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Breast Cancer Image Screening Classification Based on Convolutional Neural Networks

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Abstract: Breast cancer is a prevalent form of cancer, especially among women, and can spread to other parts of the body if not detected early. Early diagnosis is vital for improving survival rates and the effectiveness of treatment, but this process is complex and demands considerable time and expertise from pathologists. To address these challenges, computer-aided methods have become increasingly important in analyzing histopathological images for breast cancer detection. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown significant potential in this area. Unlike traditional methods that focus on low-level feature extraction, CNNs can learn high-level abstract features from images. By training a CNN on a dataset of labeled histopathological images, it learns to identify cancer-specific features, such as abnormal cell structures and patterns. Once trained, the CNN can accurately classify new images as either cancerous or non-cancerous, providing valuable assistance to pathologists. This not only speeds up the diagnostic process but also enhances the accuracy of early breast cancer detection, leading to more timely and effective treatment. Deep learning and CNNs thus play a crucial role in improving outcomes for breast cancer patients by aiding in the early and precise diagnosis of the disease.

Keywords: Convolutional Neural Network; Image Screening; Breast cancer; Hidden Layers; Artificial Neural Networks; self-driving cars; Feed Forward Neural Network; Recurrent Neural Network.

Introduction

Breast cancer develops in the breast cells and can spread to other parts in stages. It is the second most common cancer across the globe, especially in women when compared to men. The cause of breast cancer is not completely known or understood, but a few genetic conditions and environmental factors are said to have an impact. The risk factors for breast cancer include several key elements. Age is a significant factor, as women become more prone to breast cancer as they get older [11]. Family history also plays a role; women with a family history of breast cancer are more likely to develop the disease. Genetic factors, such as mutations in specific genes like BRCA1 and BRCA2, can increase the risk as well. Additionally, women who have had breast cancer in one breast are more likely to develop it in the other. Hormone exposure is another risk factor, with women who began menstruating at an early age, experienced menopause later in life, or never had children being at higher risk [12-19]. Lifestyle factors, including high alcohol consumption, lack of regular exercise, and being overweight, also contribute to the risk of developing breast cancer.

Having risk factors does not necessarily mean that a person will develop breast cancer. Sometimes, women who developed breast cancer did not have any symptoms at all [20-24].

Thickening/lump in the breast or the underarm area, changes in the shape and size of the breast, puckering of the skin, and redness of the breast skin are some of the symptoms of breast cancer. Others include fluid discharge from the nipple and a change in the position or shape of the nipple. Sometimes, these can be non-cancerous (Benign). Hence, it is always a good practice to get it checked by a healthcare specialist [25-31].

Some of the diagnosis methods include physical examination, imaging tests, and biopsy. Surgery, radiation therapy, chemotherapy, and hormone therapy are the options for treatment. Early identification and treatments can be of great help to the patient. Early diagnosis of breast cancer is increasing in demand. A patient can undergo a successful treatment once the cancer has been diagnosed early [32-39]. This decreases the death rate among patients globally. Recently, we have Computer-Aided Diagnosis, which can detect any unusual signs of breast cancer. They do not require much human intervention, are less painful, and are known to produce accurate results [40].

One subfield of AI is deep learning, which is itself a subfield of machine learning. The development process was informed by research into the anatomy and physiology of the human brain. The primary goal of developing algorithms is to comprehend and make sense of massive volumes of complicated data, a task that is not well-suited to machine learning [41-47]. Similar to how our own neurons are trained using massive quantities of data, these algorithms, known as artificial neural networks, are composed of interconnected layers of nodes. When it comes to handling complicated processes, Deep Learning algorithms perform better, and deep learning can also solve real-world situations. In order to extract features using Machine Learning techniques, we would need to manually input the features [48-55]. Deep Learning algorithms, however, can do this on their own and produce relevant features for items of interest. There are numerous medical applications of deep learning, such as tumour cell detection. Automated vehicles, translations, and robots are some of the other uses. Deep learning networks come in a variety of forms. The qualities and fields of application for each of them are distinct [56-61].

Feed Forward Neural Network: This is a general version of the neural network. This is a collection of neurons. This has one input layer, multiple possible hidden layers, and one output layer where we get out the output that we are interested in. In general, each layer may have a different size. Here, the data travels in one direction only, i.e., from the input layers, through hidden layers, and finally to the output layer [62-69]. Hence, the nodes do not form a cycle. The main goal of this network is to learn how to map inputs to outputs by training a set of input-output pairs. Extracting features is done with the help of hidden layers so that the network learns from various complex relationships and patterns. Backpropagation is one of the algorithms mostly used to train this network to lessen errors during prediction [70-75].

Recurrent Neural Network: This network is mainly trained to process time series data or language, basically sequential data, which the feed-forward network cannot do as it has no memory. This can also be called another version of the feed-forward neural network [76-81]. They use loops to pass information from one stage in the sequence to the next by maintaining this memory of previous stages. For example, if we have to guess which word will come next in a sentence, we must also know about the previous words. The only drawback of this network is that it is slow in terms of computational speed. It also does not consider any future data for the current stage. Speech recognition, text generation, and translation are some of the use cases of this network [82-89].

Convolution Neural Network : An extremely common and specialised kind of network that finds widespread application in picture categorization and grouping. These are made to be used on things or photos that have a grid layout. In this network, convolutional filters make up each layer [90-94]. In order to extract features and patterns from input data, such as size, form, edges, and corners, these filters are used. It is possible for it to have many interconnected layers, and each layer can learn to identify unique input features. They find extensive application in picture identification and classification due to their ability to automatically produce features from input photos.

Problem Statement

Among female cancers, breast cancer is by far the most prevalent. It is generally possible to cure tumours when they are detected early. Although there are gadgets that can detect breast cancer, they often produce false positives, which causes patients to endure invasive and costly procedures that were unnecessary. These malignancies are considered benign and typically do not necessitate surgical intervention. We can use machine learning to decrease these needless procedures. We train the algorithm to predict the cancer's benign or malignant status using a dataset of breast cancer patients who have previously undergone treatment. Women will have fewer unneeded procedures because to these projections, which will allow surgeons to perform surgeries just on malignant cancers.

He Paper Will Begin With Data Collection, Focusing On Gathering A Large Dataset Of Annotated Histopathological images of breast tissue, with some images labeled as having breast cancer and others as normal. Next, the dataset will undergo data pre-processing to ensure consistency in image size and format, and to eliminate irrelevant information. Following this, a convolutional neural network (CNN) will be developed and trained on the pre-processed dataset to accurately detect breast cancer in histopathological images, with the CNN being optimized to minimize error rates during training [95-101]. The trained model will then be evaluated on a test set of images not used in the training process, with its accuracy in detecting breast cancer compared to existing methods. Upon successful evaluation, the CNN will be deployed in a user-friendly interface for pathologists to use in diagnosing breast cancer in new histopathological images. Finally, the paper's results will be analyzed, and future directions for enhancing the approach will be considered [102-107].

The objectives of this paper include improving the accuracy of breast cancer diagnosis through a deep learning-based approach that automatically detects cancerous tissue in histopathological images. The project aims to reduce the time required for diagnosis by automating the examination process and minimizing the risk of human error by eliminating the need for manual image analysis [108-111]. Additionally, the project seeks to develop a user-friendly interface that pathologists can use to diagnose breast cancer in new histopathological images. The ultimate goal is to provide a scalable and efficient solution that can be seamlessly integrated into clinical workflows while evaluating the performance of this deep learning approach against existing breast cancer diagnosis methods [112-113].

In order to build an intelligent interactive mirror system, we looked at the current approaches. Displaying the current time, date, and weather predictions is the primary use case for smart mirrors. Notifications, traffic reports, and to-do lists are also included in some. Its music player and speech recognition capabilities were later added to it in an upgrade. As a result, it can be customised according to needs. Our smart mirror paper is just one of several such sheets and products on the market. Finished goods were far outnumbered by papers. Reasons for this include the fact that smart home technology is still in its early stages of development, with high production costs that put most people out of their price range. A more practical and reasonably priced smart mirror is required, as the increased number of articles shows. Despite meeting certain criteria, a company's actual products were either too costly or too new to be considered a competitive threat. Both commercial and academic efforts to include specialised mirror capabilities have been attempted. Nevertheless, the necessary area usually makes such systems impractical.

Literature Survey

Ahmad [1] used MobileNet and multi-task learning to detect breast cancer. They reported that MobileNet achieved an accuracy of 92.0%, and multi-task learning further improved the accuracy to 93.1%. The study utilized a dataset of annotated mammographic images. Sharma et al. [2] conducted a study utilizing Random Forest, KNN, and Naïve Bayes methods to classify breast cancer data. The findings revealed that KNN was the most accurate classifier among the methods tested. The study used the Wisconsin Breast Cancer dataset from the UCI Repository. Preetha et al. [3] employed data mining techniques to detect hidden cancer associated with classification. Their study utilized the Wisconsin Breast Cancer dataset to achieve these findings.

Nawaz and Hassan [4] utilized a Deep Learning Convolutional Neural Network (CNN) and achieved a 95.4% accuracy, outperforming state-of-the-art models. The Dense CNN model was employed, and the BreakHis dataset was used for this study. Z. Wang [5] utilized DenseNet and ensemble methods to detect breast cancer. Their findings showed that the ensemble methods achieved an accuracy of 95.0%, outperforming DenseNet alone, which had an accuracy of 92.8%. The study was conducted using a dataset of annotated mammographic images. Kim et al. [6] employed Convolutional Neural Networks (CNNs) and data augmentation techniques to detect breast cancer. Their study reported that data augmentation improved the accuracy of the CNN to 96.7%, compared to 94.7% for the CNN trained without data augmentation. The research utilized a dataset of annotated mammographic images.

Kim et al. [7] utilized the VGG-16 architecture combined with data augmentation to detect breast cancer. The study reported an accuracy of 91.9% using the CBIS-DDSM dataset. Xie et al. [8] employed the Inception-V3 architecture for breast cancer detection, achieving an accuracy of 89.0%. The study used the DDSM dataset, which contains 2,620 mammographic images. Shen [9] utilized deep neural network models, including ResNet 18, ShuffleNet, and Inception-V3Net, for breast cancer classification. The study reported accuracies ranging between 97.81% and 99.70% for binary and multi-class classification tasks using the BreakHis dataset.

Iqbal et al., [10] employed Inception_V3 and Inception_ResNet_V2 architectures for breast cancer detection. The study found that the Inception_V3 network achieved an accuracy ranging from 78.0% to 93.9%, while the Inception_ResNet_V2 achieved an accuracy between 80.4% and 95.3% in the same evaluation. The research utilized the BreakHis dataset, which contains 7,909 breast cancer histopathology images.

Proposed Work

One of the proposed methods for the detection of breast cancer can be carried out by getting a convolutional neural network to be trained on microscopic images of breast tissue. The first step is to gather significant data with images and conduct exploratory data analysis (EDA) to get to know the dataset better. Then, pre-processing steps are performed. We also need the dataset to be labeled so that we will know whether the breast image has a tumor or not. Then, it will be used to train the neural network. Once we train this network, it can detect characteristics and patterns and learn from them to detect tumors in the images. Then, we can feed the network with new images and carry out predictions about the presence of tumors in the breast. We can also use CNN's different architectures. The most popular ones include Dense Net, VGG Net, Mobile Net, Inception Net, and VGG Net. We can incorporate some of these in the paper to analyze which algorithm performs better. Transfer learning can also be implemented to improve the performance of our models. Once this is done, we can finally evaluate the performance of each of the models by using metrics such as precision and recall, accuracy, and area under the curve (AUC). This will help us better know the model and whether it can perform well on data it has not seen before.

Breast tumour tissue from eighty-two patients is represented by 7909 microscopic pictures in the Breast Cancer Histopathological Image Classification (Break His). Images are captured by means of magnification devices (40X, 100X, 200X, and 400X). Among its contents are 5,429 cancer samples and 2,480 noncancerous ones (700X460 pixels, 3-channel RGB, 8-bit depth in each channel, PNG format). We are grateful to the P&D Laboratory in Parana, Brazil, for their assistance in compiling this database. The image's metadata, including the biopsy technique, tumour kind, patient ID, and magnification factor, is saved in the image's filename. There are a total of eight breast tumour types in the dataset, including four benign ones (adenosis, fibroadenoma, phyllodes tumour, and tubular adenoma) and four malignant ones (carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma) (PC).

The data was collected using the SOB method (Sensible, Odd, and Bizarre), which organizes the dataset into Variables and Constraints. This method includes specific surgical procedures as key variables, such as partial mastectomy, a surgery that removes all breast tissue from a breast to treat or prevent breast cancer, and excisional biopsy, where an entire lump or area, including a portion of the skin, is removed to eliminate cancer. In some cases, an excisional biopsy may be the only surgery needed to treat breast cancer. The implementation of the research paper involved several steps: dataset collection, exploratory data analysis (EDA), data pre-processing, train-test-validation split, and finally, model evaluation and comparison.

First, histopathological images of breast tissues were gathered, and performed Exploratory Data Analysis to get to know the dataset better. Resampling and Data Augmentation were performed as a part of pre-processing steps. Once data is collected, pre-processing is done to get the data into a usable dataset. This process was relatively simple as the dataset was collected from a single resource. Resampling was performed to solve the class imbalance issue, and data augmentation was performed to increase the models' performance. Eighty percent of the dataset was used for training the models, and 10 percent each was given for testing and validation purposes. Next, different models were built. In this paper, we built a CNN model and four different architectures: VGG 16, Inception V3 Net, Mobile Net, and Dense Net. Hyperparameter tuning was done to improve the performance of all the models. Finally, all models were evaluated and compared to see which gave the highest accuracy. After data analysis, all the models are saved as a .h5 file and loaded into Django, which serves as the web application's backend. The model is then used to generate different paths in the web app to display datasets, visualizations, and other relevant information.

Results and Discussions

The results of the study demonstrate the accuracy of various models used for breast cancer detection. The CNN model achieved an accuracy of 88.12%, while MobileNet recorded 82.81%. DenseNet outperformed the others with an accuracy of 91.15%. VGG, on the other hand, showed a significantly lower accuracy at 33%. Inception V3 achieved a moderate accuracy of 84.58%. These results indicate that DenseNet was the most effective model in this evaluation, while VGG underperformed compared to the other models (Figure 1).

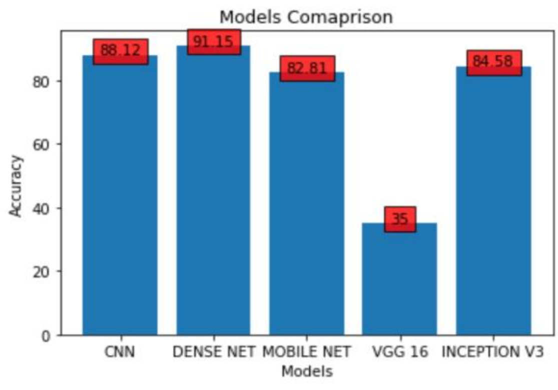

Figure 1: Comparing accuracy models

Therefore, DenseNet is the best-suited model for this dataset, as it achieved the highest accuracy among the models tested. The accuracy and loss curves have been plotted for all the models, providing valuable insights into their behavior. These curves are crucial for understanding the model's learning process, and they can guide potential adjustments to improve model performance. For example, the accuracy and loss curves for the CNN model, as shown above, help visualize how well the model is learning over time. These curves can indicate whether the model is overfitting, underfitting, or performing optimally. By analyzing these plots, one can make informed decisions on tuning the model, such as adjusting learning rates, adding regularization, or modifying the architecture, to enhance the overall performance (Figure 2).

Figure 2: Accuracy and loss curves for CNN

Training and validation loss (right) and accuracy (left) throughout multiple epochs are depicted in the provided graphs. The first graph shows that, on average, as the number of epochs increases, both the training and validation accuracy rise. The training accuracy begins at approximately 75% and gradually increases until it exceeds 88%. It is clear that the model is learning and generalising well to the validation data because the validation accuracy follows a similar growing pattern to the training accuracy towards the end, with some volatility around the middle epochs. Losses during training and validation both go down as the training goes on, as seen in the second graph. In the first epoch, the training loss is greater than 0.50; in the last epoch, it drops below 0.30. Along with the training loss, the validation loss typically decreases; nevertheless, it does exhibit some oscillations. A successful learning process devoid of overfitting or underfitting is indicated by the parallel decreasing trends in the two losses, which further imply that the model is successfully minimising errors on both the training and validation datasets.

Conclusion

Based on the deep convolutional neural networks of Inception V3 and Inception ResNet V2, which were trained utilising transfer learning techniques, our proposed methods for assessing histopathological pictures via image screening of breast cancer are presented in this research. The aforementioned networks have already been trained on ImageNet's massive image dataset. Then, as classification accuracies relied on label information, their learnt structure lagged behind. Additional research is necessary to determine how to enhance the accuracy of clustering. Furthermore, it is necessary to determine the amount of clusters in the histological images of breast cancer for both the 8-class and 2-class cases. When it comes to medical imaging, noise is a common problem that can drastically alter the outcomes. Uneven staining, white spots on deparaffinized slides, and visible patches on hydrated tissue are some typical sources of noise. Features retrieved from photos can vary greatly due to batch effects, according to reports. It is a proven truth that when it comes to histopathological photos, variations in resolution, contrast, and overall appearance are far more noticeable within the same class than to images from different classes. Classifying breast cancer images as benign, malignant, or any other specific category is made more challenging by the variability of these fine-grained histopathological images. We will be focusing our future efforts on finding ways to mitigate or eliminate these difficulties that impact the examination of breast cancer histopathology pictures.

Future Scope

This article could benefit from more investigation into how to enhance the clustering accuracy of breast cancer histopathology pictures, with an emphasis on instances with 8 or 2 classes. Possible future research directions include reducing batch effects and fixing noise-related concerns like white patches and uneven staining. Furthermore, methods should be sought for to mitigate the effects of fine-grained features' variability on classification in histopathological pictures. Medical imaging noise is an important problem that needs fixing, and there are a lot of potential solutions. You can increase the image quality and lessen the impact of noise by using image pre-processing techniques like contrast enhancement and noise reduction. Image registration and fusion are two methods that combine data from several images; they could also be useful in fixing the dataset's inconsistent image quality.

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