Proceedings of the 5th International Conference on Smart Systems and Inventive Technology (ICSSIT 2023)
IEEE Xplore Part Number: CFP23P17-ART; ISBN: 978-1-6654-7467-2

2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT) | 978-1-6654-7467-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICSSIT55814.2023.10060968

Convolutional Neural Networks (CNN) based Brain Tumor Detection in MRI Images

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***Abstract*— For the purpose of diagnosing brain tumors, Magnetic Resonance Imaging (MRI) is one of the popular diagnostic methods of choice. To determine if a brain tumor has the potential to become malignant, prompt detection plays a crucial role in medical practice. Image categorization is a common task that may be performed quickly and accurately using deep learning. Because deep learning can be used without relying on an expert in the linked subject, it has been extensively used in a variety of industries, including medical imaging. However, in order to achieve effective classification results, a large quantity of different data is necessary. Among the deep learning methods, Convolutional Neural Network (CNN) is indeed the most often used for image categorization. This study has examined two different CNN models to see which one is best suited for classifying brain tumors in MRI images. Ultimately, a CNN model is trained and prediction accuracy has also been increased to as high as 93%.**

Keywords—Convolutional Neural Network, Magnetic Resonance Imaging, Malignant, Medical Practice

I. INTRODUCTION

In 2018, the Indonesian Health Ministry reported that Indonesia has the eighth-highest number of cancer patients in Southeast Asia and the 23rd-highest number of cancer patients in Asia [1]. When it comes to cancer, astrocytoma's are the second greatest killer, behind only breast cancer. Females are statistically more likely to have brain tumors than males. Over the last decade, the prevalence of brain tumors has risen in a number of different nations [2]. Brain tumors may be diagnosed with remarkable accuracy using medical imaging, and this technology also has the potential to detect and prevent the spread of more dangerous disorders. Researchers depend on MRI as a method of imaging brain tumors [3]. Since it doesn't use ionizing radiation, magnetic resonance imaging (MRI) is one of the most popular medical imaging modalities for detecting brain tumors [4].

The identification of brain cancers using Clustering Algorithm and SVM has been the subject of several investigations, including that conducted by Parveen et al. [5]. This work demonstrates the efficacy of employing Fuzzy C-Means to differentiate between healthy brain tissue and areas where tumors are suspected. The Gray Level Run-Length Matrix (GLRLM) is utilized for feature extraction once segmentation has been completed. Finding useful aspects of an image for categorization is what feature extraction is all about. The approach employs the SVM classification technique for its classification purposes. The overall precision of the technique used was 83.33 percent.

Using fluid-attenuated inversion recovery (FLAIR), Avizenna et al. [6]. Researchers in this research recommended dividing MRI scans of brains into two groups: healthy and diseased. This research made use of the 2017 data from the BRATS database. Classifying brain MRIs utilizing logistic regression multinomial models and ridge estimators, and then evaluating them based on sensitivity, specificity, and accuracy with cross-fold validation.

Nonetheless, a human hand is still required for extracting feature extraction in unstructured technique segmented [7]. After that, there are still several challenges to overcome when attempting to segment a brain picture, such as the fact that each patient's brain will have a slightly different size, shape, and position. Scanners come in many shapes and sizes, therefore the pictures in the dataset reflect the wide variety of equipment utilized for the task (Işin A et al., p.

As a solution to the issue of complicated data, this research suggests using the CNN approach. Features may be extracted using CNN without losing any of the data's geographical context. Deep learning CNN is a computational model for handling data in just two dimensions. CNN uses both a classification approach called feedforward and a learning mechanism called backpropagation. [7]. Although CNNs have a user-friendly structure, this comes at a cost in terms of development time and data requirements contrasted to unsupervised methods of learning. This study has compared two distinct CNN models to see which one performed the best in terms of classification accuracy.

II. RELATED WORKS

The purpose of the convolutional neural network (CNN) is to process information in a grid format. In the convolution layer, the matrices of the filter is multiplied by the input picture in a linear algebraic operation called convolution [9]. The convolution layer should be used first since it is the most critical. The pooling layer is another popular choice, since it may be used to calculate the average or maximum value of the image's pixels.

By building a feature map, CNN is able to learn sophisticated features. Wrapping the convolution operation kernel around the input sequence allows for the generation of multiple feature maps. The feature map consists of tiny boxes that represent features that were discovered from the input samples. The maximal collection layer receives these maps and selects the most important characteristics to keep while discarding the rest. In the fully linked layer, the features from the at the very most layer are transformed into a feature vector of a single dimension, which is then utilized to compute the output probability depicts a typical CNN setup.

In the CNN approach, the Convnet is the central layer that performs feature extraction on the input. Convolution is a linear transformation that preserves the spatial integrity of the data it receives as input. So that CNN's convolution kernels can handle the training data, the weight of each layer is used to decide the convolution kernels to use.

Subsampling is a technique used to minimize the amount of data stored for a picture and improve the positional consistency of its features. Max Pooling is a subsampling technique that is used by CNN. Max Pooling works by taking the highest benefit from numerous smaller grids that were generated from the convolution layer's output and then combining them into a single smaller picture matrix. The following convolution layer may be processed more quickly with a smaller picture size.

In order to facilitate linear classification, the Fully Connected Layer transforms the data's dimensions. Each neuron's output is converted to one-dimensional data at the convolution layer and then sent into the next linked layer [11]. At the conclusion of the Connections Between ideas Layer network implementation, data loses its geographical information, causing this process.

To put it simply, a convolution operation is what makes a CNN tick. In it, you'll find a collection of filtrations (or kernel) whose settings will be refined as you go through training. Filters often have a smaller footprint than the final picture. Each filter operates on the picture in a convolved fashion, yielding an activation map.

III. METHODOLOGY

A. Dataset

Brain MRI Data for Medical Image Processing provided from kaggle.com [4] was utilized in this investigation. The collection contains 253 pictures divided into two categories: 155 brain images with tumors as well as 98 brain images without tumors. Figure 1 shows photos from the dataset. MRI scans of the brain may show tissue composition in two ways, depending on which relaxation time is used to depict the material. When creating a T1-weighted picture, the Repetition Time (TR) and Time to Echo (TE) values are quite short, however when creating a T2-weighted image, these values are often much larger. Table 1 provides the millisecond durations for T1- and T2-weighted scanning. Datasets utilized for training and testing in this study include both T1- and T2-weighted images.

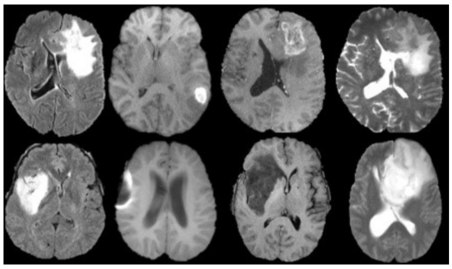

Fig. 1. Dataset Samples

B. Proposed Work

This study uses CNN to identify brain cancers automatically. This research takes raw data photos labeled (yes/no) and utilizes these patterns to discriminate among tissue which do not include tumor and those who do. CNN was trained using 2065 example pictures, 1085 of which had tumors and 980 of which did not. As a result, the suggested systemis shown in Figure 2 of this work.

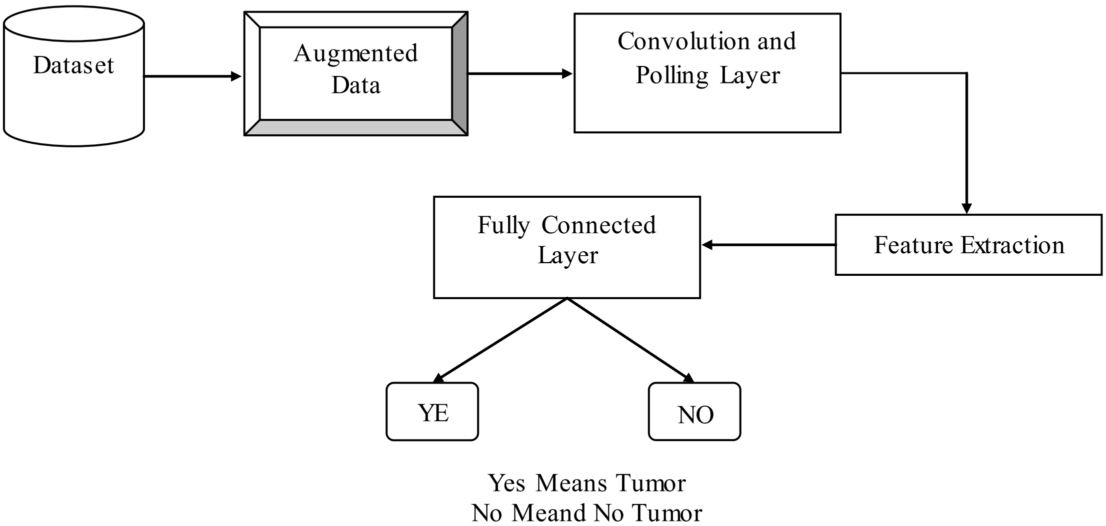

Fig. 2. Proposed Work Block Diagram

C. Augmentation of Data

The dataset has insufficient data to be utilized as training examples for CNN. As a result, the augmentation approach is employed to address the imbalance of concerns. Augmentation is a method that may use statistical data to create an integrated model. This program can generate a variety of two-dimensional pictures in a variety of postures and sizes. The use of augmentation to produce picture variations may increase CNN segmentation accuracy [12]. Each picture with something like a tumor is split into 6 photos in this article, whereas an image without a malignancy is separated into 9 image. Following data augmentation, the database includes 1085 tumor-containing samples (53%) and 980 tumor-free samples (47%), for a total of 2065 images. To boost the training set's variety, these images are derived from the originals with slight geometric alterations (such flipping, translating, rotating, or adding noise) When it comes to getting rid of "salt and pepper" noise, the median filter comes out on top.

D. Image Pre-Processing

Because pictures have distinct variations in intensity, contrast, and size, pre-processing is used to provide smooth training [13-15]. The input picture will indeed be processed in the first pre-process, which is the wrapping and cropping procedure. The input picture is tested against with the perimeter of the primary objects in an image during wrapping. The maximum edge of the picture is chosen such that when the cropping happens, the item in the image stays intact. Because the pictures in the dataset are various sizes, resize the image to form (240, 240, 3) = (image width, image height, number of channels). To help learning, use normalization to scale number of pixels to the range 0-1.

E. CNN Modeling

The Convolutional Neural Network (CNN) model used in this study consists of numerous layers, including a convolution layer, a pooling layer, a flatten layer, a dropout layer, and a dense layer. Through the use of a filter that is slid over the input picture, convolutional layers are able to detect recurring patterns in the image and produce a feature map. Performance of the classifier of the Classification algorithm is decreased because to the use of pooling layers, which down sample the extracted features to introduce invariance. The perceptions in this investigation makes use of rule activation, in additional to the layer employed in the CNN method. Two distinct CNN models were developed for this study. Figure 3 and 4 show the CNN model architecture. A 240x240 pixel picture in the set divided by the number depicting the initial convolution. As many as 32 filters and kernels of size 3x3 with thickness 3 are utilized, with the size of each component determined by the platform of the image data. The model will then carry out the activation and data pooling procedures when the outcomes of the operation have been obtained. As a result of the Pooling layer procedure, the feature map's size might be decreased. Convolution generates a feature map that is fed back into further iterations of the process. After that, a vector-based flatten feature map is used to complete a fully connected layer procedure that ultimately leads to an image categorization. With adaptive learning rates, the training algorithm may keep tabs on how well the model is doing and make necessary adjustments to the learning rate on the go.100 Epoch train time should be 3 minutes is possible.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 240, 240, 3)	0
zero_padding2d (ZeroPadding2	(None, 244, 244, 3)	0
conv0 (Conv2D)	(None, 238, 238, 32)	4736
bn0 (BatchNormalization)	(None, 238, 238, 32)	128
activation (Activation)	(None, 238, 238, 32)	0
max_pool0 (MaxPooling2D)	(None, 59, 59, 32)	0
max_pool1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
fc (Dense)	(None, 1)	6273

Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64

Fig. 3. CNN Model 1

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 7, 7, 512)	14714688
flatten_1 (Flatten)	(None, 25088)	0
dropout_1 (Dropout)	(None, 25088)	0
dense_1 (Dense)	(None, 1)	25089

Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688

Fig. 4. CNN Model 2

IV. EXPERIMENTAL RESULTS

The 2065 photos used in the experiments described in this paper included 1085 samples with tumors and 980 examples without tumors. Further, 70% of something like the data is used for training, 15% for validation, and 15% for testing. Ten separate experiments are conducted on the data, each time utilizing the previously created CNN model and a total of 25 epochs as well as 32 batches. Standard deviations, means (both absolute and relative), accuracy, and the f1 score are then used to compare the findings. The first CNN model employs a single convolution and achieves 76% accuracy and a loss of 0.14181 on the training dataset, while the results on the test set are much worse (76% accuracy and 0.44037 loss, respectively). A second CNN model with 2 convolutions yielded better results, with 96% accuracy on the training data and 0.10046 loss, and 95% accuracy and 0.23264 loss on the test data, respectively. The second model takes longer to train, but its f1 score is 93% higher shows all data values are figure 5 to 6.

To evaluate how well a deep learning algorithm matches the training data, researchers employ a statistic called training loss. In other words, it evaluates the model's error on the data used for training figure 7 and 8. You should know that the model is first trained using a subset of the whole dataset known as the training set. It is possible to compute the training loss by adding up the number of times an example failed during training.

Note that now the trained loss is assessed after each batch has been processed. The training loss is often shown as a curve to illustrate this point.

A. *Classification Report 1*

	precision	recall	f1-score	support
dataset/Normal	0.73	0.58	0.65	19
dataset/Tumor	0.76	0.87	0.81	30
accuracy			0.76	49
macro avg	0.75	0.72	0.73	49
weighted avg	0.75	0.76	0.75	49

Fig. 5. Accuracy Prediction 1

B. *Classification Report 2*

	precision	recall	f1-score	support
0	0.00	0.00	0.00	14
1	0.96	1.00	0.98	305
accuracy			0.96	319
macro avg	0.48	0.50	0.49	319
weighted avg	0.91	0.96	0.93	319

Fig. 6. Accuracy Prediction 2

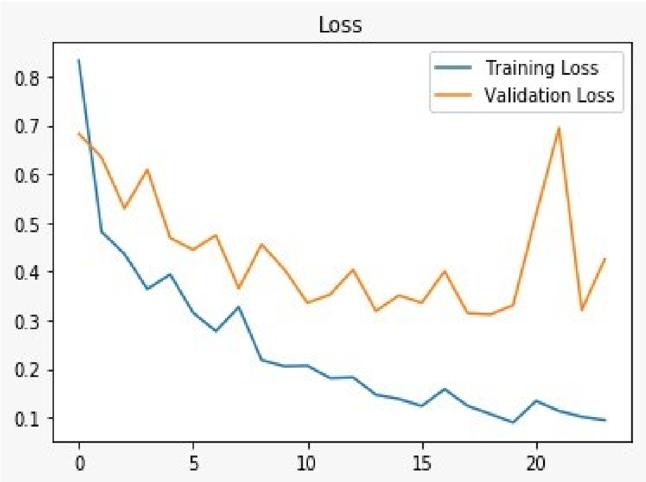

Fig. 7. Train and Test Loss comparison

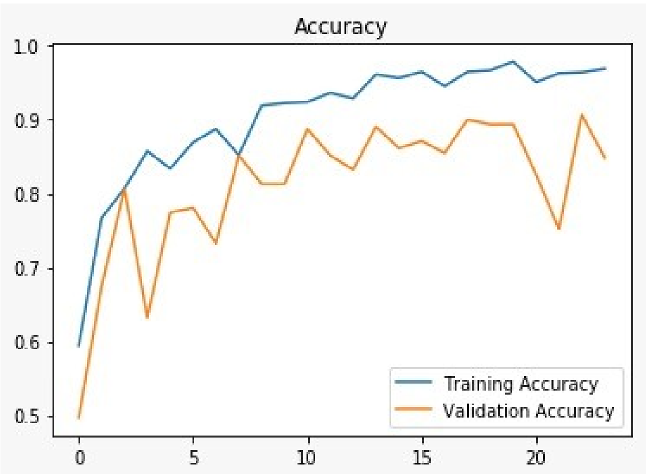

Fig. 8. Train and Test Accuracy comparison

V. CONCLUSION

To detect brain cancers in MRI scans, Convolutional Networks are enough. A 96% accuracy rate and a loss value of 0.23264 were achieved in this investigation. There is a trade-off between accuracy and training time when it comes to the optimal values of convolution layers for a given task. Image augmentation may enhance current dataset variations, leading to better classification results. Additionally, new photos may be utilized to enhance categorization results in future recommendations. Extensive research in the future will allow for the categorization of various tumor forms.

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