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A HYBRID MODEL FOR CNN-BASED MEDICAL IMAGE DIAGNOSIS BY FUTURE DIRECTION

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Abstract:

Cancer is one of the most fatal diseases and breast cancer is found to be predominantly death-causing causing disease for women. There is vast research in the direction of diagnosis, prognosis, and cure for this dreadful disease. Since the use of advanced tools in Machine Learning in medicine, there has been a rapid requirement for proper documentation of medical records. Almost every medical facility is now keeping a detailed account of radiological data. This paper focuses application of ML tools to the historical data available from the archives and developing a model that is accurate in the identification of cancerous regions from the examination of trained images.

Keywords: Breast Cancer, Diagnosis, Machine learning.

Introduction

Globally, breast cancer is the primary cause of cancer-related deaths for women and a serious public health concern. The likelihood of survival can be effectively increased by early diagnosis and identification. This is why there has been a lot of interest in the use of deep learning algorithms for breast cancer diagnosis and classification. Thus, utilizing a dataset we had developed ourselves, our study sought to develop a computational strategy based on deep convolution neural networks for the effective classification of breast cancer histopathology pictures. Data available from the Cancer Research Centre is used for this purpose.

The findings confirm that mitosis is difficult for deep learning-based classifiers trained on MIDOG and ATYPIA to identify on our dataset, indicating that the mitosis dataset was developed with distinct features and characteristics. In addition, the suggested classifier performs noticeably better than the state-of-the-art classifiers, achieving 49:0% and 68:7% F1 scores on the generated mitotic and MIDOG datasets, respectively. Additionally, the experimental results show that the overall suggested MITNET framework improves the accuracy of pathologists' decisions by identifying the mitotic cells in WSI with a high F1-score and detecting the nucleus in WSIs with high detection rates.[2]

A frequent illness with a rising death rate in recent years is cancer. The most frequent cancer in both men and women is lung cancer. It results from unchecked lung cell proliferation. There are two sorts of these cells: malignant and benign. Malignant tumors can be harmful and can spread to other body cells to develop an unevenly shaped new cancerous nodule. Benign tumors, on the other hand, are typically benign, do not spread to other cells, and have a smooth and regular shape. Lung cancer is treatable if it is found early. Although new technology and computer-aided systems can detect lung cancer at an early stage, the disease usually manifests its symptoms in the human body when it is in its latter stages. At the moment,[3] Medical image analysis has seen significant advances with the integration of sophisticated computational techniques. From canonical polyadic decomposition to deep learning models, these innovations aim to enhance tumor detection and image clarity. This review explores recent methods and their impact on improving diagnostic accuracy and efficiency in medical imaging.[4]

Literature Review

C. Venkatesh et. al.in 2023 [5] Lung cancer is one of the leading causes of cancer-related deaths globally. Early detection is crucial for improving survival rates, yet traditional diagnostic methods, including X-rays and MRI, often fail to detect the disease in its initial stages. Recent studies have focused on using deep learning, particularly Convolution Neural Networks (CNNs), to enhance detection accuracy and reduce processing time. CT imaging, preferred for its clarity and lower noise levels, is often used in these approaches. Despite advancements, challenges remain in achieving high accuracy and efficiency, necessitating further research to optimize deep learning models for early lung cancer detection.

H. El Agouri1, M. Azizi2 et. al.in 2022 [1] Deep learning (DL) has emerged as a transformative tool in breast cancer diagnosis, particularly through the use of convolution neural networks (CNNs). Studies have demonstrated the effectiveness of DL in classifying histopathological images with high accuracy, even with limited datasets. For example, ResNet50 and Xception models have been shown to achieve significant accuracy and sensitivity in detecting carcinoma, aiding pathologists in diagnostic workflows. Compared to traditional methods, DL offers improved reproducibility and efficiency, addressing challenges like pathologist shortages and increasing patient loads. However, challenges remain in terms of data availability and the need for further model refinement.

Dr. Pushpendra Anuragi, and Dr. Pratima Gautam in 2023 [1] In recent studies on medical image diagnosis, several advancements have been notable. Bharath et al. (2017) applied nonnegative canonical polyadic decomposition for tumor tissue differentiation. Zotina et al. (2018) improved MRI tumor image clarity through fuzzy C-means clustering. Li et al. (2019) combined multi-modal fusion with convolutional neural networks (CNNs) for brain tumor detection. Huang et al. (2019) used FCM clustering and rough set theory for brain image segmentation. Noreen et al. (2020) leveraged deep learning models for tumor diagnosis. These approaches highlight the evolution and effectiveness of computational techniques in enhancing medical image analysis.

Pushpendra Anuragi, et. al.in 2022 [1] In recent years, machine learning (ML) has transformed medical image diagnosis, addressing the limitations of manual analysis. Advances include Convolution Neural Networks (CNNs) for interactive segmentation and novel frameworks like the dual-sampling attention network, which enhances COVID-19 detection in chest CT scans. Techniques like Fast Medical Image Super-Resolution (FMISR) and hybrid CNN models for ultrasound images have improved feature extraction and classification accuracy. Recent approaches also integrate deep learning strategies, such as Attention Dense Circular Networks

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(ADCN), which combine dense and residual networks with attention mechanisms for efficient and effective classification. These developments underscore the growing sophistication and accuracy of ML applications in medical imaging.

P. A. Pattanaik et. al. in [13] Provided an all-encompassing identification using the concept of computer-aided diagnosis (CAD). The blood images show the presence of malaria parasites. The text should be paraphrased using the same input language and maintaining the same word count. Parameters in this model were trained through the use of methods of artificial neural networks employed by encoders stacked on top of each other. The numbers 12500-2500-100-50-2 represented the...ideal size maintained for this CAD system. The input layer comprises 12500 nodes and the output layer of the softmax classifier contains 2 node Points in a network. Also implemented was a cross-validation system with 10 folds.

Proposed Methodology

This section of the paper explains the proposed Breast Cancer Imaging Model, or BCIM displays the work's flow diagram to improve comprehension of the model. This section includes an explanation of each model block. Several of the notations were used in the study to improve the model's comprehension.

Image Normalization:

The input image contains noisy data that must be corrected by filtering the image to adjust each pixel's value. Use a wiener filter in the suggested model for noise reduction. The image is then converted into a suitable format and resized to fit the model's working environment. Thus, if I is the input image, then Ip is the preprocessed image that is obtained by the use of weiner, gray conversion, and resizing. [4]

Noise Reduction:

Because the Wiener filter estimates the original image linearly, it reduces mean square error and eliminates additive noise. [4]

3. Data Augmentation

It involves breaking down a pre-processed image into fixed n x n size pixel values. The obstructed image is being used to extract features. The suggested model has extracted the image's DWT feature and histogram to increase work efficiency. The model uses a CCM of 16 pixels. Using DWT, each image is divided into four blocks, and the low-frequency regions inside each block are utilized to classify the model.[4]

Segmentation Maps

Segmentation maps are visual representations that categorize each pixel in an image into distinct classes or regions. They are used in tasks like image segmentation to identify and separate different objects or areas within an image. This process enhances image understanding by isolating and labeling relevant features for further analysis.[3]

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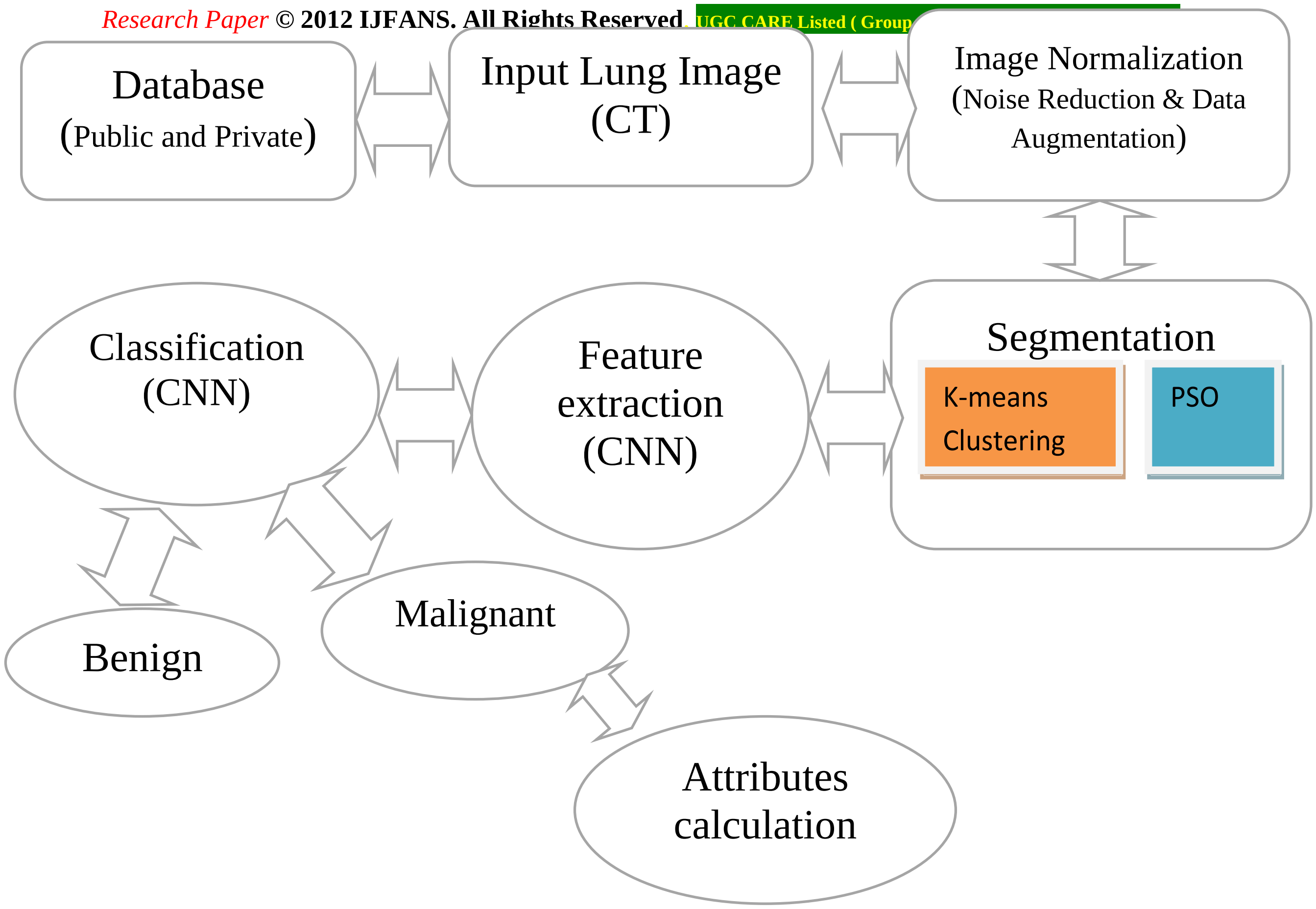

Fig. 1: Diagrammatic Representation of ML-based Processing Technique of BCIM

Annotations:

Annotations are labels or notes added to data, such as images or text, to provide context or identify key features. In machine learning, annotations are crucial for training models, as they define ground truth for tasks like object detection, image classification, or text parsing, ensuring accurate and meaningful analysis.[3]

Feature Extraction:

Convolutional Layers (CNNs)

With a specific end goal to get the surface of the image one of the vital techniques is the co-occurrence matrix. Here co-occurrence matrix exhibits the surface property by the relationship of the neighboring pixels [14]. It is quantificational and explains the surface component. In this paper, four elements are chosen including contrast, energy, inverse difference, and entropy.

Feature Maps

Feature maps are the output of convolution layers in a neural network, representing the detected features in an input image. Each feature map highlights different aspects of the image, such as edges, textures, or patterns, by applying filters. They are crucial for identifying and extracting meaningful information during the image classification process.

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Classification/Detection:

Dense Layers

Dense layers, also known as fully connected layers, consist of neurons that are connected to every neuron in the previous layer. They perform complex transformations on the features extracted by earlier layers by applying learned weights and biases. Dense layers are crucial for decision-making and classification tasks in neural networks.

Attention Mechanisms

Attention mechanisms enable neural networks to focus on specific parts of the input data, enhancing model performance by dynamically weighting different elements. This allows the model to prioritize relevant information and ignore less important parts, improving accuracy in tasks like machine translation and image captioning by capturing contextual relationships.

K-means clustering - K-means clustering is an unsupervised machine learning algorithm used to group data into clusters based on feature similarity. The algorithm works by initializing a set number of cluster centroids, typically chosen randomly. Each data point is then assigned to the nearest centroid based on Euclidean distance. After assigning all data points, the centroids are recalculated as the mean of the points within each cluster. This process iterates until the centroids stabilize, meaning they no longer change significantly. K-means is efficient for large datasets but requires the number of clusters to be predefined, which can be a limitation.

This unsupervised learning technique, which reduces clustering problems, is applied to image segmentation to distinguish the Region-of-Interest (RoI) from the background. From the input pixel set of an image of size X*Y, where x and y represent the Row and Column, respectively, the method creates a 'k' number of clusters. Now, n(x, y) is the input pixels for clustering, and o is the cluster center. Using Eq. 1, where d is the distance between each pixel in an image and the center of a cluster "oi," the cluster with the shortest distance was found. Furthermore, it assigns a "oi" to the center of each pixel based on the distance. After that, the cluster center is computed once.

K-Nearest Neighbor: Features extracted from the image blocks are arranged in the vector where CCM 16 values are arranged first and later values of DWT-LL coefficients are arranged. Each training vector has the desired class value to classify the image. As input images have two classes, hence KNN has k=2. For finding the distance of the cluster center this work uses the Euclidian distance formula.[2].

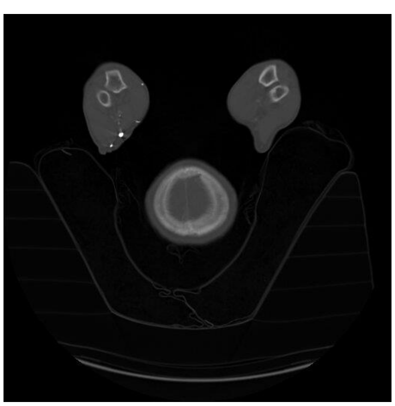 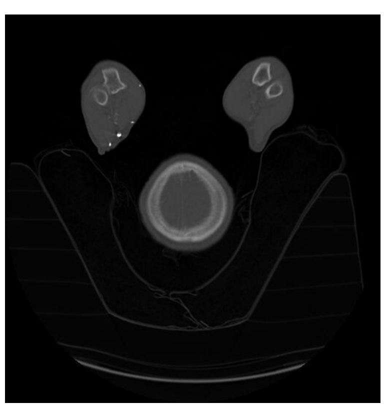 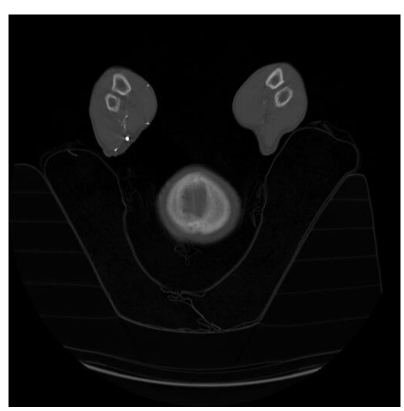

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Fig 2: Sample CT images Taken from the Cancer Imaging Archive (NBIA)

Different Parameters used as metrics in this work are as follows:

PSNR (Peak Signal-Noise Ratio): It is a measure of image quality calculated by the logarithm of the ratio of the Maximum Pixel value of the image (Max) by the square root of mean square error (MSE) and then converted into decibels by multiplying by 20.

$PSNR = 20 \log_{10}(Max / (MSE)^{1/2})$

Sensitivity:

In a classification model, Sensitivity is defined as the proportion or percentage of samples that are positive and correctly identified by the test. Sensitivity is also known as the true positive rate.

Specificity:

In a classification model, Specificity is defined as the proportion or percentage of samples that are negative and correctly identified by the test. Specificity is also known as the true negative rate.

Sensitivity and specificity are derived from a 2x2 box of outcomes (Confusion Matrix) from a diagnostic test:

- True positive (TP): The test is positive and the patient has the disease or condition.
- False positive (FP): The test is positive but the patient does not have the disease or condition.
- True negative (TN): The test is negative and the patient does not have the disease or condition.
- False negative (FN): The test is negative but the patient has the disease or condition.

The formula for sensitivity is TP / (TP + FN).

The formula for specificity is TN / (TN + FP).

Accuracy:

It is a metric that is defined as the ratio of correct predictions to the total number of predictions made.

Table 1- Image Quality Parameters Related to Images.

S.NO	PARAMETER	INPUT IMAGE-1	INPUT IMAGE-2	INPUT IMAGE-3
1	PSNR (%)	12.850	12.300	12.980
2	Specificity (%)	57.540	60.230	56.970
3	Sensitivity (%)	96.610	97.810	96.80
4	Accuracy (%)	98.810	99.577	98.61

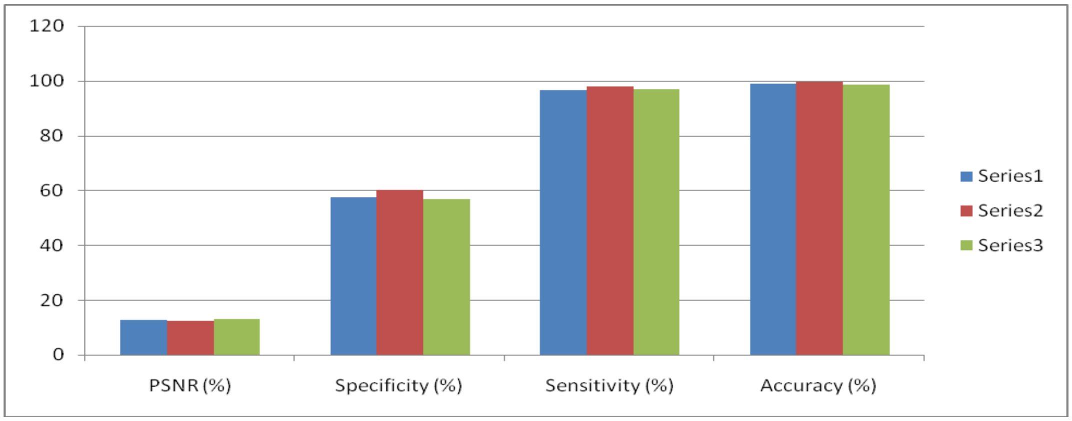

Fig. 3 Graphical Representation of Image Quality Parameters

Table 2- Comparative Results

S. No	Authors	Method	Accuracy
1	Monica Ramakrishnan et al. [9]	VGG &RNN	70.00%
2	Radhanadh Patra et al. [10]	KNN&RBF	81.25%
3	Md. Rashidul Hasan et al. [11]	SVM	72.20%
4	Suren Makaju et al. [12]	SVM	92.00%
5	Pushpendra Anuragi. [8]	ANN	84.00%
6	Dr. Pushpendra Anuragi. [2]	KNN & CNN	84.12%
7	Proposed Method	BCIM	**98.99%**

Images obtained from the public domain (source: Cancer Imaging Archive) are subjected to the procedure explained above and then the objective analysis is conducted after classification to determine positive image quality parameters such as PSNR, Specificity, sensitivity, and accuracy. Table 1 displays these characteristics for input image-1, input image-2, and input image-3. According to this data, the accuracy of input image-1 is 98.810%, of input image-2 is 99.577% and that of input image-3 is 98.61%.

The graphical representation of statistical parameters in terms of these indices is also shown in Fig. 3. Finally, the proposed method demonstrated high accuracy (98.99%) in the detection and classification of breast cancer-related tumors in CT images compared to the existing systems as mentioned in Table 2.

Conclusion

Though Cancer is a dangerous disease and it requires a careful and detailed examination of images at early stages, Machine learning techniques come to the rescue in the accurate classification of the images, helping incorrect diagnosis. Advanced technology such as CNN are presently taking the research forward and different simulation techniques can be successfully applied to enhance the diagnosis more quickly and accurately. Historical data is also available to aid in this aspect and computer-based study is growing at a rapid pace and is expected to give the most accurate results with less human intervention AI is also entering this field.

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