# A Survey on Role of Deep Learning in Medical Image Classification

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***Abstract*—Cancer is a disease by which cells in parts of body start growing without any control and spread over the body. Cancer is a very dangerous disease in the world. Nowadays the death rate increases due to the cancer. If the cancer is diagnosed at its earliest stage, there is a chance for a cure. There are lot of approaches to diagnosing cancer such as physical examination, laboratory test, imaging test and biopsy. The manual process of finding the existence of cancer is quite time consuming and tedious. To assist the physician in the diagnosis, effective CAD (Computer Aided Diagnosis) based tools have been developed for early diagnosis and treatment. Deep Learning has produced algorithms capable of diagnosing the disease at an earlier stage with more accuracy. In this work, different deep learning models deployed for specific four kinds of cancer classifications viz., Brain tumor, Breast cancer, Cervical cancer and Lung cancer have been surveyed. This work shows that even though the number of researches and publications are increasing in the medical analysis, most of the place is occupied by Convolution Neural Network (CNN).***

***Indexed Terms*— CNN. Deep Learning, Medical Image, Transfer Learning.**

## I. INTRODUCTION

Image processing and computer vision have assisted the diagnosing process of various diseases. Second opinion can be provided through the image processing. Among all the dangerous diseases, cancer is the most significant one due to its fatal nature. The prior detection of cancer is highly necessary for the effective and timely treatment of a patient. In recent years, Deep Learning makes a revolution in computer vision field. The deep learning method mimics the human neural network. This survey focuses on current research progress of deep learning techniques for medical image classification in the context of four different cancers viz., brain tumor, breast cancer, cervical cancer and lung cancer.

## II. BRAIN TUMOR

The most significant organ in our body is brain which controls the functions of all the parts of the human body. It is a collection of billions of cells. Some external factors result in uncontrollable growth of cells that causes tumor. Brain tumors are broadly classified into Benign tumors and malignant tumors. Benign tumors are not the cancerous cells and are less harmful as they do not spread across the other cells. But malignant tumors are cancerous, harmful and spread rapidly across other cells and tissues which leads to death.

To avoid the death or to increase the life span of the patient, the early prediction of the tumor is more important. Magnetic resonance (MR) imaging plays a vital role to determine the presence of a tumor. With the help of computational intelligence and deep learning techniques, finding of tumors in the early stage is possible. Some of the important works done in the prediction of brain tumor with the help of deep learning techniques are discussed below.

In the work of A. Ari et al. [1], tumor was classified as benign or malignant by using ELM-LRF (Extreme Learning Machine Local Receptive Fields) and achieved 97.18% accuracy, 96.80% Sensitivity and 97.12% Specificity. Automatic brain tumor system

[2] was proposed to classify the brain tumor using CNN with deeper architecture and small kernel. This model classified the images into two classes namely tumor and non tumor based on the probability score and achieved 97.5% accuracy with low complexity.

In DNN with DWT[3] model, brain MRI images of malignant brain tumors were classified into 3 types viz., glioblastoma, sarcoma and metastatic bronchogenic carcinoma by combining Discrete Wavelet Transform (DWT) for feature extraction and Deep Neural Network (DNN) for classification. This model is similar to CNN architecture but it needs less hardware resources and less time to process large size of images.

Random Forest (RF) classifier[4] was applied for classifying MRI images into three sub tumoral sections such as complete, enhancing and non-enhancing tumor. This model segments the tumor and extracts the following features viz., Gabor wavelet, HOG, LBP and SFTA. Features are combined and given as input to RF classifier to classify the tumor. With the combination of these features, the model shows improvement in sensitivity, specificity and accuracy.

H. H. Sultan et al. [5] proposed a CNN model to classify the tumor as glioma, meningioma and pituitary tumor. Stochastic Gradient Descent with momentum is applied as optimizer to minimize the loss function. It achieved good performance with the best overall accuracy of 96.13%. A hybrid feature extraction method referred as PCA-NGIST [6] was proposed to extract the most important features and RLEM(Regularized Extreme Learning Machine) classifier was employed to classify the tumor and accuracy of 94.93% was achieved.

VGC19 CNN pre-trained model [7] was fine- tuned by applying blockwise fine-tuning strategy. There are many pre-trained CNN models such as AlexNet, VGC16 and VGC19 among which VGC19 showed better performance [8]. GoogleNet [9] was modified and fine-tuned to extract the features of brain MRI images with tumors and KNN and SVM were applied as classifiers. As a result, KNN got 98% accuracy and SVM got 97.8 % accuracy.

G-ResNet(Global Average Pooling Residual Network)[10] was proposed to perform classification on brain tumor images. The overfitting problem was avoided by using global average pooling layers than flatten layer.

DensNet201 and Inceptionv3 pre-trained models [11] were also applied to extract the features. The extracted features were concatenated and given to softmax classifier. This model produced high accuracy in brain tumor classification.

Small size of data will cause overfitting problem in a model and it affects the performance of the model. Data augmentation, usage of drop out layers are the most common methods to reduce the overfitting[5] [12]. A hybrid architecture of Neural Autoregressive Distribution Estimation(NADE) and a CNN [13] was proposed to eliminate the unnecessary features and to smooth the edge of a brain tumor.

M. I. Sharif et al. [14] proposed a model in which the best features are selected by merging the output of two different techniques namely EKbHFV (Entropy–Kurtosis-based High Feature Values) and MGA (Modified Genetic Algorithm). The selected features were used to classify the brain tumor using multiclass SVM cubic classifier and achieved high accuracy.

A brain tumor classification model has proposed by using CDLLC(Convolutional Dictionary Learning with Local Constraint) [15]. To extract the selective information, multilayer dictionary learning was used with CNN and attained high performance in classification.

Feature map plays an important role in CNN architecture. In the differential deep-CNN architecture model [16], differential operations were employed to derive differential feature map from the original CNN model. This derivation movement resulted in the better performance of the model by attaining high accuracy and complexity reduction in CNN structure.

A hybrid model [17] was proposed by combining Fine-tuned Google-Net model with SVM to recognize and classify the tumor categories such as meningioma, pituitary tumour, glioma and not a tumour. This model outperformed the standing models by achieving high performance in terms of recall, precision, and accuracy. RNGAP [18] was proposed by integrating pre-trained ResNet-50 and global average pooling which minimizes the computation time. SGDM optimizer was employed to attain fast convergence.

To design the optimal CNN architectures for increasing the performance, different approaches were applied to robotically obtain CNN architectures, which achieved good results. In order to optimize CNN hyper-parameters, a variety of meta-heuristic algorithms such as FGSA, harmonic search, firefly algorithm and whale optimization algorithm are used. Here, firefly algorithm was modified and named as mFA(modified Firefly Algorithm) which optimized robotically the hyperparameters' values of the CNN architecture which were hired for image classification process. This model achieved higher accuracy than other methods [19]. From the above-mentioned detailed analysis, it can be concluded that fine-tuning and transfer learning with the help of hybrid model in deep learning have achieved good performance.

Some of deep learning models for classification of brain tumor and their performance are outlined in Table 1 and Figure 1.

Table 1. Comparison of deep learning models for brain tumor classification.

| S.No | Model | Dataset | Accuracy (%) |
|---|---|---|---|
| | ELM-LRF based tumor classification | BRATS 2013 dataset. | 97.18 |
| | CNN | BRATS 2015 | 97.50 |
| | DNN+DWT | | 96.97 |
| | Random Forest+ Feature Fusion | BRATS 2012-BRATS 2015 | 95.00 |
| | CNN | MRI | 97.54 |
| | PCA-NGIST+RELM classifier | MRI | 94.93 |
| | Pre-trained VGC19 | CE-MRI | 94.82 |
| | GoogLeNet + SVM<br>GoogLeNe + KNN | MRI | 97.80<br>98.00 |
| | G-ResNet | MRI | 95.00 |
| | Inception-v3<br>DensNet201 | 3064 T1-weighted contrast MR images | 99.34<br>99.51 |
| | GAN + ConvNet | MRI | 95.60 |
| | CNN+ NADE | MRI | 95.00 |
| | (EKbHFV+MGA) +DenseNet201 | MRI | 99.90 |
| | CDLLC | REMBRANDT | 97.55 |
| | Differential Deep CNN | MRI | 99.25 |
| | Google-Net +SVM<br>Google-Net+Fine Tuning | MRI | 98.10<br>93.10 |
| | RNGAP (ResNet-50 +GAP) | MRI | 97.48 |

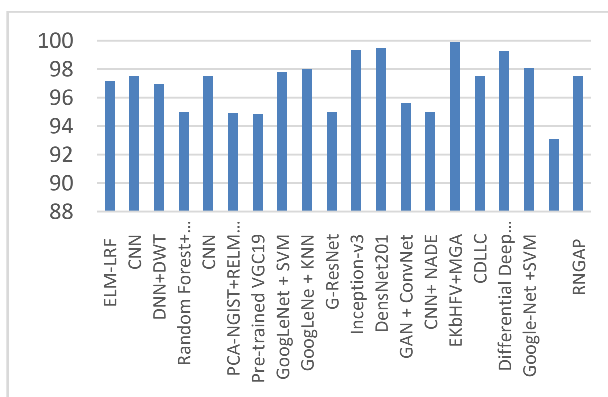


Fig.1. Performance analysis ofdifferent model for brain tumor classification

## III. BREAST CANCER

Breast cancer is most dangerous and primary diseases which causes women's death. It may be classified into two types: benign, and malignant tumors. malignant cells are very dangerous due to their asymmetrical growth in the body. There were lot of research work in the classification of benign, and malignant tumors using different deep learning models.A CNN model [20] was proposed to extract the features from the breast cancer histopathology images and classify into benign and malignant tumor image class. The performance of this model has been measured in terms of accuracy and its accuracy is 90%.

Inception was compared with ResNet models using transfer learning strategy to classify the Histopathological Images of Breast cancer (BreaKHis) as benign and malignant type. This comparison gave a conclusion that ResNet models were more reliable and sensitive than Inception model [21]-[22].

One more popular CNN model is VGCNet 16 which is compared with ResNet50 using IRMA dataset to classify the tumor as normal tumor and abnormal tumor. It concluded that VGC16 outperformed the ResNet50 in the performance metrics of Accuracy, Recall and Precision [23].

The ensemble method for feature extraction leads the improvement in terms of accuracy. A CNN model with softmax activation [24] provides a vector of probabilities for each sample. It gives different accuracy in different iteration. So, 10 different predictive models were used to create the probabilities for the testing data. Then the data were summed and the maximum value among them was taken and given to the class as output. This model provided an accuracy in the range of 96.15% to 98.33% for the binary classification.

The researchers have not only compared the CNN models, but have also performed the comparison on supervised learning and unsupervised learning. In a work by D. Selvathi et al. [25], CNN was compared with Sparse Auto Encoder (SAE) and stacked sparse autoencoder which are unsupervised learning techniques. In this comparison, the author concluded that stacked sparse autoencoder outperformed the remaining two techniques.

Even though CNN model solves various problem in medical image analysis, it has some negative impact due to the class-imbalanced data. This problem was addressed by using oversampling and under-sampling approaches[26]. Among these two approaches, the oversampling algorithm SMOTE (Synthetic Minority Over-sampling Technique) produced high sensitivity, Over-sampling with Replacement resulted in high accuracy and specificity. The author concluded that synthetic based oversampling is a good approach to address the problem of class imbalance in histopathological image classification.

DenseNet is one of the fine-tuned CNN models [27] and has the benefit of feature concatenation which helps to learn features without compression. This model processes these features. It eliminates the overfitting problem and reduces the training process. This model outperforms the existing methods.

GoogLeNet, VGGNet, and ResNet have been selected for transfer learning [28] to extract generic features. The output of each network was combined and given to the fully connected layer to classify the malignant and benign cells by applying average pooling. This model provides an average accuracy of 97.67%.

BHCNet [29] is a novel CNN model with a small SE-ResNet for reducing the training parameters and Gauss error scheduler to set the learning rate automatically. The learning parameters were reduced to 33.3% by small SE-ResNet. It attained an accuracy between 98.87% and 99.34%.

Stacked Generalized Ensemble algorithm [30] was proposed to classify the images into benign and malignant tumors which outperformed on different deep learning classifiers. SGE model used the best prediction learnt by different models such as CNN, DA, VGG16, VGG19, Xception (ReLu) and Xception (Elu).Z. Hameed et al., proposed a model in whichVGC16 and VGC19 models were fine-tuned

[31] and ensembled to classify the histopathology images of breast cancer as non-carcinoma and carcinoma. It provides good accuracy than the fully trained VGC16 and VGC19 model.

In a model developed by Y. Yari et al., ResNet and DenseNet were fine-tuned [32] by replacing the fully connected layer with a new layer. In the new layer, weights are transferred and fine-tuned. It is performed by training and backpropagation on the resnet50 and DenseNet121. By using this model, 100% accuracy was obtained in binary classification and 98% accuracy was obtained in multi class classification.

OMLTS-DLCN [33] model comprises a CapsNet for feature extraction and Back-Propagation Neural Network (BPNN) to classify the mammogram images for finding the presence of breast cancer. It achieved 98.50% accuracy.

A novel deep learning model was proposed to improve the classification results on the MIAS dataset via pre-trained CNN models such as Inception-V2, Inception V3, VGC-16, VGC-19, ResNet50 and Inception-V2 ResNet. The fine-tuning and freezing strategies were applied to improve the mass-lesion classification accuracy. Among these models, VGC-16 achieved highest accuracy [34].

In a work by K. Jabeen et al., Pre-trained DarkNet-53 model [35] with output layer modification was proposed by applying transfer learning accompanying with global average pooling layer for features extraction. Reformed Gray Wolf (RGW) and Reformed Differential Evaluation (RDE) optimization algorithms were used to pick up the most important features. The nominated features were fused with this model and this model classified tumor into three classes namely Normal, Benign and Malignant with 99.1% accuracy.

A comparative study was done by V. Allugunti [36] among Convolutional Neural Network (CNN), the Support Vector Machine (SVM), and Random Forest classifiers with mammography pictures and found that CNN achieved the best accuracy of 99.67%.

EDLCDS-BCDC technique [37] employed three well-known deep learning models of SqueezeNet, VGG-16 and VGG-19 for feature extraction. The generated feature vectors were given to MLP classifier to assign right class labels. The EDLCDS-BCDC technique produced the highest accuracy of 97.09%. Table 2 and Figure 2. shows the performance level of different models in terms of accuracy.

Table 2. Comparison of deep learning models for Breast Cancer classification.

| S.No | Model | Accuracy(%) |
|---|---|---|
| | CNN | 90.00 |
| | Inception<br>ResNet | 94.10<br>98.40 |
| | VGG16<br>ResNet50 | 94.00<br>91.70 |
| | CNN | 96.15 to 98.33 |
| | CNN<br>Sparse autoencoder<br>Stacked sparse autoencoder | 97.00<br>98.50<br>98.90 |
| | DenseNet | 96.00 |
| | GoogLeNet, VGGNet, and ResNet | 97.67 |
| | BHCNet + SE ResNet+ Gauss error scheduler (learning rate scheduler) | 98.87 to 99.34 |
| | SGE(Logistic) | 97.53 |
| | Fine- tuned ResNet and DenseNet | 100.00(Binary classification)<br>98.00(Multi class classification) |
| | OMLTS-DLCN | 98.50 |
| | Inception V3, ResNet50, VGG19, VGG16, and Inception-V2 ResNet | 98.96(VGC-16) |

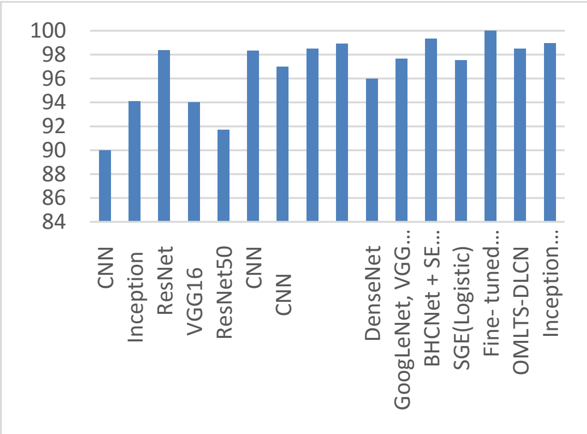


Fig.2. Performance analysis ofdifferent model for brain tumor classification

## IV. CERVICAL CANCER

Cervical cancer is the most common cancer in women. Human Papilloma Virus (HPV) makes an abnormal growth of cells in cervix region which leads to Cervical cancer. It is a curable disease only when it is identified at an early stage. There were many attempts to use deep learning algorithms for classification in the early prediction of cervical cancer. Some of the significant works in cervical cancer prediction using deep learning are given below.

A DCNN model [38] was proposed based on AlexNet which is easily trainable and optimizable. Before doing classification, data preprocessing was done such as re-sizing the images and data augmentation. The pre-trained model was fine-tuned with original image data set and augmented data set. The model with original image data set provided 89.48 accuracy and the model with augmented data set provided 93.33% accuracy.

A schematic CNN [39] was proposed and experimented with different learning rate, batch size and momentum on the data set. It achieved 100% accuracy in the classification of VIA negative and VIA positive areas.LeNet architecture of convolutional neural network [40] was proposed and achieved an accuracy of 83% in cervical cancer classification.

CervixNet methodology [41] classified the cervical cancer data set by employing different technologies in different stages such as flat field correction and image intensity adjustment technique for image enhancement, Mask R-CNN for segmentation of RoI and Hierarchical Convolutional Mixture of Experts algorithm.

The major issue of machine learning algorithm is dimensionality reduction. It was eliminated by stacked encoder model [42] which is deep learning approach. A reduced dimension dataset was prepared by applying stacked encoder to the raw dataset. By applying softmax classifier, this model achieved 97.8% accuracy.

A fully-automated deep learning pipeline [43] was proposed to uncover the cervix regions and classify the cervical tumors. This model pipelined the components such as Cervix recognition, cervical RoI abstraction, RoI pre-processing, Augmentation, Automatic feature extraction and classification of cervical tumors. This model showed its benefits such as speed in the detection of cervix region and classification of cervix region.

An automatic CAD cervical smear image classification system [44] was proposed based on PsiNet-TAP(adaptive pruning deep transfer learning) to classify the cervical cell images. This model engaged the regularization of loss function to avoid the over fitting and gave excellent performance in classification.

## V. LUNG CANCER

Lung Cancer is a complicated health issue with a high death rate in recent years. The detection of cancer is most important and easy to identify using image processing with deep learning. The following portion depicts the different works on lung cancer classification using deep learning algorithms.

Multi path VGC-like network [45] was proposed to classify the lung modules. Before classification, segmentation was done using U-Net architecture. This model used VGC-16 and fully convoluted layer for classification. It employed SoftMax as classifier. It achieved an accuracy of 95.66 %.

A MixNet (Mixed Link Network) [46] was designed to work on 3D lung CT scan images to classify the malignancy of nodules. The proposed model combined two deep 3D faster R-CNN and U-Net encoder-decoder to learn the feature of lung nodule. After learning the nodules, Gradient Boosting Machine (GBM) with MixNet was used to classify the nodules. It was evaluated in terms of specificity, sensitivity and area under the Receiver Operating Curve (ROC) and achieved the values of 94%, 90% and 0.90 respectively.

Noise signals in image capturing process will reduce the quality of cancer image and leads to wrong prediction. To avoid this, pre-processing is activated with the key parts as denoising, resampling and image upgrade [47]. The weighted mean histogram equalization approach was used to remove the noise in the image. Profuse clustering technique was applied for segmenting the affected region and instantaneously trained neural network was employed for the prediction of lung cancer. This model achieved 98.42 % of classification accuracy.

Optimal Deep Neural Network was developed and Modified Gravitational Search Algorithm was applied for optimization [48]. This model was applied to CT images for classification and got the accuracy, sensitivity and specificity of 94.56%, 96.2% and 94.2% respectively.A deep neural network [49] was proposed with adaptive boosting algorithm to classify the lung images into normal or malignant. This model achieved 90.85% accuracy.

A novel FPSOCNN [50] was proposed to classify benign and malignant pulmonary nodules. In this model, different feature extraction methods have been applied to extract multiple features such as intensity, geometric, texture and volumetric. Fuzzy Particle Swarm Optimization (FPSO) was applied to select the features and the selected features were given to the proposed classifier. The FPSOCNN achieved 94.97%, 96.68% and 95.89% of Average Accuracy, Average Sensitivity and Average Specificity respectively.

AlexNet with softmax classifier model [51] was proposed to classify the lung images into normal and abnormal image. This model has achieved 99.52% accuracy in classification. Wilcoxon Signed Generative Deep Learning (WS-GDL) method[52] was proposed to detect the lung cancer. The redundant and irrelevant attributes were eliminated and Generative Deep Learning method was applied to learn deep features and predict the disease. This method was evaluated in terms of time complexity, space complexity, disease diagnostic accuracy, and false-positive rate and achieved better results.

D. M. Ibrahim et al. [53] proposed four architectures namely VGG19-CNN, ResNet152V2, ResNet152V2 with Gated Recurrent Unit (GRU), and ResNet152V2 with Bidirectional GRU (Bi-GRU) to classify the chest image into four class such as COVID-19, pneumonia, lung cancer, and normal images. Among these four, VGC19 with CNN outperformed the remaining three models in the performance metrics of accuracy, recall, specificity, precision, negative predictive value (NPV), F1 score, Area Under the Curve (AUC), Matthew's Correlation Coefficient (MCC), with 98.05%, 98.05%, 99.5%, 98.43%, 99.3%, 98.24%, 99.66% and 97.7% using CT images and X-ray. The Analysed models' performance is illustrated in Table 3 and Figure 3.

Table 3. Accuracy level of different Classification model in Lung Cancer.

| S.No | Model | Accuracy |
|---|---|---|
| | VGC 16+ Softmax U-NET for Segmentation | 95.66 |
| | AlexNet + SVM | 98.42 |
| | Optimal Deep Neural Network | 94.56 |
| | Deep Neural Network | 90.85 |
| | FPSOCNN | 94.97 |
| | AlexNet | 99.52 |
| | VGC19+CNN | 98.05 |

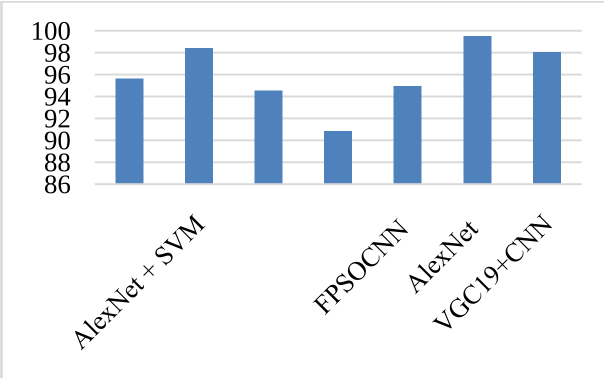


Fig.3. Performance analysis ofdifferent model for Lung cancer classification

## CONCLUSION

This paper surveyed existing deep learning models in the field of cancer detection from medical images. The reviewed papers have been selected from academic journals and conferences which were published from 2019 to 2021. This study provides clear vision into the existing work on Brain Tumor, Breast Cancer, Cervical Cancer and Lung cancer using Deep learning techniques. This paper outlined the topical achievement in the classification of the disease using image data set. Several pretrained CNN models were analysed in this study. It is concluded that the ensemble method plays a vital role in feature extraction to improve the accuracy and Data Augmentation contributes more in the terms of accuracy improvement. Moreover, Transfer learning beats all these by reducing the learning time, with high accuracy. Through this survey, the researchers will know the impact of noise in dataset and methods to remove the noise in data during the pre-processing and the impact of optimization in the positive way of performance improvement. It is also concluded that AlexNet , ResNet, GoogleNet and DensNet are having prominent place in the image classification process.

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