Health Data Science

Comparative Analysis of Machine Learning and deep learning for Breast Cancer Detection

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In this report, we compare two research articles focused on improving breast cancer diagnosis using machine learning. The first study, titled "A Novel Machine Learning Approach for Breast Cancer Diagnosis" by Bacha Sawssena and Taouali Okba (Study 1), explores an expert system that uses Differential Evolution (DE) to optimize Radial-Based Function Kernel Extreme Learning Machines (RBF-KELM). This approach aims to enhance the model's efficiency, and it was tested on the MIAS and Wisconsin Breast Cancer Database (WBCD) datasets, showing promising results.

The second study, titled "A Novel Approach for Breast Cancer Detection Using Optimized Ensemble Learning Framework and XAI" (Study 2) by Raafat M. Munshi and colleagues, introduces a more complex framework. This approach combines image and numerical data with explainable AI (XAI) techniques. The study uses U-NET for analyzing images and integrates an ensemble model that includes CNN, Random Forest, and SVM. This method achieved an impressive 99.99% accuracy in detecting breast cancer using the WBCD dataset.

In this report, we will critically examine both studies, focusing on their methodologies, results, and their potential impact on breast cancer diagnostics. We'll discuss the strengths of each approach, highlight any areas that could be improved, and suggest future research directions to make machine learning-based diagnostic tools more effective and reliable in clinical settings.

2. Introduction

2.1 General Introduction:

Breast cancer among women is rapidly increasing, emphasizing the need for early diagnosis to improve prognosis. Traditional methods are slow and dependent on the expertise of radiologists, leading to inconsistencies. With advancements in machine learning and deep learning, these studies explore improved diagnostic methods.

The datasets used primarily include mammograms, which are breast images, and biopsies. A mammogram is an imaging technique that captures detailed images of the breast from different angles. Abnormal results from a mammogram may lead to further tests, such as ultrasound, MRI, or biopsy. In which biopsy is a procedure to remove and examine breast tissue. Confirms abnormality is benign or malignant and detects cancer type.

2.2 Research Problems:

The research problem focuses on improving breast cancer detection and diagnosis by developing novel machine learning approaches. These approaches aim to enhance accuracy and reliability through optimized ensemble methods, addressing limitations in existing diagnostic tools that may suffer from lower precision or inconsistency in results. The goal is to create more effective diagnostic systems that can better assist in early detection, thereby improving patient outcomes.

3. Material And Methods

3.1 Data Description(Machine learning approach for breast cancer diagnosis)

The MIAS database from London, UK, includes 322 grayscale mammogram images (1024 × 1024 pixels) of left and right breasts. Among these, 207 are normal, and 115 are abnormal, categorized into six types of abnormalities. All are grouped for classification.

The Wisconsin Breast Cancer Diagnostic (WBCD) dataset consists of 569 instances, with 63% benign and 37% malignant cases. It provides 30 attributes derived from fine needle aspirate (FNA) images of breast tissue, including mean, standard error, and "worst" values.

3.2 Data Description (breast cancer detection using optimized ensemble learning framework and XAI)

The study uses the "Breast Cancer Wisconsin Dataset" from the UCI repository, containing 32 features, including metrics like texture, radius, and symmetry. The dataset comprises 45% malignant and 55% benign cases, with numeric attributes and a categorical target class (benign or malignant) for breast cancer detection.

4. Methods

4.1 Pre-processing

In Study 1, the original mammograms were manually cropped to remove unwanted regions such as the background, pectoral muscles, and labels. This cropping was guided by the ground truth data, which provided the position and radius of the abnormal regions in the images. To better distinguish the tissue structures of the image, especially in low-contrast areas, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied. CLAHE enhances the local contrast of the image, making the abnormalities more visible.

Discrete Chebyshev Transform(DCT) is used to compute the Discrete Chebyshev Moments (DTM), which provides a mathematical representation of the image’s texture. DTMs serve as a set of features that describe the image patterns efficiently.

For the ensemble learning approach, initially 9 Machine learning classifiers were introduced and Convolutional neural networks were used for feature extraction.Some image data was processed, but the study did not provide detailed information on this process.

4.2 Feature Extraction and Dimensionality Reduction:

Kernel Principal Component Analysis (KPCA) is used to reduce the dimensionality of the features extracted from the images MIAS dataset, which helps in improving the performance of the machine learning models by focusing on the most relevant features for performing proposed model DE_RBF_KELM.

In Study 2, a Convolutional Neural Network (CNN) is utilized for feature extraction. The CNN architecture consists of an embedding layer, a convolutional layer with 5000 filters, a max-pooling layer, and a flattening layer. The embedding layer processes input data, which is then passed through the convolutional and pooling layers to extract significant features. These features are subsequently flattened into a 1D array for further processing, enabling the CNN to effectively contribute to the detection of breast cancer.

4.3 Proposed Methods

4.3.1 DE RBF KELM

In Study 1, a hybrid model named DE_RBF_KELM is introduced, integrating the Radial Basis Function Kernel Extreme Learning Machine (RBF-KELM) with the Differential Evolution (DE) algorithm. Before explaining DE_RBF_KELM, the initial classification steps must be understood.

ELM & KELM

Extreme Learning Machine (ELM) is a single hidden layer feed-forward network (SLFN) focused on fast learning but can suffer from "dead nodes" due to random input weights, impacting

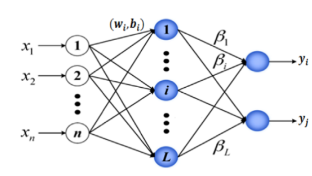


Fig. 2. Structure of ELM.

accuracy. Kernel ELM (KELM) improves ELM by transforming nonlinearly separable data into a linearly separable form using kernel functions, enhancing regression and classification accuracy. Unlike ELM, KELM's output function is independent of network architecture, utilizing various kernel functions such as radial basis (RBF-KELM), polynomial (Poly-KELM), and wavelet (Wav-KELM).

The **DE_RBF_KELM** model combines Differential Evolution (DE) with Radial Basis Function Kernel Extreme Learning Machine (RBF-KELM) to optimize hyperparameters. DE improves solution quality by generating and adapting new candidates through perturbations. The process involves initializing hyperparameters, calculating learning precision, and updating parameters using DE's mutation, crossover, and selection. The best hyperparameters are displayed once the optimization criteria are met.

The DE_RBF_KELM model begins by randomly generating hyperparameters C and σ for each individual in the population. It then creates new candidates through mutation, where existing individuals are adjusted using a randomly selected vector and a scaling factor F. In the crossover step, these mutated individuals are combined with the original ones to form new candidates. Finally, during selection, the model compares the performance of these new candidates with the previous generation, ensuring that only the best-performing individuals are carried forward to the next generation.

4.3.2 Ensemble Method and U-Net

Initially, 9 machine learning classifiers were computed, from which the most effective were selected for the ensemble process.

1. Random Forest (RF):Think of a team of experts giving opinions. RF builds many decision trees, each looking at different data parts, then combines their answers for a more accurate prediction.

2. Decision Tree (DT): A DT is like a flowchart, asking yes/no questions that lead to a final decision on whether a case is cancerous.

3. K-Nearest Neighbor (k-NN): k-NN classifies a new patient by finding the 'k' most similar cases and deciding based on the majority.

4. Logistic Regression (LR):   LR separates two groups by drawing a line and calculates the probability that a patient belongs to one group (e.g., cancerous) or the other.

5. Support Vector Machine (SVM): SVM finds the best divider between two groups, creating a boundary that maximizes the margin between different classes.

6. Gradient Boosting Machine (GBM): GBM builds a strong prediction model by adding weak models that correct previous mistakes, resulting in high accuracy.

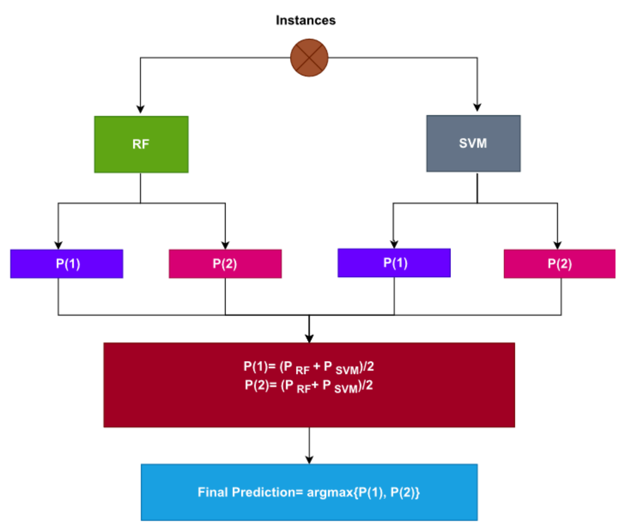
7. Extra Tree Classifier (ETC): Similar to Random Forest, Extra Trees build many trees, but it adds more randomness when creating each tree. This makes the overall model more diverse and robust, improving its ability to generalize.

8. Gaussian Naive Bayes (GNB): GNB uses probability, assuming each feature is independent, to predict the likelihood of each class, often performing well.

9. Stochastic Gradient Descent (SGD): SGD trains models by making small, gradual adjustments based on data subsets, improving accuracy efficiently, especially with large datasets.

Proposed Ensemble Voting Classifier for numerical data features

– The study uses an ensemble learning approach combining Random Forest (RF) and Support Vector Machine (SVM).
– A voting classifier is employed, using the soft voting criterion to merge predictions from RF and SVM.



Architecture of the proposed voting classifier (RF + SVM) model.

– The model predicts breast cancer by selecting the class with the most votes from RF and SVM.

–The Breast Cancer Wisconsin Dataset is used for testing the model's performance.

– The data is split into 70% for training and 30% for testing to evaluate the model's accuracy.

– Predictive probabilities generated by RF and SVM are processed through soft voting to determine the final prediction, as shown in the flowchart.

U-Net and Mobile-Net

U-Net is a convolutional neural network designed for precise biomedical image segmentation, featuring a u-shaped architecture that combines contracting and expansive paths for enhanced resolution and accuracy.

On the other hand, **MobileNet** is a lightweight CNN but designed by Google for mobile vision, using depthwise separable convolutions to reduce parameters, making it fast and efficient for mobile devices.

4.4 Evaluation metrics

The evaluation of the both study used the same performance metrics which are Accuracy, Precision, Recall and F1 Score which are computed from the values in the confusion matrix

5. Results

5.1 DE_RBF_KELM :

To validate the efficiency experiments were carried out to compare the proposed model with SVM algorithm, Poly_KELM, RBF_KELM and Wav_KELM, in which the proposed model showed overall performance in all 4 metrics over 100% in both Normal/Abnormal and Malignant and benign models for the mammogram dataset. And overall superior performance in the WBCD data with all the performance with above 91%. Furthermore, the competitiveness of the suggested model has been compared with nine recent schemes and it has been noticed that the suggested model achieves improved results over the competent schemes. The high success rate with respect to the accuracy of the suggested technique helps radiologists to make an accurate diagnosis decision to reduce unnecessary biopsies.

5.2 Optimized Ensemble Method with convoluted features

5.2.1 Feature based Datasets

The present study proposes an ensemble model that optimizes RF + SVM with convoluted features, achieving an average performance of 95% on the original feature set. This model outperforms other ensemble optimizers, such as RF + ETC, RF + LR, ETC + SVM, and ETC + LR. Notably, it also excels with a significant score of 99.99% across all evaluation metrics when applied to the convoluted feature set.

A 5-fold cross-validation shows that the proposed ensemble model achieves an average accuracy of 0.996, with precision, recall, and F1 scores of 0.998, 0.998, and 0.997.

5.2.2 Image based dataset and comparison analysis with feature-based

The table initially shows that the UNET model outperforms MobileNet in accuracy, precision, recall, and F1 score. Additionally, comparing image-based and feature-based datasets revealed a significant improvement with the U-Net transfer learning model over the original features. Overall, the proposed model using both feature datasets and image data achieves an accuracy of 99.9%.

5.2.3 Comparison of Results

Both studies present highly accurate and effective models for breast cancer detection, though they use different approaches. Furthermore, the comparison between the planned and existing studies were performed to find the significance and performance in which the results were also promising. However, since the dataset was different in compared studies the accuracy and the robustness might be debatable.

6. Discussion

6.1 Interpretation of results:

Both studies reported impressive performance across all evaluation metrics, achieving 100% accuracy with the DE_RBF_KELM method and 99.99% with the Ensemble Voting Classifier (combining RF and SVM), both of which claim to incorporate explainable AI. Moreover, the proposed methods from these studies demonstrated significantly superior performance. However, to offer a critical perspective, it's important to thoroughly analyze these results.

6.2 Critical Evaluation Of Study

In Study 1, the initial presentation of the WBCD dataset's features lacked clarity, making it difficult to fully understand the dataset's structure. Additionally, during the pre-processing step for the MIAS dataset, the study did not provide sufficient detail on how the images were cropped. Specifically, there was no clear explanation of how the position and radius of the abnormal regions were used for cropping. Furthermore, the study did not specify where the ground truth information was sourced or how normal images were arbitrarily cropped to obtain the Region of Interest (ROI), reducing the image size from 1024x1024 pixels to 127x127 pixels.

In Study 2, there was no explanation provided for the use of explainable AI (XAI), and the author seemed to confuse XAI with U-Net and MobileNet. XAI involves understanding why an AI model produces a specific result to build trust and transparency, but this study lacked such details. Additionally, the term "transfer learning" was mentioned without clarity or explanation. Transfer learning involves applying knowledge from one problem to a related problem, but the study did not clarify where the previous learning models for U-Net or MobileNet were sourced from or how they were applied.

6.3 Limitations

The limitations of both studies highlight key challenges in applying machine learning to breast cancer detection. Study 1 encountered dataset-specific constraints, including higher calculation times for certain classifications in the MIAS dataset and incomplete risk assessment data in the WBCD dataset, which limited the analysis. Additionally, the study noted challenges in applying machine learning algorithms to clinical decisions, particularly when diagnostic doubts remain before surgery. Study 2 emphasized the need for a larger and more diverse dataset to enhance model performance and generalizability, suggesting that external validation on datasets from different demographics could improve the robustness of the models. Despite these limitations, both studies contribute valuable insights into advancing diagnostic methodologies through machine learning.

7. Conclusion and future works

Both studies introduced innovative approaches to improving breast cancer detection through machine learning techniques. With a few tweaks for clarity and consistency it will be even more effective in communicating the key findings and their implications.

Study 1 developed a novel mammogram classification method using the differential evolution algorithm to optimize the RBF-KELM classifier, achieving superior classification, specificity, and sensitivity rates compared to state-of-the-art methods. The study recommends future work on developing portable devices for automatic breast cancer classification using mammography images and further integrating RBF-KELM with CNN for enhanced results.

Study 2 presented a comprehensive framework that combines image and numerical data features with explainable AI (XAI) for high-precision breast cancer diagnosis. It utilized a U-NET transfer learning model for image-based prediction and an ensemble model integrating CNN, random forest, and SVM, achieving an impressive accuracy rate of 99.99%. Future research will focus on applying this model to diverse datasets, including microscopic image analysis, to further validate and improve its effectiveness.

8.References

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