The Use of Deep Learning in Biomedical Imaging with Applications to Brain Tumor Classification and Diagnosis for COVID-19

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ABSTRACT

The use of deep learning models in medical imaging has the potential to improve the accuracy, speed, and reliability of medical image analysis, and ultimately, to help doctors make more informed decisions about medical diagnoses. Many deep learning (DL) models, such as convolutional neural networks (CNNs), have been applied to a variety of medical imaging tasks in the literature, including the classification of brain tumors from magnetic resonance imaging (MRI) data and the detection of disease infection from chest X-ray and chest computed tomography (CT) scan data [1]. MRI, X-ray, and CT are medical imaging technologies that use different techniques to produce detailed images of the inside of the body. MRI uses a strong magnetic field and radio waves to create detailed images of the body's organs and tissues, while X-ray uses a small amount of ionizing radiation to produce images of the body's bones and other dense structures. CT uses X-rays and computer processing to produce detailed cross-sectional images of the body.

In this study, main architecture of deep learning, transfer learning will be explored and various examples of deep learning applications in biomedical imaging will be investigated. These applications include brain tumor classification and covid-19 diagnosing using CNN-based methods for MRI, CT, and X-ray data by covering the main idea of machine learning and biomedical imagining technologies. The deep learning models that developed for using classification and segmentation tasks on covid-19 diagnosis will investigated. As an example, CNN model will be trained on datasets of MRI scans to classify brain tumors in new MRI scans. Similarly, transfer learning will be applied on MRI dataset. Also, brain tumor classification example will be implemented using "TensorFlow" and "Keras" in "Python".

Keywords: Computer-Aided diagnosis in medical imaging, CNN applications, Transfer learning, Tumor classification, Covid-19 diagnosis

1. INTRODUCTION

In Accurate disease diagnosis frequently depends heavily on image acquisition and interpretation systems [1]. Recent advancements in image acquisition and reconstruction technology, such as those found in computed tomography (CT) and magnetic resonance imaging (MRI) scanners, enable the collection of higher resolution medical images. On the other hand, medical image interpretation is a critical component of diagnosis and the development of novel therapies for researchers, doctors. Medical image analysis requires diligence and expertise to extract useful information from large amounts of data [2]. In order to diagnose and develop treatment procedures more quickly, experts use automated analysis techniques integrated with computer models and from the late 1990s, machine learning models have been utilized for automated analysis [3].

The idea of machine learning models are gather data, look for patterns, and then use that information to forecast or decide respectively. There are three common types of machine learning includes supervised learning, unsupervised learning and reinforcement learning where we will investigate supervised machine learning methods. The supervised machine learning models are trained on a labeled dataset, where dataset has the exact output for train the model. The goal of supervised learning is to build a model that can make predictions about new, unseen data based on the patterns it learned from the training labeled data.

Deep learning is a type of machine learning model that is neural network with huge amount of layer. Deep learning models are one of the underlying models of many new technologies that includes self-driving cars, chat bots and it has many application area such as natural language processing, object detection, speech recognition as well as medical imaging [4]. Deep learning models have the ability to learn complex patterns and relationships within medical images, enabling them to accurately identify and classify various structures and abnormalities [1]. The use of deep learning in biomedical imaging has grown in popularity as a result of the expansion of the fields in which these models can be applied and the development of the tools required to train them.. Deep learning algorithms are capable of extracting image features automatically, which makes them more suitable for automated medical image analysis and able to pro- vide accurate diagnoses [5,6,7]. For image processing, deep learning algorithms can be used to train models for automatic identification of objects by analyzing millions of images.

In addition, deep learning models in medical imaging has different tasks such as classification, detection, and segmentations. In this article, all tasks with application to biomedical imaging will be explained and concentrate on classification and segmentation tasks utilizing chest CT scans to determine if patient has covid 19 or not and classification task on brain MRI images to whether a tumor is malignant.

2. DEEP LEARNING ARCHITECTURES

2.1. Artificial Neural Network(ANN)

Artificial neural networks (ANNs) are computing systems inspired by the biological neural networks that constitute animal brains [8]. In human brain, neurons receive electrochemical signals from other neurons and sends signals to other neurons. The signals are processed by each neuron and depending on the interactions with the other neurons. This signal transmission is that make up all our senses, such as vision. By using the similar idea, in artificial neural networks, the perceptron, which is the main element of the network, also known as the artificial neuron, is connected to other perceptron with weight, receiving information from other perceptron to produce the activation of the neuron through a mathematical element known as the activation function.

Neural networks have an input layer, an output layer, and one or more hidden layers in a structure. In deep learning models, number of hidden layers are large. Each perceptron adds up the input values after multiplying them by weights. The weights are modified after the network has been trained. In order to simulate the activation or produce the output of each perceptron, the weighted sum is finally given to the activation function such as sigmoid function, relu function.

In this structure, idea is having such a weight between neurons that fits quite sufficient for output. To decide or get a weight, there is training part of algorithm which is trains to model to have better weights using backpropagation methods such as gradient descent.

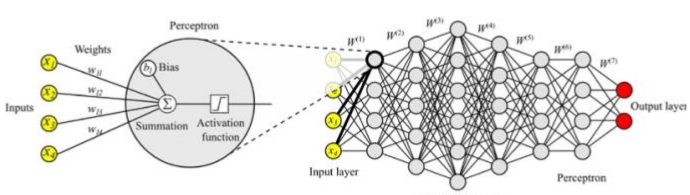

Fig. 1. ANN architecture and perceptron [8].

2.2. Convolutional Neural Network(CNN)

When we consider a small “100x100” pixel image input for ANN with one input layer, one hidden layer with 100 neurons and one output layer then we will need 1000 neurons in input layer and there will be more than million parameters that we need to train. This is huge number of parameters to train. Therefore, we need another architecture for the image inputs due to this problem. In here, CNN handles with this situation [11]. Also, CNN is used for feature extraction from audio, image, matrices so CNN has been used in other applications such as natural language processing.
General model of CNN consists of convolutional layer, pooling layer, and fully connected layer [4].

Convolutional Layer. These layers apply a series of filters to the input data called convolution operation, which allows the network to extract key features of an input data. The convolution operation is a linear operation that computes the dot product of a set of weights (filter or kernel) and receptive fields to produce an output (feature map). The convolutional layer can have more than one filter and can produce more than one feature map [1].

In contrast to a linear neural network, a CNN uses a collection of weights known as a filter or kernel, which is a multidimensional array (2D for grayscale pictures and 3D for color images). Each filter in a CNN stands for a particular feature. It means that, there may be more than one different filters. Each overlapping patch of the filter is smaller than the input data to allow for repetition. The filter moves horizontally to the right by the stride length, beginning at the top left of the input data. The filter restarts from the left side of the input data when it reaches the top right corner of the input data, moving vertically downward by the same stride length. Once the entire picture has been covered by the procedure, the feature map is calculated. If there is no left column while moving with stride length, padding can be applied. Padding is a means of increasing the size of the feature map; it adds extra pixels of value zero around the perimeter of the input image and, consequently, each pixel in the image gets a chance to be at the center of the filter. A feature map that is smaller than the input picture is produced as a result of the filter's interaction with the input image.

In this structure, idea is having such a filter that can sufficiently extract features. To decide or get a weight, we train algorithm which is similar to ANN where activation function used. The rectified linear unit (ReLU) is the one of the most popular activation function for CNN [9]

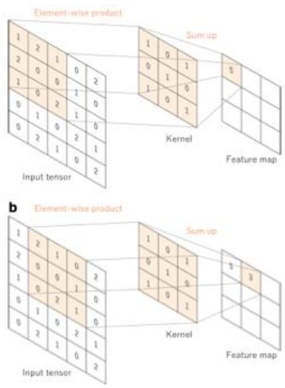

Fig. 2. Illustration of convolution operation on 5x5 image with a kernel size of 3x3, a stride of 1 [10].

Pooling Layer. A pooling layer provides a typical down sampling operation which reduce the number of parameters, computational usage [10]. There is no parameter to train in any of the pooling layers, pooling layer has two option which are max and average. Max pooling extracts patches from the input feature maps, outputs the maximum value in each patch, and discards all the other and the other one is average pooling where simply takes the average of all the elements in each feature map.

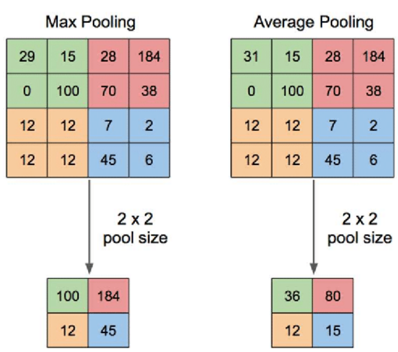

Fig. 3. Illustration of pooling layer.

After convolution and pooling layer, there is dense layer. The last pooling layer's output feature maps are typically flattened, converted into a one-dimensional (1D) array of numbers (or vector), and connected to one or more dense layers, also known as fully connected layers, in which each input and each output are related by a learnable weight. Once the features extracted by the convolution layers and down sampled by the pooling layers are created, they are mapped by a sub- set of fully connected layers to the final outputs of the network, such as the probabilities for each class in classification tasks.

Koala example shown in the figure 4, the first convolutional layer is extracting features such as eye, nose of the koala from the image using more than one filters and then pooling layer applied, smaller matrix of features extracted. The second convolutional layer is extracting more general features of koala using the matrix that comes from pooling layer and then flatten is applied with dense layer to predicted whether is koala image or not.

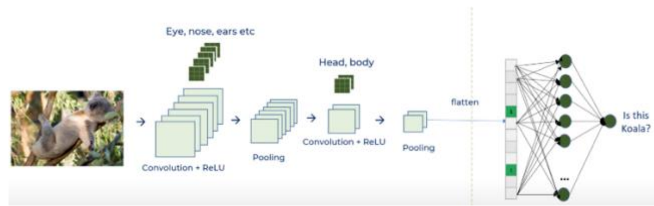

Fig. 4. Example CNN for Koala prediction [11].

2.2. Evaluation of Classification Task

For classification tasks, the performance metrics use the true positive (TP, a model that accurately predicts the positive class), the true negative (TN, a model that accurately predicts the negative class), the false positive (FP, a model that incorrectly predicts the positive class), and the false negative (FN, a model that incorrectly predicts the negative class) approach to calculate accuracy, precision, recall, specificity, and recall [4]. The accuracy refers to the proportion of all correct predictions to the total number of predictions where accuracy will consider as the main metric in this article [4].

$$\boldsymbol{Accuracy} = \frac{(\boldsymbol{TP}+\boldsymbol{TN})}{(\boldsymbol{TP}+\boldsymbol{TN}+\ \boldsymbol{FP}+\boldsymbol{FN})} \quad (\mathbf{1})$$

2.3. Transfer Learning

Due to the expense and required workload of specialists, it is desirable but rarely feasible to have a so much well-labeled data in medical imaging. Transfer learning is a method that can be used to effectively train a model on a smaller dataset [10]. On the other hand, transfer learning has also resolved the hardware challenge of training deep learning models with an extreme number of hidden layers. Transfer learning is a popular and efficient method for training a network on a small dataset. In this method, a network is first pretrained on a very large dataset, such as ImageNet, which contains 1.4 million images with 1000 classes, before being reused and applied to the relevant task [12]. The fundamental assumptions of transfer learning is that general features can be shared across datasets that appear to be very different if they were learned on a large enough sample size. Deep learning has a unique advantage in that it can be applied to a variety of domain tasks with small datasets thanks to the portability of learned generic features. Currently, a large number of models, including AlexNet [13], VGG [14], ResNet

[15], Inception [16], and DenseNet [17], are available to the public and easily accessible, along with their learned kernels and weights. These models were pretrained on the ImageNet challenge dataset. To apply transfer learning into area of application, there is two ways of doing this [10]. The first approach is fully connected layers of trained model can be removed from trained model and new fully connected layers can be added and the new layers would train accordingly. Another approach is applying fine-tuning to all layers of pre-trained model. The second method is more common one.

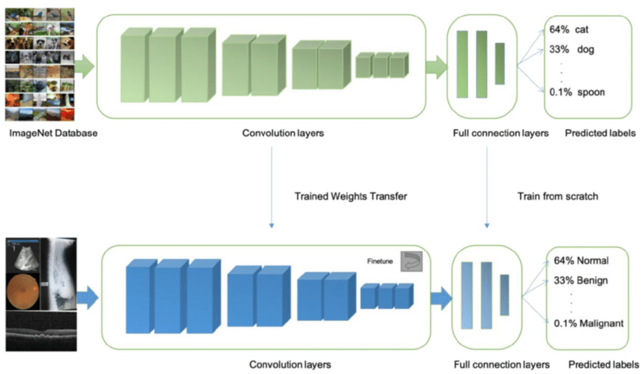

Fig. 5. Illustration of Transfer Learning

3. APPLICATION of DEEP LEARNING in BIOMEDICAL IMAGING

3.1. Deep Learning Tasks in Medical Imaging with Examples

Classification, detection, and segmentation activities are three categories of medical image processing tasks that are often carried out manually by clinicians. Deep learning can be used to do predictive modeling for the diagnosis of disease, such as cancer cells, and to automate laborious medical picture processing.

Classification. Objects are divided into groups or types according to distinct characteristics in classification. In computer-aided diagnosis (CAD), The purpose is to classify distinct characteristics of image according to biomedical images of patient. Applications for classifying MRI, X-ray, and CT images are becoming very popular [21]. The performance of imaging-based classification using recently introduced deep learning, particularly CNN, has been demonstrated in a number of medical applications, including the diagnosis of skin cancer, diabetic retinopathy, and tuberculous [18,19,20]. Also, examples include classifying lung nodules on computed tomography (CT) images as benign or malignant using deep learning which shown in figure 6 [10].

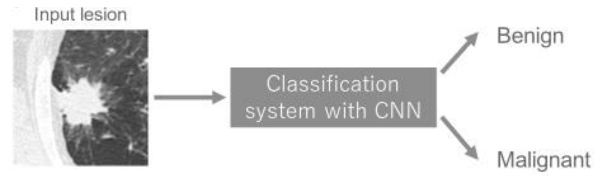

Fig. 6. classification of lung nodules on computed tomography (CT) [10]

The one of the another example for classification of biomedical imaging is brain tumor classification using MRI where we will explore next sections.

Classification models were created utilizing x-ray and computed tomography pictures in the case of covid 19, which has lately rocked the whole world. These models assisted in the identification of the covid 19 condition, which we will explore later.

Segmentation. One of the fundamental image processing technique for medical image analysis, such as the quantitative evaluation of clinical parameters, is the segmentation of organs or anatomical structures (organ volume and shape).Segmentation has many different applications in biomedical imaging that includes skin cancer segmentation, blood vessel of retinal images to screen diabetic retinopathy [22]. Similar to this, skin lesion boundary segmentation using dermoscopy pictures is a critical step in helping doctors distinguish melanoma from other skin cancer types in the disease's early stages by including knowledge such as the lesion's size and contour's shape [23].

As an illustration, the segmentation of brain tumors in MRI images may significantly improve the provision of precise quantitative analysis and diagnosis of ischemic stroke and Alzheimer's diseases [24].

On the other hand, there is many application on tumor segmentation using MRI images in the literature [25-26].

One of the well know model is the U-net architecture for segmentation of images [27]. For example, there is different method that uses U-net for segmentation of covid 19 lesions using CT images [28-29-30].

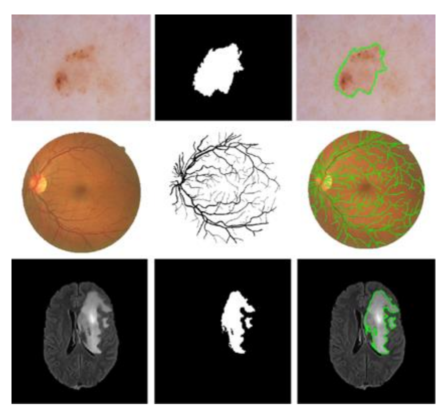

Fig. 7. Example for Segmentation of Biomedical Images [31]

Detection. When examining biomedical imaging, many abnormalities may be seen, and spotting abnormalities is crucial for diagnosis and treatment. Rare abnormalities must be found among many normal cases because they are uncommon. Deep learning models are capable of identifying these anomalies [10]. For example, in a prior study, the effectiveness of 2D-CNN for detecting tuberculosis on chest radiographs was examined. [32]. Detection involves finding the region of objects in an image by drawing bounding boxes.

3.2. Deep Learning in Covid 19 Diognosis

Since its appearance in late 2019, COVID-19, also known as the novel coronavirus, has had a significant impact on the world. There have been significant morbidity and mortality as well as significant disruptions to daily life and the global economy as a result of the global pandemic it has caused. In order to comprehend the virus and create practical strategies for its prevention, diagnosis, and treatment, research on COVID-19 has been urgently needed. The medical community has been looking for alternative or supplementary methods, including screening chest X-ray or Computed Tomography (CT) scans of patients for patterns of pneumonia caused by the COVID-19 infection, due to the lengthy time it takes to obtain the RT-PCR results and the prevalence of false negative results [33]. Therefore, many deep learning-based models developed for detection of Covid-19 using CT and X-ray images.

Both CT and X-ray imaging technologies can be used, however, there is some advantages of using CT. First of all, CT is generally considered to be more sensitive and specific for detecting COVID-19 than x-ray, and it is also able to provide more detailed information about the extent and severity of the disease and CT scan can consists of a variable number of 2-dimensional axial slice images. Therefore, there will be many slices of 2d CT images which means CT is provides more advantages than X-ray. However, there is different developed models based on bot x-ray and CT images.

There are mainly two tasks of deep learning applied for covid-19 which are classification and segmentation.

Segmentation. According to [34], segmentation for covid-19 can be grouped into two group which are lung-region-oriented methods and the lung-lesion-oriented methods. The lung-region-oriented methods aim to separate lung regions, i.e., whole lung and lung lobes in CT or X-ray. The lung-lesion-oriented methods aim to separate lesions (or metal and motion artifacts) in the lung from lung regions.

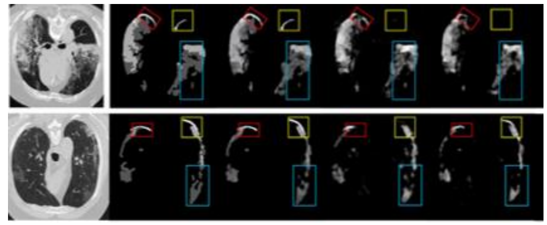

Fig. 7. Illustration of segmentation tasks on covid-19 [35]

For both task, U-net architecture is mainly used architecture which can be seen from the figure 8 where figure shows the different developed deep learning models on segmentation for covid-19.

Literature	Modality	Method	Target ROI	Application	Highlights
Zheng *et al.*	CT	U-Net	Lung	Diagnosis	Weakly-supervised method by pseudo labels
Cao *et al.* |	CT	U-Net	Lung Lesion	Quantification	
Huang *et al.*	CT	U-Net	Lung Lung lobes lesion	Quantification	
Qi *et al.* [54]	CT	U-Net	Lung lobes Lesion	Quantification	
Gozes *et al.* [55]	CT	U-Net/ Commercial Software	Lung Leson	Diagnosis	Combination of 2D and 3D methods
Li *et al.* [56]	CT	U-Net	Lesion	Diagnosis	
Chen *et al.* [57]	CT	UNet++	Lesion	Diagnosis	
Jin *et al.* [58]	CT	UNet++	Lung Lesion	Diagnosis	Joint segmentation and classification
Shan *et al.* [59]	CT	VB-Net	Lung Lung lobes Lung segments Lesion	Quantification	Human-in-the-loop
Tang *et al.* [61]	CT	Commercial Software	Lung Lesion Trachea Bronchus	Quantification	
Shen *et al.* [62]	CT	Threshold-based region growing [63]	Lesion	Quantification	

Fig. 8. Summary of image segmentation methods in covid-19 applications [34].

Classification. For the classification task on covid 19, there are two possible interpretations for the diagnosis of covid 19 on CT and X-ray images. The first one is that there can be two classes that classify the images as covid 19 positive or covid 19 negative. However, It may be necessary to take the other possible pneumonias such as influenza since these pneumonias has so much similarity with covid 19 when chest images considered. Therefore, another approach considers this condition and classify the images as pneumonia or covid 19 positive or covid 19 negative.

For the previous mentioned classification task, numerous different deep learning models have been developed using transfer learning or custom CNN.

The table of these models that was created in the reference article [34] and that was evaluated using the accuracy method which we previously mentioned is shown figure 9.

Literature	Modality	Subjects	Task	Method	Result
Ghoshal *et al.* [73]	X-Ray	70 COVID-19 Others (# of subjects not available)	Classification: COVID-19/ Others	CNN	92.9% (Acc.)
Narin *et al.* [10]	X-Ray	50 COVID-19 50 Normal	Classification: COVID-19/ Normal	ResNet50	98.0% (Acc.)
Zhang et al. [75]	X-Ray	70 COVID-19 1008 Others	Classification: COVID-19/ Others	ResNet	96.0% (Sens.) 70.7% (Spec.) 0.952 (AUC)
Wang *et al.* [12]	X-Ray	45 COVID-19 931 Bac. Pneu. 660 Vir. Pneu. 1203 Normal	Classification: COVID-19/ Bac. Pneu./ Vir. Pneu./ Normal	CNN	83.5% (Acc.)
Chen *et al.* [57]	CT	51 COVID-19 55 Others	Classification: COVID-19/ Others	UNet++	95.2% (Acc.) 100% (Sens.) 93.6% (Spec.)
Zheng *et al.* [51]	CT	313 COVID-19 229 Others	Classification: COVID-19/ Others	U-Net CNN	90.7% (Sens.) 91.1% (Spec.) 0.959 (AUC)
Jin *et al.* [70]	CT	496 COVID-19 1385 Others	Classification: COVID-19/ Others	CNN	94.1% (Sens.) 95.5% (Spec.)
Jin *et al.* [58]	CT	723 COVID-19 413 Others	Classification: COVID-19/ Others	UNet++ CNN	97.4% (Sens.) 92.2% (Spec.)
Wang *et al.* [76]	CT	44 COVID-19 55 Vir. Pneu.	Classification: COVID-19/ Vir. Pneu.	CNN	82.9% (Acc.)
Song *et al.* [71]	CT	88 COVID-19 100 Bac. Pneu. 86 Normal	Classification: COVID-19/ Bac. Pneu./ Normal	ResNet-50	86.0% (Acc.)
Xu *et al.* [77]	CT	219 COVID-19 224 Influ.-A 175 Normal	Classification: COVID-19/ Influ.-A/ Normal	CNN	86.7% (Acc.)
Li *et al.* [56]	CT	468 COVID-19 1551 CAP 1445 Non-pneu.	Classification: COVID-19/ CAP/ Non-pneu.	ResNet-50	90.0% (Sens.) 96.0% (Spec.)
Shi *et al.* [78]	CT	1658 COVID-19 1027 CAP	Classification: COVID-19/CAP	RF	87.9% (Acc.) 90.7% (Sens.) 83.3% (Spec.)
Tang *et al.* [79]	CT	176 COVID-19	Severity assessment	RF	87.5% (Acc.) 93.3% (TPR) 74.5% (TNR)

Bac. Pneu.: Bacterial pneumonia; Vir. Pneu.: Viral pneumonia; Influ.-A: Influenza-A; Non-pneu.: Non- pneumonia

Fig. 9. Summary of studies with classification of CT and X-ray images for covid-19

3.3. Deep Learning in Brain Tumor Classification using MRI

Brain tumors are a diverse group of typical intracranial tumors that are seriously fatal and morbid. With mortality rates of 5.4/100,000 men and 3.6/100,000 women per year reported between 2014 and 2018, malignant brain tumors are among the most aggressive and lethal neoplasms in people of all ages [35]. Brain tumors are divided into four grades (I to IV) of escalating malignancy and deteriorating prognosis, according to the 2021 World Health Organization (WHO) Classification of Tumors of the Central Nervous System.

There are several imaging technologies, such as magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT), which can visualize brain tumors. MRI provides details about the lesion's position, size, extent, characteristics, relationship to the nearby structures, and associated mass effect. In addition to structural data, MRI can evaluate microstructural characteristics like lesion cellularity, microvascular architecture, and perfusion [36]. Therefore, in many application in the literature, MRI data has been used for tumor classification.

One of the main focuses of tumor classification is the determining is tumor LGG (low grade tumors) or HGG (highly malignant, high-grade glioma). Many CNN models and transfer learning models have been proposed for this classification task in the literature.

The authors in [36] reviewed the list of these studies and some part of the list is as follows:

Author and Year	Classification Tasks	Model Architecture	Validation	Performance	ACC% [1]
2 classes					
Özcan et al. [27] 2021	LGG (grade II) vs. HGG (grade IV)	Custom CNN model	5-fold CV	SEN = 98.0%, SPE = 96.3%, F1 score = 97.0%, AUC = 0.989	97.1
Hao et al. [102] 2021	LGG vs. HGG	Transfer learning with AlexNet	No info shared	AUC = 82.89%	
Tripathi et al. [103] 2021	LGG vs. HGG	Transfer learning with Resnet18	No info shared		95.87
Ge et al. [40] 2020	LGG vs. HGG	Custom CNN model	No info shared	SEN = 84.35%, SPE = 93.65%	90.7
Mzoughi et al. [28] 2020	LGG vs. HGG	Multi-scale 3D CNN	No info shared		96.49
Yang et al. [45] 2018	LGG vs. HGG	Transfer learning with AlexNet, GoogLeNet	5-fold CV	AUC = 0.939	86.7
Zhuge et al. [77] 2020	LGG vs. HGG	Transfer learning with ResNet50	5-fold CV	SEN = 93.5%, SPE = 97.2%	96.3
		3D CNN	5-fold CV	SEN = 94.7%, SPE = 96.8%	97.1
Decuyper et al. [73] 2021	LGG vs. GBM	3D CNN	No info shared	SEN = 90.16%, SPE = 89.80%, AUC = 0.9398	90
He et al. [78] 2021	LGG vs. HGG	Custom CNN model	5-fold CV	TCIA: SEN = 97.14%, SPE = 90.48%, AUC = 0.9349	92.86
				BraTS 2017: SEN = 95.24%, SPE = 92%, AUC = 0.952	94.39
Hamdaoui et al. [104] 2021	LGG vs. HGG	Transfer learning with stacking VGG16, VGG19, MobileNet, InceptionV3, Xception, Inception ResNetV2, DenseNet121	10-fold CV	PRE = 98.67%, F1 score = 98.62%, SEN = 98.33%	98.06
Chikhalikar et al. [105] 2021	LGG vs. HGG	Custom CNN model	No info shared		99.46
Ahmad [106] 2019	LGG vs. HGG	Custom CNN model	No info shared		88

Fig. 10. Overview of studies that focus on CNN-based deep learning methods for brain tumor classification [36]

As can be seen in the table, deep learning models that give many successful predictions have been applied in this area. There are custom CNN models that applied and get high accuracy and there are transfer learning models that uses pre trained models including ResNet50, AlexNet, Densenet. These models may not be used directly because of possibility of crucial mistake, ethical part for AI and the bias part of the models but the models will be serving assistance to experts in the field to classify the tumors.

To have deeper understanding in the application and to have an example of these models, a uncovered CNN model was developed using python and the brain tumor MRI data, which is public in Kaggle which can be found on supplemental document part. In addition, a different model was developed over the same data using resnet50 as a transfer learning example. The code of the models can be found in the web page and the github page of the author which shared in the supplementary part.

CNN Model. CNN model developed on brain tumor classification using Kaggle data. Data consist of 253 raw MRI images which labeled as malignant tumor or benign tumor. All of these images were first read, resized, and changed to 128x128. Then, 80 to 20 percent of data was split into train and test data. After these steps, CNN model started to create.

Convolutional layer added with 32 filters of 4x4 filter size and relu activation function as a first layer. Another Convolutional layer added with 16 filters of 4x4 filter size and relu activation function as a second layer of model. After the second convolutional layer, maximum pooling layer with 2x2 pool size. Added 3 layers again with the same order and parameters: convolutional layer, convolutional layer, max pooling layer. After the sixth layer which is the max pooling layer, flatten performed then fully-connected layer which is dense layer that has one perceptron with sigmoid function added as a output layer. Binary cross entropy has been used as loss and adam optimizer used while training the model.

The architecture of the model shown in the figure 11 as 3d that generated using Keras visualizer [37].

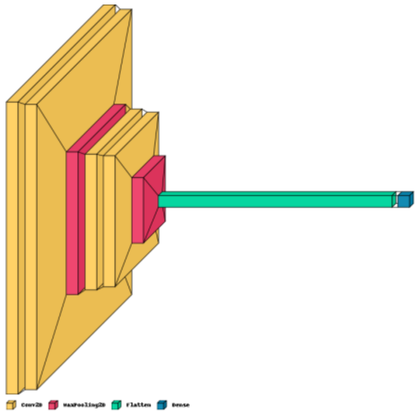

Fig. 11. Architecture of CNN Model

The model trained with the training data. After the training step, model is tested using test data and model is evaluated with accuracy. Accuracy of the model is 78%.

Resnet50. Deep convolutional neural network architecture, Resnet50 is developed by Microsoft researchers created. Resnet50 has 50 layers and convolutional and pooling method is used in each layer of the to extract features from the input data. ResNet50 has been trained on the ImageNet dataset. Resnet50 has different architecture since the network also includes skip connections, which are used to bypass layers and allow the network to learn residual functions.

Transfer Learning with Resnet50. Initial part of the model which uses transfer learning, same as the previous model. However, now, pre-trained resnet50 model is used. As mentioned earlier, there is two ways while using transfer learning where the first one is adding fully-connected layers and the other one is fine tuning. In this example, we have removed the fully-connected layers of resnet50 and added the new fully-connected layers to model and just train the fully-connected layers.

Flatten was applied to the output layer of resnet50 and then the dense layer with 256 neurons was added. Another fully-connected layer with 128 neurons was added to this layer. The activation function of these layers was determined as relu. Then the output layer with the sigmoid activation function was added to the model and the model was completed. Again, bnary cross entropy has been used as loss and adam optimizer used while training the model.

The architecture of the model shown in the figure 12 as 3d where functional part stands for resnet50.

Fig. 12. Architecture of Transfer Learning Model

The new dense layers of the model trained with the training data. After the training step, model is tested using test data and model is evaluated with accuracy. Accuracy of the model is increased to 92%.

Transfer learning with resnet50 model has higher accuracy than CNN model. This result can be expected since we have very small amount of training data.

4. CONCLUSION

In this paper, the application of CNN based deep learning models in biomedical images has been investigated. CNN, transfer learning explained in detail, the application task has been reviewed by considering the biomedical imaging technologies and the applications in the literature. Applications in COVID-19 diagnosing has been reviewed with different biomedical imaging including X-ray and CT on different deep learning tasks including segmentation and classification. Also, CNN model has been developed as an example of the application of CNN in brain tumor classification task.

Data availability. The Kaggle dataset that used in chapter 3.3 can be found through this link: https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection

Code availability. Code of the models that developed as an example of CNN and transfer learning in chapter 3.3 can be found github page of the author: https://github.com/sonurdogan/DL-in-Biomedical-Image-Classification

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