A Novel Approach for Micro Tumor Cancer Classification Detection Using Convolution Neural Network Medical Image Diagnostics

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Annotation.

Micro cancer detection is critical for early diagnosis and effective treatment of various cancers. This study presents a novel approach utilizing Convolutional Neural Networks (CNNs) to enhance the detection of micro tumors in medical imaging. We developed a CNN architecture tailored to process histopathological images, employing techniques such as data augmentation and transfer learning to improve model accuracy and generalization. The dataset consisted of annotated images from diverse cancer types, ensuring a comprehensive evaluation. Our results demonstrated significant improvements in sensitivity and specificity compared to traditional diagnostic methods. This CNN-based approach not only facilitates earlier detection of micro cancers but also assists pathologists in making more accurate assessments,

ultimately contributing to better patient outcomes. Future work will focus on expanding the dataset and refining the model to further enhance detection capabilities and reduce false positives.

Detection are mammography and biopsy. In mammography, breast images of a specific type are used to detect early cancer symptoms in women by the radiologist. It has been observed that due to the use of mammography for Micro cancer detection, the death ratio has decreased. A biopsy is another well efficient and accurate diagnosis method for breast cancer detection. In this approach, a tissue sample from an affected region of the breast is analyzed under a microscope by a pathologist for the detection and classification of the tumor

Keywords: CNN architecture, generalization, Neural Network, Classification

1. Introduction:

Micro tumors, often undetectable by conventional imaging techniques, represent an early stage in cancer development that significantly impacts treatment outcomes. Detecting these small tumors is crucial for timely intervention, as they can evolve rapidly and lead to more advanced disease stages if left unnoticed. Traditional diagnostic methods, such as manual histopathological examination, are time-consuming and can be prone to human error, particularly when differentiating between benign and malignant lesions.

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Recent advancements in artificial intelligence, particularly in machine learning and deep learning, have opened new avenues for enhancing tumor detection. Convolutional Neural Networks (CNNs) have proven particularly effective in image classification tasks, including medical image analysis. By leveraging CNNs, we can automate the classification and detection of micro tumors, improving both accuracy and efficiency.

This paper explores the application of CNNs in the classification and detection of micro tumors in histopathological images. We aim to build a robust model that can effectively distinguish between malignant and benign tissues at a microscopic level. Through this research, we seek to contribute to the growing body of work in medical imaging, providing a powerful tool for pathologists and oncologists in the fight against cancer.

1. 1 Background and Context

Micro tumors, often defined as tumors that are difficult to detect due to their small size and subtle features, pose significant challenges in cancer diagnosis. These tumors can be critical indicators of early-stage cancer, making their accurate identification essential for timely intervention and treatment. Misdiagnosis or delayed detection can lead to worse patient outcomes, emphasizing the need for advanced diagnostic techniques. Early detection of micro tumors can significantly improve survival rates and treatment efficacy. For many cancers, including breast, lung, and prostate cancer, identifying tumors at a smaller size can facilitate less invasive treatments and improve the overall prognosis. Traditional imaging techniques, while useful, often struggle to identify these small lesions, necessitating the development of more sophisticated methods.

1.2 Role of Medical Imaging

Medical imaging technologies, such as MRI, CT scans, and histopathological slides, play a crucial role in cancer diagnosis. These images provide essential insights into tumor characteristics, including size, shape, and location. However, the interpretation of medical images is complex and requires significant expertise, which can lead to variability in diagnosis among clinicians.

1.3 Artificial Intelligence in Medical Diagnostics

Artificial Intelligence (AI) and, in particular, machine learning techniques have shown great promise in enhancing diagnostic accuracy. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image analysis. CNNs excel at automatically

extracting features from images, allowing for more accurate classification and detection of tumors compared to traditional methods.

1.4 Convolutional Neural Networks (CNNs)

CNNs are a class of deep learning models designed specifically for processing structured grid data, such as images. They consist of layers that automatically learn hierarchical features, making them particularly effective for visual recognition tasks. The architecture typically includes convolutional layers, pooling layers, and fully connected layers, enabling the model to capture spatial hierarchies and intricate patterns in medical images.

1.5 Current Challenges in Micro Tumor Detection

Despite advancements in CNNs, several challenges remain in micro tumor classification:

- **Data Imbalance**: Datasets may have an unequal representation of tumor types or stages, leading to biased models.
- **Variability in Imaging**: Differences in imaging protocols, equipment, and patient anatomy can affect model performance.
- **Interpretability**: Understanding the decision-making process of CNNs is crucial for clinical acceptance and trust.

2.4. Objectives of the Study

- This study is designed to organize and present CNN algorithms (including improved architectures), activation functions, popular frame works, optimization approaches, relevant datasets, data preprocessing techniques and model ensemble methods in one place and make them available for researchers and clinicians who are interested in setting up their own CNN experiments.

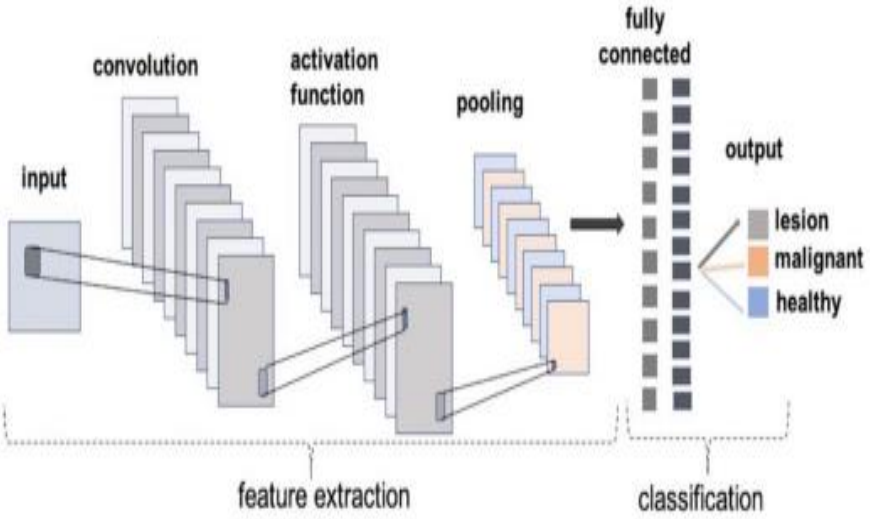


Figure 2. Basic architecture of convolutional neural network showing the main components and steps involved in medical image classifications.

Each layer, in a typical CNN architecture (Figure 2), has a specific purpose: • The input layer is the first layer which receives the input image. • The convolutional layer is the core layer of the CNN architecture, where the convolution operation is performed using a set of learnable kernels or filters to detect edges, corners and textures (to extract features from the input data) [25]. Feature extraction may involve strides and paddings along with kernels (1). WO = Wi − F + 2P S + 1 where Wo is the output size, Wi is the input size, F is the kernel size, P is the padding size and S is the size of the stride.

• The activation function introduces non-linearity to capture complex relationships in the data, and it is applied element-wise to the output of the convolutional layer.

• The pooling layer is applied to reduce the spatial dimensions (width and height) of the feature maps obtained from the convolution layer [16] by performing down-sampling.

• The fully connected layer is used to learn high-level representations by combining features learned from the previous layers. • The output layer is the last layer which produces the

desired output based on the task at hand. CNN architectures can have additional components like dropout and normalization layers, depending on the specific application and network design. 2.2. Improvements in Architectural Designs of CNNs Improved or hybrid structures of CNNs with other algorithms such as transformers (Figure 3a), recurrent neural networks (RNNs), generative adversarial networks (GANs) and shallow methods have shown better performances in medical image segmentations and classifications [26].

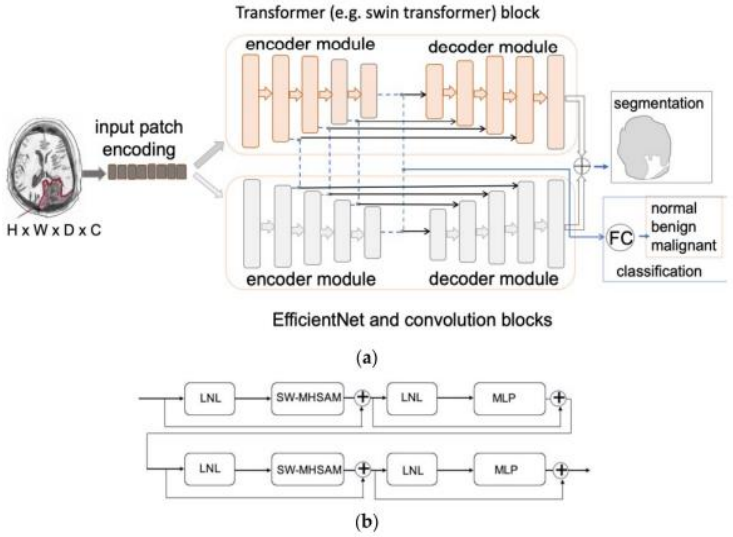


Figure 3. (a) Hybrid structure of convolutional neural networks with transformer (applied for diagnosis of brain tumor). (b) Consecutive Swin transformer block.

Copyright notice: (a,b) were redrawn from Figures 1 and 2 from Wang et al. [27] (published with open access under the Creative Commons License). Each Swin transformer block consists of residual connection, and two-layer perceptron (MLP) with Gaussian error linear units, a Layer Norm layer (LNL) and a multi-head self-attention module (Figure 3b). The query (Q), key (K) and value (V) of the self-attention can be given as (2): attention(Q, K, V) = SoftMax(QKT √ Qd + B)V

Here Qd is the query dimension and B is the bias matrix High-precision medical image segmentation is a challenging task due to the existence of inherent distortion and magnification in medical images as well as the presence of lesions with similar density to normal tissues. Recently, hybrid structures of transformers with CNN along with attention blocks have been designed and progressively improved to tackle the problem of medical segmentation. Many of the hybrid and/or improved structures are also designed for medical image classifications in addition to segmentation tasks (Table 1).

2.5 Pre-trained CNN Architecture for Feature Extraction

In the beginning, separate CNN architectures are used for feature extraction, which are combined into a fully connected layer for classification tasks. The combined features may contain multiple features extracted from single descriptor, these features may represent the shape descriptor like circularity, roundness, compactness, etc. In the proposed framework, three most recent and up-to-date deep CNN architectures: GoogLeNet [33], Visual Geometry Group Network (VGGNet) [34] and Residual Networks (ResNet) [35] are adopted as a feature extractor for the classification of breast cancer in cytology images. These architectures are pre-trained for various generic image descriptors, followed by relevant feature extraction from microscopic images on the basis of transfer learning theory [36]. The basic structure of each adopted CNN architectures are described in the following sub-sections.

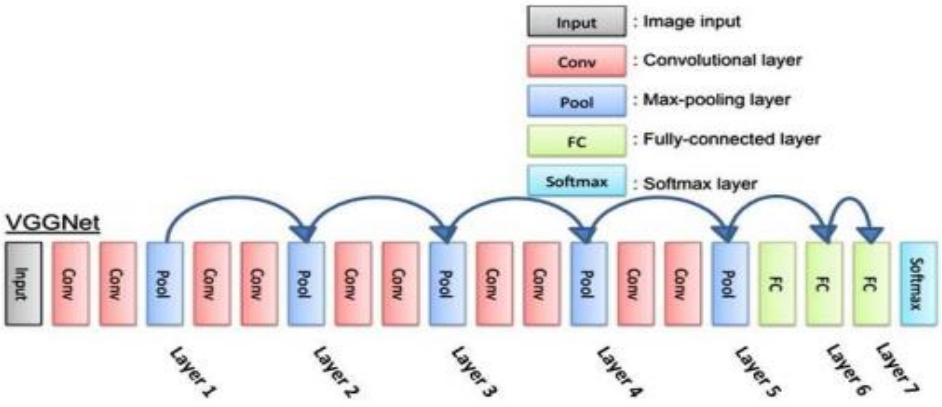
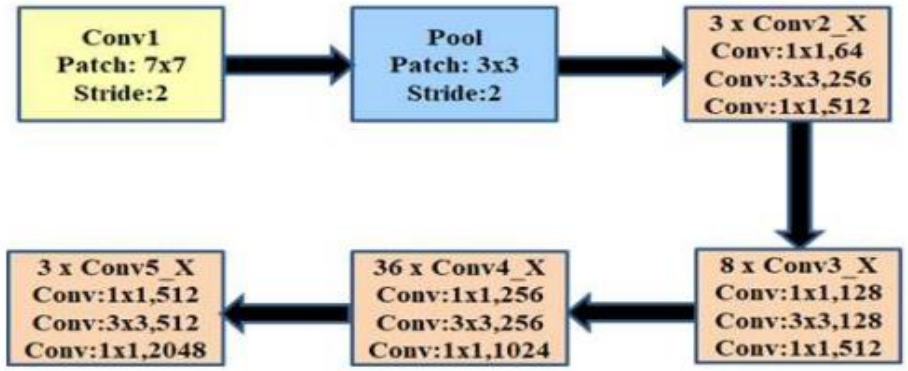


Fig. 3. Basic Architecture of VGGNet [34]



2.6 Transfer learning

In practices, large size of data is required to train a cnn from scratch but in some cases, it is very difficult to arrange a big data set of relevant problems. Contrary to an ideal situation, in most of the real world applications, it is not the case, or it is a complicated task to gain matching training and testing data. Therefore, the concept of transfer learning has been introduced. Transfer learning is one of the most well-known methods of machine learning which learned the background knowledge applied for solving one problem and reused on the other.

Relevant Problems, Initially the Base Network is Trained for a Specific Task on their Relevant Data Set and then Transfer to the Target Task Trained by Target Data Set [38]

3. Experimental Results and Discussion

3.1. Dataset

To evaluate the performance of the proposed framework two Micro microscopic image data sets are used: the first one is a standard benchmark data set [39], and the other is developed locally at LRH hospital Peshawar, Pakistan. For both data sets, first augmentation technique is applied by scaling, rotation, translation and colors modeling to produce a total of 8000 images. In these 8000 images, 6000 images are used for training the architecture while 2000 images are used for testing the trained model. In both data sets, images are captured by microscope with various magnifications (the enlargement process of images seen by microscopic lens known as lens magnification). In the proposed framework various magnified images (100X, 140X, 200X and 500X) are used for accurate evaluation. During the execution of the proposed framework, 75% of data set is used for training purpose while 25% of data set is used for testing the accuracy of the proposed architecture. Moreover, to control the over-fitting issues, the initial stopping criteria is designed which is based on the performance validation, i.e., to stop the training process when the system shows no or less improvement after 1000 iterations.

-**The Cancer Imaging Archive (TCIA):** A large archive of medical images of cancer available for public access. It includes various datasets with annotated images for tumor detection.

- **NCI Genomic Data Commons (GDC):** Offers access to genomic data from various cancer studies, including RNA-seq and DNA-seq data.

-Cancer Genome Atlas (TCGA): A comprehensive resource that provides genomic and clinical data for various cancer types, including some associated with micro tumors.

***Kaggle Datasets: Kaggle*:** A platform that hosts datasets and competitions. You can find specific datasets related to cancer detection and classification. Searching for "cancer" or "micro tumor" on Kaggle may yield relevant datasets.

 Coco Dataset for Medical Imaging:

- A large-scale dataset that may include various medical imaging annotations.
- Check on their platform for specific medical imaging datasets.

 UCI Machine Learning Repository:

- Contains several datasets related to health and medical diagnoses, though not exclusively focused on images.

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