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DEEP LEARNING FOR TUMOR MALIGNANCY DETECTION AND CLASSIFICATION

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Abstract

A tumor is an abnormal lump or growth of cells in any part of body. Such a mass of abnormal cell growth that lacks ability to invade neighbouring tissues is called benign tumor. When this abnormal, uncontrollable cell growth possesses ability to spread to other parts of the body; they are cancerous, also called malignant tumor or cancer. Early detection of this abnormality can help to cure it timely. The deep learning based methods offers number of techniques in image classification that helps in diagnosis of cancerous cells. It can significantly reduce the surgeon's workload and make a better prognosis of patient conditions. This study is aimed to review the role of deep learning based approaches in identification and classification of cancer in different parts of human body.

1. Introduction

Cancer is one of the most deadly diseases with growing number of cases that has led to development of several diagnosis tools and techniques. Manual identification of cancer by pathologists is cumbersome task. Machine Learning (ML) offers versatile techniques that play vital role in healthcare [1]

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including medical diagnosis. It thus also serves as promising weapon for automatic detection of cancer at early stages that can overcome issues that prevail in manual process. ML is discipline of artificial intelligence that relies on making predictions by finding relationships and patterns in data based on mathematical models [2]. ML methods are classified mainly into two types: Supervised and Unsupervised. Deep learning itself is a form of supervised ML technique that uses Artificial Neural Networks (ANN) to extract patterns and relationships in voluminous datasets [3]. There are different types of deep networks like Recurrent Neural Networks (RNN), Recursive Neural Network (RevNN), Convolutional Neural Network (CNN) [4]. CNN is one the most prominent type of deep network that is suitable for processing of spatial data such as images. Potential limitation of classical ML methods is that it requires handcrafted feature engineering. Deep neural networks such as CNN on other hand possess power of automatic feature selection. There are many imaging techniques like Ultrasound, MRI (Medical Resonance Imaging), CT scan (Computed Tomography), X-Ray that provide medical data for cancer detection and classification in the form of images of the body part that is suspected of abnormal cell growth. Given the significance of deep learning techniques in processing spatial data like images, this study presents a review of these learning techniques applies for cancer or tumor malignancy identification and classification. It also identifies challenges faced by researchers and presents future research directions.

2. Literature Review

Technological advancements in the area of artificial intelligence have revolutionized pathology practices. Especially machine learning and deep learning methods have spurred much interest to use it as diagnostic tool for medical ailments like cancer detection and classification [5]. Leading cause of death among women is breast cancer; detection of this malignancy at early stages can reduce mortality. ResNet-18 based deep extracted features with improved Crow-Search Optimized Extreme Learning Machine (ICS-ELM) algorithm for breast cancer detection is implemented in [6]. The performance of different deep learning architectures: Inception V3, DenseNet121, ResNet50, VGG16, MobileNetV2 with U-net segmentation (MSU) is tested in [7] that provided good improvement in accuracy. Apart from whole image classification, [8] proposed a technique where model is trained using annotated dataset with ROI (Region of Interest) information and parameters of patch classifier are then used to initialize full image classification model. Authors in [9] presented a study that inculcates mass detection and patch extraction based on the feature matching of different regions using Maximally Stable Extremal Regions (MSER) [10]. Extracted patches are then classified using deep CNN. AlexNet and GoogleNet are modified and evaluated using Adam and Stochastic Gradient Descent (SGD) optimizer for breast cancer classification. Customized network “ResHist” comprising of 152 layers inspired by ResNet50, with 13 residual blocks, in which 46 layers are learnable (45 convolutional layers and 1 fully connected) is presented in [11]. Model provides comparable performance for breast cancer classification. Brain tumors are graded as slow-growing/low grade/Gliomas (grade-1,2) or aggressive (grade--3,4) with MRI as most commonly used image modality used for its diagnosis [12]. Low complex architecture with channels is proposed in [13] to classify between Glioma and healthy tumor MRI with motive to reduce execution time. Further same architecture is used as the feature extractor of an RCNN to detect tumor regions and classify them as Meningioma and Pituitary. Final classification of deep extracted features can also be done using traditional ML classifiers. Such a classification model for brain tumor is proposed in [14], that adopts transfer learning and uses a pre-trained GoogLeNet to extract features from brain MRI images and classify them using Support Vector Machine (SVM) and K-Nearest Neighbour (KNN). Similar study called hybrid CNN-SVM is proposed in [15] for binary classification of brain tumor. Before classification threshold segmentation is applied on BRATS2015 dataset. Three CNN-based pretrained models-MobileNetV2, VGG19, and InceptionV3 are used in [16] to classify brain X-ray images with transfer learning from ImageNet. MobileNetV2 has shown remarkable performance on small dataset of brain X-ray images. Using cropped, cropped, uncropped, and segmented brain MRI images, a study is conducted for multi-classification where maximum accuracy is reported for uncropped lesion images [17]. This signifies the contribution of background information towards accuracy of classification. Five stage framework comprising of initial preprocessing, skull stripping, tumor segmentation using CNN, post processing, and finally classification is proposed in [18] for labeling brain MRIs, model has significant performance improvement as compared to different models from literature used for BRATS datasets. Fusion of Local Binary Pattern (LBP) features and statistical features followed by classification by CNN presented in [19]. Skin cancer is another deadly type of cancer that poses various challenges to dermatologists [20]. Deep CNN for binary classification of skin cancer is proposed in [21] using transfer learning from ImageNet. Proposed work provides better classification accuracy when compared with standard models like AlexNet, VGGNet. Melanoma stage classification system is proposed in [22] that uses CNN with custom loss function based on similarity measure for classification of 81 features extracted from dermoscopic images Melanoma dataset. Proposed model outperforms traditional machine learning classification using SVM. CNNs are usually developed at a fixed resource cost which is then scaled up to improve accuracy as more resources are available. Based on similar lines EfficientNet architecture is developed and is used in [23] to perform multiclass classification of skin cancer. Study on one of the malignant form of bone tumor called "osteosarcoma" is presented in [24]. Performance of Six deep networks InceptionV3 and NASNetLarge, VGG16, VGG19, ResNet50, DenseNet201 is evaluated where VGG19 model achieved the highest accuracy in both binary and multi-class classifications (Non-Tumor (NT), Necrotic Tumor (NCT), Viable Tumor (VT)).

3. Discussion

The research papers that have been cited in the literature have primarily focused on deep learning approaches. There are different deep learning architectures like RNN, LSTM (Long Short Term Memory), DBN (Deep Belief Networks) etc. Among them most often used neural network architecture in literature is CNN that offered good classification results. Comparative results reported in various studies have also marked the improvement in classification performance with use of DL techniques over traditional ML methods. Despite the fact that AI-based techniques have significant impact in cancer prediction research, researchers still face a number of obstacles and challenges that must be overcome. Computational time, class imbalance and limited datasets are main issues faced by researchers in training of deep networks. Also majority of the studies have developed a prediction model that has been validated on just one location of cancer. Availability of well annotated datasets with relatively large number of images is must for training of deep neural architectures efficiently. However there are few publicly available benchmarks dataset. Due to this fact comparison of different techniques also becomes difficult.

4. Conclusion

Review of literature signifies that deep learning models have much potential to accelerate the pathological diagnostic process for cancer. Remarkable improvement in accuracy is observed as compared to traditional ML methods. One of the limitations of deep learning models used in pathological process of cancer diagnosis is their characteristic of being "black box", posing a major challenge in their clinical implementation. Future research in this direction must focus on developing low complex models to minimize the cost of computational resources required for training large networks.

Table 1. Comparative analysis of recent studies on cancer classification.

[Ref.] Site of cancer	Dataset: Accuracy
[6] Breast ResNet-18 based deep extracted features with Improved ICS-ELM	DDSM [27]: 97.193% MIAS [28]: 98.137% INbreast [29]: 98.26%
[7] Breast Inception V3, DenseNet121, ResNet50, VGG16, MobileNet V2 with modified U-net segmentation	DDSM [27]: Inception V3 + MSU :98.87% MIAS [28]: Inception V3 + MSU: 96.87%

[8] Breast CNN architecture of VGG-16 and ResNet-50 and hybrid of both is used initially for patch classification using ROI annotations. Patch classifier weights are the used for initialization of whole image classifier.	CBIS-DDSM[30]: AUC-0.91,sensitivity-86.1%,specificity- 80% INbreast [29]: AUC-0.98, sensitivity-86.7% specificity- 96.1%
[9] Breast Patch extraction +(AlexNet and GoogleNet) for classification	ACC: AlexNet, GoogleNet DDSM [27] :100%, 98.46% INbreast [29]: 100%, 88.24% MIAS [28] 98.53%, 91.58% Data from Egypt National Cancer Institute:97.89%, 88.24
[11] Breast Customized residual network of 152 layers with 13 residual blocks inspired from ResNet50.	BreaKHis [31]:Acc-92.52% F1-score-93.45%
[13] Brain At stage-1 two channel CNN to classify healthy and Glioma samples. At stage-2 RCNN is used to classify Glioma samples into Meningioma and Pituitary.	Dataset from two leading hospitals andKaggle: Stage-1. Acc-98.21% Stage-2. VAL_Acc-100%
[14] Brain GoogleNet for deep feature extraction and classification using SVM, KNN, Dense layers of CNN.	Figshare [32]: Deep CNN 92.3% Deep features + SVM : 97.8% Deep features + KNN :98.0%

[15] Brain Hybrid CNN-SVM with threshold segmentation	BRATS2015 [33]: 98.495%
[16] Brain MobileNetV2 ,VGG19, InceptionV3 based classification	Kaggle dataset [34]: MobileNetV2: 92.00 % VGG19: 88.22 % InceptionV3: 91.00%
[17] Brain 18 layers architecture for classification. Performance is evaluated on cropped, uncropped and segmented dataset	Figshare [32]: Cropped dataset: 98.93% Uncropped: 99% Segmented: 97.62%
[18] Brain Two stage classification model is proposed. Segmentation of MRIs (pre-processed using median filtering) is performed using CNN and GoogleNet transfer learned model is used for classification	ACC: Segmentation, Classification BRATS2018[35]:96:50%,96.49%, BRATS2019[36]: 97:50 %, 97:31% BRATS2020 [37]98%, 98:79 %
[19] Brain Fuzzy deformable fusion model for segmentation + LBP feature extraction, Statistical features+ Binary classification of brain MRIs using CNN	BRATS [38]:95.3% SimBRATS:96.3%
[21] Skin Deep CNN with pre-processing	HAM10000[39]: 93.16%

[22] Skin 81 features extracted and classified using CNN using SMTP as loss function.	Melanoma dataset [40]: For Stage 1,2,3: 96% For Stage 1,2 :92%
[23] Skin Transfer learning and fine tuning of EfficientNets variants B0-B7.	HAM10000[39]:87.9% Max accuracy with EfficientNet B4

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