a feature. This operation $XT.X$ provides the dot product of features across samples, arriving at a matrix exhibiting the extent of variability of each pair of features concerning one another. Dividing by n normalizes this summation and produces as output the average covariance between features. Then C is a matrix showing the covariance between all feature pairs. The diagonal entries correspond to the variance of each feature.

4.4 Classification

The aim in the Classification phase is to predict if a tumor is malignant or benign based on the indices extracted from the Breast Cancer Dataset. This is done using a Feedforward Neural Network (FNN) designed for deep learning binary classification. The FNN models learn how to relate the tumor and preprocessed and PCA-extracted features to classification. The input layer consists of 30 neurons corresponding to the 30 features in the dataset: radius, texture, smoothness, etc. Following this, there are hidden layers with nonlinear activation functions, namely ReLU or Rectified Linear Unit, to capture highly complex and nonlinear data patterns. The output layer consists of a single neuron, which gives the probability value between 0 and 1 that the tumor is malignant. The neuron in the output layer uses a sigmoid activation function.

FNN training shall be performed by minimizing the binary cross-entropy loss function, which evaluates the divergence between predicted output and true label. The loss function is expressed as:

$$L(y, \hat{y}) = -[y\log(\hat{y}) + (1-y)\log(1-\hat{y})] \quad (6)$$

Where the actual label represented as y (malignant or benign) and the predicted label as y ^, the training of this model made use of differentiable optimization selection schemes, Such as Adam or stochastic gradient descent SGD, to obtain minimized loss.

Then, evaluate the model by the performance metric that includes accuracy, precision, recall, F1-score, and ROC-AUC. The above condition will determine the performance of the model regarding malignant tumors and benign tumors. Once training is done and evaluations are made, the application of a live-prediction stage will help improve proper diagnoses by doctors using new tumor data. Hence, this feed-forward neural network (FNN) approach provides a robust answer concerning automizing breast cancer classification, thereby increasing the speed and reliability of healthcare diagnostics.

4.5 Encryption

AES can be an encryption method to secure sensitive medical data during encryption by transforming it into the Advanced Encryption Standard. It is a symmetric algorithm during which the same keys are used in both encryption and decryption. Thus, this encryption will protect tumor-characteristics information from unauthorized access during its storage and transmission concerning patients through the AES. Moreover, this is all set to encompass other data privacy laws such as the HIPAA and the GDPR, and, therefore, will further secure sensitive medical data from unauthorized access.

4.6 Cloud storage (GCP)

GCP handles the Cloud stage of model execution for data storage and model training for breast cancer classification. It is a cloud resource that is scalable and flexible. It allows data storage for the Breast Cancer Dataset to be safe in a cloud storage service such as Google Cloud Storage. The GCP allows for the machine learning model training using Google Compute Engine and AI Platform Services with the Feed Forward Neural Network (FNN) architecture. Then deploy the model into Google AI Platform for real-time prediction delivery. After all, with unimpeachable cloud availability and accessibility records, there are tangible security policies, perhaps including data encryption, but some other items deserve to be discussed to protect sensitive health information. In general, GCP has horizontal scaling options for the entire infrastructure of the cloud, specifically regarding heavy datasets for the best performance and efficiency.

5. Dataset description

The Breast Cancer Wisconsin (Diagnostic) Dataset comprises information regarding 569 instances, each with 30 distinct features describing the characteristics of the cell nuclei found in breast cancer biopsies. The features include attributes like radius, texture, perimeter, area, and smoothness. The outcome is binary as whether tumors were malignant (M) or benign

(B). This dataset is one of the popular datasets for training classification models to classify between malignant and benign tumors of the breast.
Dataset link:
https://www.kaggle.com/datasets/yasserh/breast-cancer-dataset

6. Result and Discussion

The work is situated on a system configuration consisting of the 12th Gen Intel(R) Core (TM) i5-12400 Processor, 8 GB RAM, and a 64-bit OS based on the x64 processor architecture. The additional system requirements for the work should consist of a minimum of 4 GB RAM (with 8 GB recommended), an OS of at least Windows 7, a fairly modern CPU (Intel i3 or better), and reasonable storage space (100 GB recommended). The implementation work used PyCharm version 3.11.

6.1 performance metrics

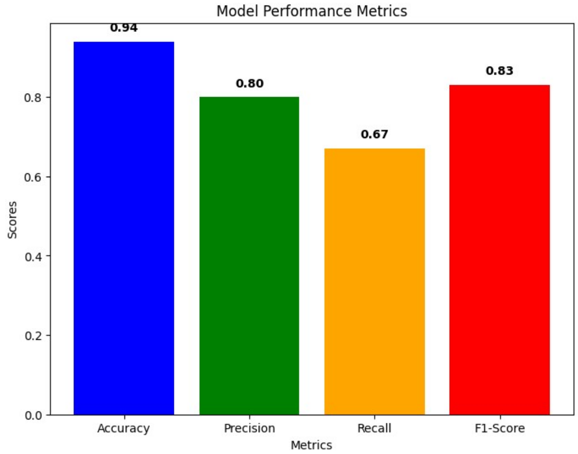

Figure 2: Performance metrics

Figure 2 shows that the 94% accuracy indicates the performance measures of the model, a value that typically characterizes powerful performance in classifying not only malignant but also benign tumors. The precision is 80%, indicating that 80% of the cases predicted as positive (tumors that were judged as malignant) were indeed accurate, while recall is somewhat lower at 67%, meaning that this system does miss some real positives. The F1 Score brings out an 83% balance of precision and recall. Very high accuracy and F1-Score, but relatively low recall means that further research must be performed before a system is suitable for detecting all malignant tumors in its setting, particularly because, in the medical environment, false negatives are to be avoided.

6.2 ROC curve

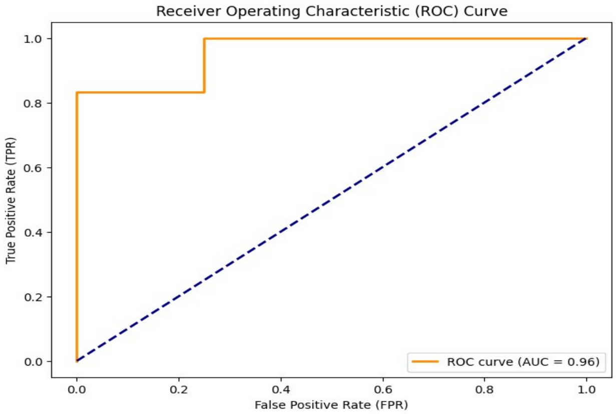

Figure 3: ROC Curve

The ROC curve in Figure 3 demonstrates the capacity of the model to distinguish a malignant from a benign tumor case. The ROC curve is plotted with increasing FPR against TPR, whenever the threshold is adjusted to yield more positives. An AUC value of 0.96 indicates that excellent discrimination exists, with larger values indicating better performance of the model in differentiating between the two classes. The curve, almost being a perfect one, implies a good number of true positives and very few false positives.

Conclusion

This paper finally proves that AI-based classification for breast cancer detection is seamlessly transferable to cloud computing, as well as secure data handling with accuracy and effectiveness in cancer classification. Besides that, advanced methods like PCA with the Breast Cancer Wisconsin Dataset can be improved, bringing out better effectiveness for the model to classify between malignant tumors and benign tumors. In addition, AES integrates functionality related to sensitive data protection under privacy regulations, such as HIPAA and GDPR, regarding personal health records. Notwithstanding the very high accuracy and F1-scores, improvements are still needed in recall rates to lower the incidence of false negatives, very crucial in medical diagnosis. The authors conclude the study by proposing continuous and real-time monitoring predictions so that the decision-making process can be enhanced in healthcare, as well as reliability in diagnostics.

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DOI:10.22192/ijamr.2024.11.03.010

How to cite this article:
Sreekar Peddi, Dharma Teja Valivarthi, Swapna Narla, Sai Sathish Kethu, Durai Rajesh Natarajan, R. Pushpakumar. (2024). AI-based breast cancer classification using cloud computing and secure data handling. Int. J. Adv. Multidiscip. Res. 11(3): 103-115.
DOI: http://dx.doi.org/10.22192/ijamr.2024.11.03.010