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Brain Tumor Classification Using Machine Learning Algorithms

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Abstract: Classifying brain tumors is a crucial and challenging task that is required to identify the most effective treatment plan based on the many types of brain tumors. An individual's health and quality of life can be profoundly impacted by brain tumors. It is imperative that these cancers be promptly and precisely identified. Identification at an early stage is most crucial. A highly preferred diagnostic technique, Magnetic Resonance Imaging (MRI) is characterized by its outstanding picture quality and non-ionizing radiation. In this model, we integrated the CNN-based model with an overall accuracy of around 80-90%.

I. Introduction

When we initially begin our medical careers, picture something like this: an intracranial tumor, or brain tumor, if we want to get fancy [1]. It looks like an overabundance of brain cells that are rapidly multiplying and going insane. The irony is that our immune system, the superhero that guards us most of the time, struggles under these conditions. The reason? It cannot identify precisely what kind of trouble these hyperactive cells are because they share the same ID card as the rest. It's true that our immune system is unable to recognize the intruders, and it seems that these rebellious cells have a special invitation to the body's festivities. A little devious, eh?[13]

The World Health Organization (WHO) divides brain tumors into classes I–IV. On the other hand, class I tumors are the easiest to treat, develop slowly, and cause the least amount of damage [3]. The tumor that poses a threat is Review III. This kind of tumor can usually progress to more advanced stages and is readily pierced. A pituitary tumor may develop from abnormal cells in the pituitary tissues [13]. Although the majority of pituitary tumors are benign, meaning they don't transmit to the other parts of human body, because they are near the brain, they have the same potential to spread like cancer to other parts of the body as well as the central nervous system. It is distinct from the other pituitary tumors discussed above in that a formal classification system is absent [14]. As mentioned before, early detection is critical because these brain tumors have a tendency to spread and grow. quick Furthermore, the categorization phase that comes after discovery could be hard and time consuming for specialists or radiologists [2]. only a few complex instances and is entirely dependent on the shortage of knowledgeable professionals and radiologists, which makes it hard to penetrate developing countries all over the world [21]. Professionals are needed in these situations to locate the tumor, compare its tissues with surrounding zones, if necessary, apply distinctive channels to the image, improve people's eyesight, and ultimately determine whether the mass is indeed a tumor in addition to sorting and reviewing it, if any. In the realm of counterfeit goods, a progressive mechanical innovation might lead to this precise and speedy discovery [24].

New insights that have emerged promise to advance computer vision with image categorization, and image accuracy division. Deep learning might be a branch of machine learning in which a neural network mimics the structure of the human brain and is trained using enormous amounts of data [8]. In the realm of therapeutic image research, these administered, semi- supervised, or unsupervised systems have shown a lot of promise. These systems are divided into several levels, starting with the base layer. The outermost layer is referred toas the yield layer, the innermost layer as the covered-up layers, and the ultimate layer as the input layer. These courses of action of several organize layers are used in profundity learning computations to extract and encode highlights. each successive layer is input and passed through [8]. Two well-known types of neural systems that often used in industry are fake neural systems and convolutional neural systems. These days, CNNs typically used in image classification tasks because they perform decision-making that involves merging channels and input designs, selecting the key elements, and then starting to train the classification scheme's layers [12]. Using the same amplified information set, we presented a comparison study of CNN classification of brain tumors in this publication. We organized and prepared several ANN and CNN models, as well as a number of pre- trained exchange learning (TL) models that were compared and a thorough analysis of how various types of arrangement designs varied from the identical information set used for thefour-class classification problem [20].

II. LITERATURE REVIEW

When deep learning techniques, especially Convolutional Neural Networks (CNN), are integrated, the research into brain tumor categorization advances significantly. This survey of the literature looks at important research that progress this topic. A notable study "Multi-Classification of Brain Tumor Images" (IEEE 2019),[1] by Hossam H. Sultan focuses on enhancing classification accuracy by CNN-Based Classification with Augmentation. The study employs augmentation approaches to multi classify images of brain tumors in order to improve the dataset and CNN model's resilience. [2] Another significant contribution is "Brain Tumor Classification Using Convolutional Neural Networks" by J. Seetha. This paper provides insight into the efficacy of neural network in the processing of medical pictures by investigating its application in the categorization of brain tumors. Furthermore, [3] A The categorization-based method is described in Li Ari "Deep Learning-based Brain Tumor Classification and Detection System" (“Turkish Journal of Electrical Engineering and Computer Sciences 2018”). The paper represents a deep learning-based system for brain tumor diagnosis and classification, adding to the body of techniques to classification. [4] "A Review on Image Processing and Image Segmentation" (IEEE, 2016) by Jiss Kuruvilla, provides a comprehensive analysis of image processing and segmentation techniques. This study provides important insights into the field, laying the groundwork for future improvements in the concepts used in brain tumor image processing. [5] A novel sorting technique based on type-specific features is presented in "Brain Tumor Segmentation Using Deep Learning by Type-Specific Sorting of Images" (Research Gate 2019) by Zahra Sobhaninia et al. The significance of photo sorting for improved brain tumor segmentation accuracy is highlighted in this paper, which highlights the continuous innovation in this emerging field.

III. ARCHITECTURE DIAGRAM

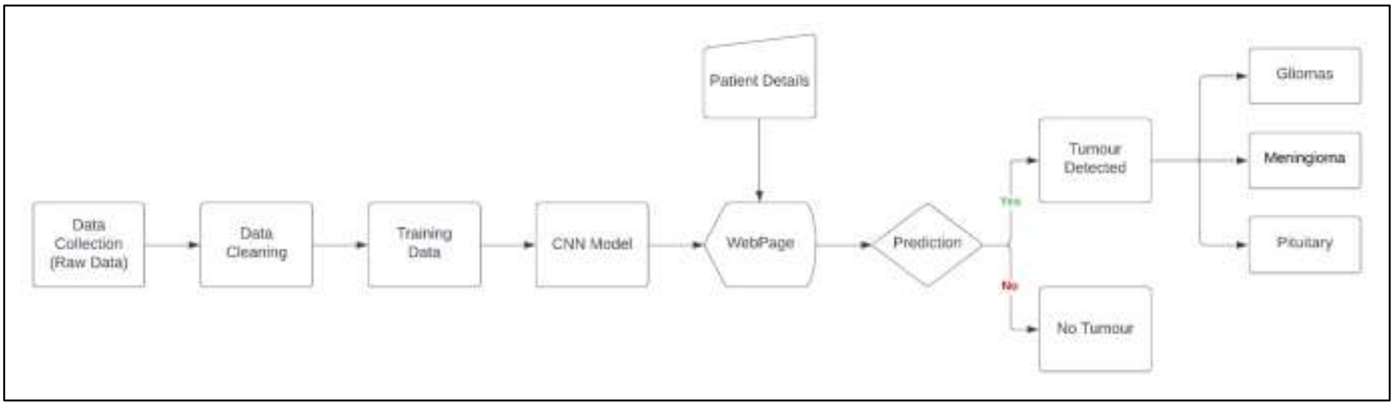

Figure 1 : Block Diagram

DATASET

The goal of preprocessing is to make sure that the data is homogeneous before feeding it to neural networks. Our highresolution photos were first reduced in size to 224x224x3 in order to preserve important details. Regarding MRI images, which included a black backdrop around the main picture of the brain, this background was trimmed around the main contour since it was considered unnecessary for categorization [17]. To efficiently remove undesirable backdrop and some original picture noise, the technique entails locating and labelling the biggest contour, figuring out its extreme points, and cropping the image accordingly. Each image in the dataset undergoes this phase [18]. It's important to note, though, that on sometimes, the cropping and contour mapping method algorithm was unable to identify the right contour, leading to distorted photos. In order to rectify this, these incorrectly cropped photos were manually inspected and removed after augmentation.

Figure 2 : Tumor positions

Type	Training Sample	Testing Sample	Total
Glioma	300	100	400
Meningioma	306	115	421
Exchange rate	11	0.003	0.467
No Tumor	404	105	510
Pituitary	300	75	375

Table 1: Initial Count

1) Training Set Data

Sr. No.	Class	Initial Count	Augmented Count	Discarded Count	Final Count
1	Glioma	826	17346	7100	10246
2	Meningioma	822	17262	7000	15590
3	No Tumor	395	8295	16	14088
4	Pituitary	827	17367	7100	15040

Table 2 : Training Data

2) Testing Set Data

Sr. No.	Class	Initial Count	Augmented Count	Discarded Count	Final Count
1	Glioma	100	2100	0	2015
2	Meningioma	115	2415	65	2350
3	No Tumor	105	2205	100	2105
4	Pituitary	75	1575	5	1570

Table 3 : Testing Data

IV. APPROACH

CNN

Among neural networks, Convolutional Neural Networks (CNNs) are a unique class that exhibit exceptional performance in image categorization [11]. Convolutional, pooling, fully connected (sometimes called dense), and normalization layers are the commonly known hidden layers of a convolutional neural network. After reading the input picture, the Convolution layer applies many filters, initializing them at random as parameters that will be learnt repeatedly during the next backpropagation [16]. In order to create a feature map, these filters are essential for extracting relevant features from the input data.

The spatial characteristics of a picture, such as the arrangement of pixels and their interactions, are best captured by the CNN [6]. The ability to precisely recognize items, locate them, and understand their relationships depends on having this spatial awareness.

Each feature map is then subjected to a pooling layer, which gradually reduces the representation's spatial dimensions [12]. Through the lowering of parameters and computing demands, the network is made more efficient. The network functions in the same way as a conventional ANN after that, producing output at the last layer and causing errors to spread backward through the network.

All in all, CNNs offer a strong foundation for classifying images by efficiently obtaining and using spatial characteristics from the input [11]. The network's capacity to identify subtle patterns and relationships inside pictures is largely down to the complex interplay of convolutional, pooling, & fully connected layer. The network then uses this mistake to modify the weights in order to minimise the error in the epochs that follow.

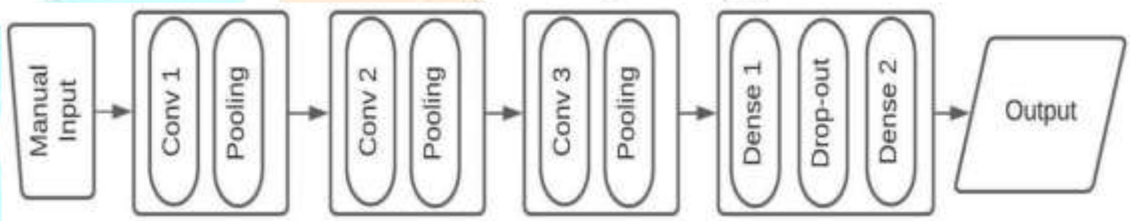

Figure 3 : CNN Architecture

Using our enhanced data set, we created and trained 27 distinct CNN models for this research [12].Our suggested CNN model, 3-convo-128-nodes-1-dense, with a total of 16 layers, is depicted in the figure.

The input layer, which can handle up to 16 224x224x3 pictures in a batch, is where the model starts. Three convolution layers are then implemented, each combined with max-pooling layer and activation function. A carefully placed dropout layer is used to combat overfitting [14]. After that, a fully connected layer with 128 nodes is added, and SoftMax layer for output prediction comes next. The output is determined within one of four projected classes by the final classification layer. The network may be broken down into the following detail: Images with a resolution of 224x224x3 are read by the input layer, which then passes them through one of the three convolution layers. Convolution, activation, and max-pooling components are all included in these convolution layers. First, a sequence of sliding K convolutional filters with size (M) are applied by the convolution layer[8].

An activation layer using the Rectified Linear Unit (RLU) as the chosen activation mechanism comes after each of the three convolution layers. A pooling layer is added after the activation. The neural network's layer structure is influenced by the pooling layer, which may be repeated in a particular model. It continually reduces each feature map's size by the pooling factor while working independently on each feature map to create a new pooled feature map. Each zone is represented by a filter in the context of max pooling, which extracts the maximum value and generates a new output matrix [14]. The result has dimensions of 17x17x128 after the third convolution layer set's final max-pooling.

The fully connected layer in neural networks is accountable for most of parameters. The mutual reliance between overfitting during training is frequently caused by neurons. A dropout layer is added after max to remedy this. Pooling. A portion of the layer outputs is "dropped out," or arbitrarily disregarded, during training. This reduces co- dependency by providing each layer with a different viewpoint during updates. The network is completed with a 128-nodes fully connected layers and a SoftMax activation layer that generates output according to one of four categories. Our best CNN model has the maximum accuracy of 88%, equivalent to a loss of 0.2883 and an F-1 of 0.8825.

CNN Models	Accuracy	Loss	F1 - Score
1-convo-32-nodes-0-dense	0.9467	0.1751	0.9398
2-convo-32-nodes-0-dense	0.9450	0.1473	0.9392
3-convo-32-nodes-0-dense	0.9700	0.0997	0.9655
1-convo-64-nodes-0-dense	0.9483	0.1401	0.9393
2-convo-64-nodes-0-dense	0.9767	0.0922	0.9729
3-convo-64-nodes-0-dense	0.9733	0.0882	0.9691
1-convo-128-nodes-0-dense	0.9417	0.1605	0.9290
2-convo-128-nodes-0-dense	0.9750	0.0925	0.9712
3-convo-128-nodes-0-dense	0.9783	0.0943	0.9750
1-convo-32-nodes-1-dense	0.9517	0.1467	0.9447
2-convo-32-nodes-1-dense	0.9317	0.1829	0.9242
3-convo-32-nodes-1-dense	0.9783	0.0824	0.9150
1-convo-64-nodes-1-dense	0.9567	0.1406	0.9484
2-convo-64-nodes-1-dense	0.9683	0.1071	0.9638
3-convo-64-nodes-1-dense	0.9700	0.0973	0.9656
1-convo-128-nodes-1-dense	0.9667	0.1213	0.9613
2-convo-128-nodes-1-dense	0.9750	0.0865	0.9710
3-convo-128-nodes-1-dense	0.9750	0.1053	0.9713
1-convo-32-nodes-2-dense	0.4283	0.6983	0.5997
2-convo-32-nodes-2-dense	0.9433	0.2445	0.9372
3-convo-32-nodes-2-dense	0.4283	0.6983	0.5997
1-convo-64-nodes-2-dense	0.4283	0.6983	0.5997
2-convo-64-nodes-2-dense	0.4283	0.6983	0.5997
3-convo-64-nodes-2-dense	0.8050	0.4296	0.8078
1-convo-128-nodes-2-dense	0.4283	0.6983	0.5997
2-convo-128-nodes-2-dense	0.4283	0.6983	0.5997
3-convo-128-nodes-2-dense	0.8300	0.4015	0.8253

Table 4 : CNN Models

V. CONCLUSION

In conclusion, the classification of brain tumors using deep learning algorithms represents a significant advancement in medical technology. The application of artificial intelligence (AI), particularly deep learning, has demonstrated promising outcomes in terms of increasing the efficiency and accuracy of tumor categorization using medical imaging data. Brain tumor identification and classification may be greatly automated with the use of deep learning models, such as CNN, recurrent neural networks, and their variations. These algorithms have the ability to precisely analyses complex patterns and characteristics seen in medical pictures, which can help medical practitioners make better judgements.

VI. RESULTS

With a maximum accuracy 88%, a loss of 0.2883, and an F1 score of 0.8825, our best-performing Convolutional Neural Network (CNN) model has demonstrated its performance. Deep learning has advantages for brain tumor classification that go beyond accuracy. Large datasets can be handled by these algorithms, which can also speed up the diagnosis process and perhaps help with early tumor identification. Being able to categorize tumors fast and properly is extremely important in the medical industry, as treatment Plans and results are often determined by the amount of time available. Still, there are obstacles to overcome, such as the addressing these issues will be essential to realizing the full dormant of deep learning ats brain tumor classification.

In conclusion, integration of deep learning algorithms in this model holds promise for revolutionizing the field of medical diagnostics. Continued research, collaboration between medical professionals and AI experts, and advances in technology will help deep learning become more refined and widely applied, increasing the precision and effectiveness of brain tumor categorization.

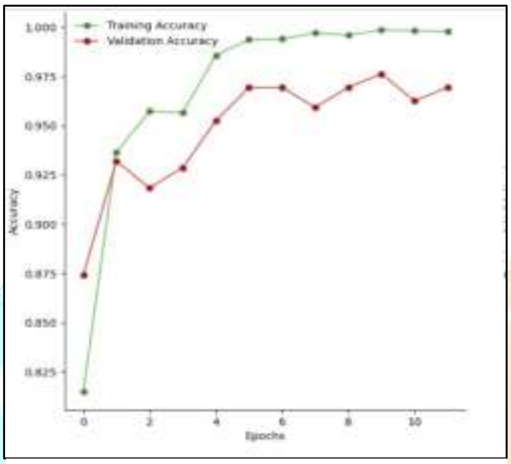

Figure 4 : Accuracy

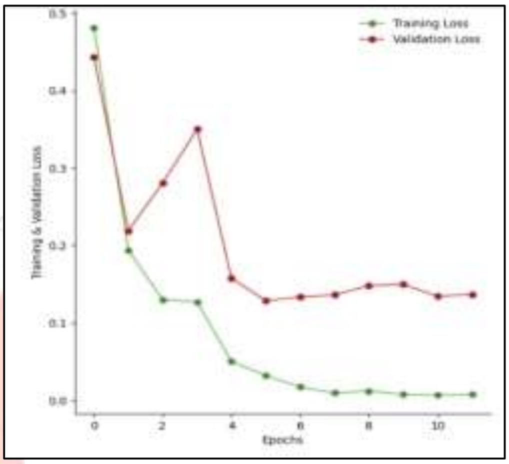

Figure 5 : Loss

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