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EXPLORING HYBRID GENETIC ALGORITHMS FOR PREDICTING BREST CANCER TUMOR

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ABSTRACT:
Artificial intelligence (AI) technologies have seen strong development. Many applications now use AI to diagnose breast cancer. However, most new research has only been conducted in centralized learning (CL) environments, which entails the risk of privacy breaches. Moreover, the accurate identification and localization of lesions and tumor prediction using AI technologies is expected to increase patients' likelihood of survival. To address these difficulties, we developed a federated learning (FL) facility that extracts features from participating environments rather than a CL facility. This study's novel contributions include (i) the application of transfer learning to extract data features from the region of interest (ROI) in an image, which aims to enable careful pre- processing and data enhancement for data training purposes; (ii) the use of synthetic minority oversampling technique (SMOTE)
to process data, which aims to more uniformly classify data and improve diagnostic prediction performance for diseases; (iii) the application of FeAvg-CNN
+ MobileNet in an FL framework to ensure customer privacy and personal security; and
(iv) the presentation of experimental results from different deep learning, transfer learning and FL models with balanced and imbalanced mammography datasets, which demonstrate that our solution leads to much higher classification performance than other approaches and is viable for use in AI healthcare applications. Key words: Genetic Algorithm,AI

According to statistics published by the International Agency for Research on Cancer in December 2020, breast cancer has overtaken lung cancer as the most diagnosed cancer worldwide [1]. Over the past two decades, the total number of people

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INTRODUCTION

diagnosed with cancer has nearly doubled,

from an estimated 10 million in 2000 to 19.3

million in 2020. Today, one in five people worldwide will develop cancer in their lifetime. It is estimated that the number of people diagnosed with cancer will further increase in the future: nearly 50% by 2040 compared to 2020. The number of people who die from cancer has also increased, from

6.2 millionin 2000 to 10 million in 2020. Late diagnosis and a lack ofaccess to treatment have become increasingly prevalent issues that require more attention and follow-up. Breast cancer is a malignant tumor of the breast. A tumor can be benign (noncancerous) or malignant (cancerous). Most breast cancers begin in the milk ducts, with a small percentage of cases developing in the milk sacs or lobules. If detected and treated late, breast cancer may metastasize to the bones and other organs and the pain will multiply. Therefore, early detection of breast cancer is critical for treating and saving patients. When the disease is in its early stages, its manifestations may not be accurate and precise; as a result, many abnormalities may be overlooked [2]. Currently, many studies apply machine learning to improve early detection, reduce the risk of death, and prolong the patient's life. However, sharing patient data is not widely considered at present due to privacy, technical, and legal issues.Security and privacy techniques enable stricter protection of patient data and the use of data for research and routine clinical purposes [3], [4]. A study on breast mass classification from mammograms using convolutional neural networks (CNN) was published in 2016 [5], where the authors gave results with recall for identifying lesions estimated to be between 0.75 and 0.92, which means that up to 25% of abnormalities could remain undetected. Therefore, the ability to automatically detect lesions and predict their likelihood of malignancy would be valuable for doctors and could dramatically improve survivalrates. Thus, we developed an FL base to extract features from multiple participating environments rather than a centralized learning environment. To investigate the real-world performance of FL, we conducted a study for the applied development of numerous breast cancer classification models using mammography data. An international group of hospitals and medical imaging centers joined this collaborative effort to train models in a completely decentralized fashion, without any data sharing between hospitals. This placed higher requirements on the robustness of algorithms and the selection of hyperparameters. In our study, we believed that the analysis of recall performance was more important than accuracy as false negatives can be life-threatening and false positives are likely to be viewed by humans in diagnosing breast cancer, and that is the main objective of this study. Recently, FL has become a novel research trend in AI applications. It aims to train a machine learning (ML) algorithm across multiple decentralized nodes while holding the data samples (i.e., without locally exchanging them) [6]. Training such a decentralized model in an FL setup presented four main challenges:

(i) system and data heterogeneity,

(ii) pre-trained data processing,

(iii) data protection and privacy, (iv) efficiency selection of distributed ML algorithms.

We addressed these challenges for breast cancer classification in the context of FL.The first challenge was system and data heterogeneity. Different system vendors produce images with considerably different intensity profiles for the same imaging modality. To address this diversity, many recent studies have found that a data-balancing solution such as the unsupervised domain adaptation method forces the model to learn solution domain- agnostic features through adversarial learning [7] or a specific type of batch normalization [8]. However, more straightforward methods were used in the current study toaddress this challenge; we present a solution more efficientlybalances data.The second challenge is imperative to process the data before training because of its heterogeneity. There are many data processing methods [9], [10].We chose transfer learningdue to its many benefits, such as saving training time, betterneural network performance (in most cases), and the fact thatlarge amounts of data are not needed [11].To address the third challenge, data protection and privacy[12], [13], many studies haveincorporated more secu rity and privacy solutions. Our solution assumes that an international group of hospitals and medical imaging centers have joined this collaborative effort to train the model in a completely decentralized manner, with no data sharing between hospitals. This places higher requirements on the robustness of algorithms and the selection of hyperparameters. The fourth challenge concerned the distributed learningability of the FL models [14], [15] employed. Many distributed learning models are used in FL for different applications. However, most studies focus on hypothetical data, and each model is only suitable for one dataset, which makes it difficult for researchers with practical applications as in breast cancer. To evaluate the effectiveness of these models,we tested the evaluation by other methods for comparison.The contributions of this paper are as follows:

- Design of an FL framework for breast cancer classification that includes a global server, which acts as a weight aggregator and mobile replacement edge clients in tissue training deep learning (DL). This solution is useful for AI healthcare applications and can be widely deployed in different hospitals or clinics.
- Pioneering use of a transfer learning pre- training dataset in FL for breast cancer classification. Various models in transfer learning were selected for performance evaluation, including k-nearest neighbors (kNN), AdaBoost, and eXtreme Gradient Boosting (XGB). First, the image's features are extracted using the Convolutional Neural Network

(ConvNet) of the pre-trained model, and a linear classifier is used to classify the images. Next, we used data equalization techniques such asSMOTE and data augmentation in combination with ImageNet to enrich and further optimize the training data

- With both balanced and imbalanced methods, experimental results from the Digital Database for Screening Mammography (DDSM) dataset demonstrate that our solution's FeAvg- CNN + MobileNet is much better forcentralized learning, which is more than 5% recall [5] in improved performance. Moreover, the accuracy of our research results reached nearly 98%; by comparison, the maximum results

were only 88.67% for the two-classcases (calcifications and masses) and 94.92% (mass vs. malignant mass and benign calcification vs. malignant calcification) in the study [6].

Existing System:

Because of the unbalanced input data, one way to address unbalanced datasets is to oversample the minority. The most straightforward approach is to duplicate examples in the minority class. However, these examples do not add any new information to the model. Instead, recent examples can be synthesized from existing measures. This data augmentation type for the minority class is called the synthetic minority oversampling technique, abbreviated as SMOTE. Since the Fig. 6 and 7 show that the class distribution predictive breast cancer before and after SMOTE use.

LITERATURE REVIEW

Communication-Efficient Learning of Deep Networks

from Decentralized Data

Modern mobile devices have access to a wealth of data suitable for learning models, which in turn can greatly improve the user experience on the device. For example, language models can improve speech recognition and text entry, and image models can automatically select good photos. However, this rich data is often privacy sensitive, large in quantity, or both, which may preclude logging to the data center and training there using conventional approaches. We advocate an alternative that leaves the training data distributed on the mobile devices, and learns a shared model by aggregating locally-computed updates. We term this decentralized approach Federated Learning. We present a practical method for the federated learning of deep networks based on iterative model averaging, and conduct an extensive empirical evaluation, considering five different model architectures and four datasets. These experiments demonstrate the approach is robust to the unbalanced and non-IID data distributions that are a defining characteristic of this setting. Communication costs are the principal constraint, and we show a reduction in required communication rounds by 10– 100× as compared to synchronized stochastic gradient descent Increasingly, phones and tablets are the primary computing devices for many people [30, 2]. The powerful sensors on these devices (including cameras, microphones, and GPS), combined with the fact they are frequently carried, means they have access to an unprecedented amount of data, much of it private in nature. Models learned on such data hold the promise of greatly improving usability by powering more intelligent applications, but the sensitive nature of the data means there are risks and responsibilities to storing it in a centralized location. We investigate a learning technique that allows users to collectively reap the benefits of shared models trained from this rich data, without the need to centrally store it. We term our approach Federated Learning, since the learning task is solved by a loose federation of participating devices (which we refer to as clients) which are coordinated by a central server. Each client has a local training dataset which is never uploaded to the server. Instead, each client computes an update to the current global model maintained by the server, and only this update is communicated. This is a direct application of the principle of focused collection or data minimization proposed by the 2012 White House report on privacy of consumer data [39]. Since these updates are specific to improving the current model, there is no reason to store them once they have been applied. A principal advantage of this approach is the decoupling of model training from the need for direct access to the raw training data. Clearly, some trust of the server coordinating the training is still required. However, for applications where the training objective can be specified on the basis of data available on each client, federated learning can significantly reduce privacy and security risks by limiting the attack surface to only the device, rather than the device and the cloud. Our primary contributions are 1) the identification of the problem of training on decentralized data from mobile devices as an important research direction; 2) the selection of a straightforward and practical algorithm that can be applied to this setting; and 3) an extensive empirical evaluation of the proposed approach. More concretely, we introduce the FederatedAveraging algorithm, which combines local stochastic gradient descent (SGD) on each client with a server that performs model averaging. We perform extensive experiments on this algorithm, demonstrating it is robust to unbalanced and non-IID data distributions, and can reduce the rounds of communication needed to train a deep network on decentralized data by orders of magnitude.

Deep Learning Based Methods for Breast Cancer diagnosis: A Systematic Review and Future Direction

Breast cancer is one of the precarious conditions that affect women, and a substantive cure has not yet been discovered for it. With the advent of Artificial intelligence (AI), recently, deep learning techniques have been used effectively in breast cancer detection, facilitating early diagnosis and therefore increasing the chances of patients' survival. Compared to classical machine learning techniques, deep learning requires less human intervention for similar feature extraction. This study presents a systematic literature review on the deep learning-based methods for breast cancer detection that can guide practitioners and researchers in understanding the challenges and new trends in the field. Particularly, different deep learning-based methods for breast cancer detection are investigated, focusing on the genomics and histopathological imaging data. The study specifically adopts the Preferred Reporting Items for Systematic Reviews and Meta- Analyses (PRISMA), which offer a detailed analysis and synthesis of the published articles. Several studies were searched and gathered, and after the eligibility screening and quality evaluation, 98 articles were identified. The results of the review indicated that the Convolutional Neural Network (CNN) is the most accurate and extensively used model for breast cancer detection, and the accuracy metrics are the most popular method used for performance evaluation. Moreover, datasets utilized for breast cancer detection and the evaluation metrics are also studied. Finally, the challenges and future research direction in breast cancer detection based on deep learning models are also investigated to help researchers and practitioners acquire in-depth knowledge of and insight into the area. One of the common cancers identified globally among women is breast cancer, which has become the leading cause of death [1,2,3]. Based on the recent findings by the American cancer society, over 40,000 women and about 600 men died as a result of breast cancer disease [3]. There are four basic forms of breast cancer: benign, normal, in situ carcinoma and invasive carcinoma [1]. A benign tumor slightly alters the breast's anatomy, it is not toxic and does not fit the description of dangerous cancer [4]. In situ carcinoma, on the other hand, only affects the system of mammary duct lobules and does not spread to other organs [5]. This kind of cancer is not very harmful and is treatable if detected early. The most severe type of breast cancer is invasive carcinoma, which has the potential to spread to all other organs [6]. Over many years, breast cancer can be identified through several methods such as mammography, X-ray, ultrasound (US), Portion Emission Tomography (PET), Computed Tomography, temperature measurement and Magnetic Resonance Imaging (MRI) [2,7,8]. Usually, the golden standard approach for breast cancer diagnosis is a pathological process. In order to maximize visibility, the extracted tissue is stained in the lab before being subjected to imaging analysis. The staining procedure frequently employs Hematoxylin and Eosin (H&E) [9]. In most cases, Histopathological image analysis and genomics can both be utilized to identify breast cancer [4,10]. A histopathological image is a microscopic picture of breast tissues and is very helpful in the early treatments of cancer [11]. The genomics field is primarily concerned with multi-scale connections between data on gene expression and medical imaging [4]. A more accurate diagnosis can be achieved with the use of radio-genomics [10]. In order to predict and identify cancer early, molecular analyses of tissues can be performed.

Recently, Computer-Aided Design (CAD) has been introduced [12,13] to simplify breast cancer identification. However, traditional computer-aided design systems generally depend on manually created features and therefore weaken the overall performance [13]. With the advent of machine learning and AI methods, deep learning-based techniques were recently studied for breast cancer detection [14,15]. Representation learning is the basis of deep learning techniques, which come from several layers. The representation is transformed from the lower to the higher levels at each end by combining the non- linear and simple modules, in which the lower-level features are more comprehensible and the higher-level features more abstract [14]. Compared to the ML methods [10,16], deep learning is more effective and requires fewer human interventions for the related pattern recognition schemes. This makes it capable of effectively solving complex problems in various areas such as image analysis [17], pattern recognition and natural language processing.

Following its successful applications in breast cancer detection, the number of research works on deep learning-based approaches has increased exponentially recently. This begs for a systematic review and summary of the existing works to help successive researchers and practitioners gain better insight into and understanding of the field. In the past, several literature reviews on breast cancer detection have been published. For instance, Yassin et al. [2] investigated the existing ML-based methods for breast cancer diagnosis. The authors comprehensively assessed different image modalities as well as the different ML-based classifiers used for breast cancer detection. The authors in [18] reviewed various deep learning-based methods for classifying breast cancer based on image processing. However, this work focuses on shallow feed-forward networks, while other deep learning-based methods were not emphasized. A study in [19] summarized recent studies that used deep learning (DL) methods to detect breast cancer disease based on different imaging approaches. The authors specifically focused on the three breast cancer imaging approaches, namely, MRI, mammography and ultrasound.

The authors in [20] examined several DL- and traditional ML-based methods for breast cancer prediction by reviewing a total of 8 papers and 27 papers in DL and ML, respectively. The authors discovered that most of the reviewed literature employed the imaging process; however, only a few of the reviewed articles applied genetics. The authors in [21] reviewed several imaging methods based on mammography for breast cancer diagnosis. Gupta et al. [22] presented a brief survey of different systems and methods for the early detection of breast cancer. In this study, various imaging methods which comprise radar-based imaging and microwave tomography were examined. Oyelade et al. [23] examined different deep learning-based methods for breast cancer diagnosis from digital mammography. Husaini et al. [15] examined the application of ML techniques and thermography for detecting breast cancer problems. In this method, various ML methods were investigated to process the breast cancer thermographic images.

Considering the above-mentioned several reviews on the deep learning-based methods for breast cancer detection, it could be seen that most of the existing review works particularly focus on the image-based methods for breast cancer detection problems. It can be seen that most of the existing studies emphasize the traditional ML-based approaches, while those focused on the deep learning-based techniques particularly covered very limited studies, with no clear comprehensive and systematic analysis of the existing approaches.

Breast Mass Classification from Mammograms using Deep Convolutional Neural Networks

Mammography is the most widely used method to screen breast cancer. Because of its mostly manual nature, variability in mass appearance, and low signal-to-noise ratio, a significant number of breast masses are missed or misdiagnosed. In this work, we present how Convolutional Neural Networks can be used to directly classify pre- segmented breast masses in mammograms as benign or malignant, using a combination of transfer learning, careful pre-processing and data augmentation to overcome limited training data. We achieve state-of-the-art results on the DDSM dataset, surpassing human performance, and show interpretability of our model.

Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis

Breast cancer is one of the most dangerous diseases and the second largest cause of female cancer death. Breast cancer starts when malignant, cancerous lumps start to grow from the breast cells. Self-tests and Periodic clinical checks help to early diagnosis and thereby improve the survival chances significantly. The breast cancer classification is a medical method that provides researchers and scientists with a great challenge. Neural networks have recently become a popular tool in cancer data classification. In this paper, Deep Learning assisted Efficient Adaboost Algorithm (DLA-EABA) for breast cancer detection has been mathematically proposed with advanced computational techniques. In addition to traditional computer vision approaches, tumor classification methods using transfers are being actively developed through the use of deep convolutional neural networks (CNNs). This study starts with examining the CNN-based transfer learning to characterize breast masses for different diagnostic, predictive tasks or prognostic or in several imaging modalities, such as Magnetic Resonance Imaging (MRI), Ultrasound (US), digital

breast tomosynthesis and mammography. The deep learning framework contains several convolutional layers, LSTM, Max-pooling layers. The classification and error estimation that has been included in a fully connected layer and a softmax layer. This paper focuses on combining these machine learning approaches with the methods of selecting features and extracting them through evaluating their output using classification and segmentation techniques to find the most appropriate approach. The experimental results show that the high accuracy level of 97.2%, Sensitivity 98.3%, and Specificity
96.5% has been compared to other existing systems.

Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion With CNN Deep Features

A computer-aided diagnosis (CAD) system based on mammograms enables early breast cancer detection, diagnosis, and treatment. However, the accuracy of the existing CAD systems remains unsatisfactory. This paper explores a breast CAD method based on feature fusion with convolutional neural network (CNN) deep features. First, we propose a mass detection method based on CNN deep features and unsupervised extreme learning machine (ELM) clustering. Second, we build a feature set fusing deep features, morphological features, texture features, and density features. Third, an ELM classifier is developed using the fused feature set to classify benign and malignant breast masses. Extensive experiments demonstrate the accuracy and efficiency of our proposed mass detection and breast cancer classification method. A computer-aided diagnosis (CAD) system based on mammograms enables early breast cancer detection, diagnosis, and treatment. However, the accuracy of the existing CAD systems remains unsatisfactory. This paper explores a breast CAD method based on feature fusion with convolutional neural network (CNN) deep features. First, we propose a mass detection method based on CNN deep features and unsupervised extreme learning machine (ELM) clustering. Second, we build a feature set fusing deep features, morphological features, texture features, and density features. Third, an ELM classifier is developed using the fused feature set to classify benign and malignant breast masses. Extensive experiments demonstrate the accuracy and efficiency of our proposed mass detection and breast cancer classification method.

THE PROPOSED METHOD

This section highlights our proposed approach in the FL framework. First, its overall structure is presented in Sub-section III-A. Next, Sub-section III-B describes he use of transfer learning for data feature export. Next, in subsection III-C, we introduce the two mammography datasets used in this study and how they were processed to improve classification quality. The FedAvg algorithm is introduced in Sub-section III-D, which we summarize in pseudocode to explain the implementation of the FL framework. Next, section IV, we evaluate the results and provide explanations.

A. AN OVERALL ARCHITECTURE OF THE PROPOSED METHOD

The current sub-section III-A presents a complete system model, including an overview diagram of how DL models work in FL and simulation designs. Fig. 1 depicts how the general behavior of the federated model was tested. The model structure includes a global server that acts as a weight aggregator and edge stations that replace mobile devices in training the deep learning model. The FL process occurs in three stages: stage (1) priming the initial model in the first round of FL or updating the new model after aggregating weights after the Nth round of learning, stage (2) local training with terminal data at the edge stations, and stage (3) aggregating the weights to the server and updating the global model. Taking advantage of transfer learning in the local environment of edge stations, here are hospitals that connect locally to machine learning-approaching technology devices using models that optimize performance, traffic conditions, etc. Homogeneous communication does not impose data labels on devices for prediction. However, it only uses personalized data features to learn, limiting transmission weights, limiting computation on edges, helping local training at the edge take place rapidly in reinforcement learning, back- distribution, cross-linking increasing data on the edge device sent to the edge increases over time.

The objective of the current study was to test the FL models' distributed learning ability. Thus, the server and edge devices were simulated by initializing a similar DL model in both the global and local phases. Therefore, the weight update between the host and the edge device was also directly be performed and ignored transmission time in the network.

At the beginning of the FL process, the starting server initiated a DL model. It sent the newly initialized set of weights to participating stations to create the first round of FL (cloud server). The local model updated this set of weights and began the training process. At the input of the local model, data is the data that is optimally learned from pre-trained modeling with IMAGENET [35] on incoming edge devices (phones, computers, doctors, medical devices, etc.) (client feature extraction). Due to the limitation in simulation, local learning occurred by training each edge with a piece of data from the processed dataset and grouping it to mark the order of the participating stations' FL network (edge sharing). Therefore, updating and training for the entire edge station were sequentially performed until the number of data groups in the divided dataset was exhausted instead of simultaneous parallel learning on all devices, as in real situations. In addition, the decentralized exchange sequential sharing system mechanism has strict privacy conditions.

During the local training phase, the pre-split data will be trained with the local model. The learning process is akin to a regular DL network training process, which includes the following steps: fitting, forward propagation, and backward propagation. Local training is completed only after all stations have concluded training with their data. The weights of all stations will be aggregated for the global model update according to the expression of the FedAvg algorithm. In addition to local weights, the number of data points in the data group used for training at each station must be collected to perform the aggregation. Therefore, in addition to storing weights, each edge station also calculates and retains the number of data points that it has trained to prepare for the synthesis process at the server. The entire local learning process at the edge stations is performed with DL models. Specifically, the network model FedAvg-ANN (MLP) and FedAvg-CNN and machine learning models kNN, AdaBoost, and XGB were used in this study. After the local training is complete, the set of weights and data points for all stations is updated on the server. Currently, the server plays the role of aggregator and runs the algorithm with the set of weights and number of data points from the stations to find a new set of weights for the global model. Once the global model has been updated, the server checks the results of the FL round by running the classification problem on the test data, saves the test results, and moves on to the next learning round. The entire FL process is run with N given learning rounds. At each edge station, the number of epochs (DL cycles) is also performed with n pre-selected cycles. The number of FL rounds selected for the simulation is 200. The timing and predictive power of the model both depend on the number of epochs performed at each station. To check for relativity, the model was sequentially tested with one, two, and five epochs in the first 200 FL rounds. Both cases will be tested with only a DL model applied in FL.

CONCLUSION

In this study, we presented a solution for classifying breast cancer images using feature extraction from multiple participating environments instead of a centralized learning facility. The centralized environment consisted of an inter-national group of hospitals and medical imaging centers that joined collaborative efforts to train the model to be completely datadecentralized, without sharing any data between hospitals. Moreover, we focused on analyzing recall performance more than accuracy because false negatives can be life- threatening. By contrast, like studies, humans can consider false positives instead of a whole before. The results demonstrate that the accuracy was higher than that of other models. In the future, we plan to create a system that will scan the entire mammogram as input, segment it, and analyze each segment to yield results for the entire mammogram to make an end- the complete to-end for mammogram analysis. In addition to improved data processing, simulations can be extended with multiple clients or groups of clients on separate devices, and individual patient interventions share privacy security.

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