Classification Of Brain Tumor using Deep Learning CNN

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***Abstract*—Brain tumors are a common and serious illness that, at their most advanced stages, can reduce life expectancy to a few years. Therefore, coming up with a treatment plan is essential to improving patients' quality of life. To assess malignancies in the brain, lungs, liver, breast, and prostate, among other parts of the body, methods including computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are commonly used. Certain forms of brain cancer can be detected with MRI in particular. However, it might be difficult to differentiate between tumor and non-neoplastic regions due to the large amount of data produced by MRI scans, and the lack of images can result in errors. A trustworthy and automated technique for tumor separation is necessary to get around this. Automatically distinguishing between brain tumors is a particularly difficult endeavor, especially when dealing with huge regions and the intricate differences in tumor morphologies.**

Convolutional Neural Networks (CNNs) are used in this study to automatically detect brain tumors. Small, intricate structures can be processed by the network architecture. A brain tumor is a malignant development brought on by aberrant and unchecked cell partition. Medical diagnosis has benefited greatly from developments in deep learning for pictures of medical conditions. This field makes extensive use of machine learning methods, particularly those that employ sight-based learning or image perception (CNNs).

Keywords—Tumor, Deep-learning, CNN.

I. INTRODUCTION

According to the National Brain Tumor Community, approximately 800,000 people in the US have been diagnosed with brain tumors, and estimates indicate that by 2021, this figure may rise to 885,000. Brain tumors continue to be the biggest cause of mortality globally, although they are less common than other cancers like respiratory organ and chest. About 18,020 people lose their lives to brain cancer each year.

A brain tumor has a long-lasting and mental effect on a person's well-being. Brain function is affected by these tumors, which arise when aberrant tissue develops between the cerebrum and the backbone nerve.

A brain tumor's classification as non-cancerous or cancerous depends on its type. Cancer cells are absent from healthy brain tissue, which also grows slowly.

While non-cancerous brain cells do not spread or usually remain in one place inside the brain, cancerous brain cells are dangerous, multiply quickly, and have the ability to spread to other sections of the cerebrum and the backbone nerve. Brain tumors are extremely dangerous.

Based on how they behave in the brain, the World Health Organization (WHO) divides brain tumors into two categories: grade 1 and grade 2. These tumors are also known as non-cancerous or grade 1 tumors. The most serious, or "bad," tumors are grade 3 and grade 4.

There are a number of ways to identify brain cancer, including CT scans and EEGs, but magnetic resonance imaging (MRI) is the most popular and successful method. MRI creates fine-grained images of inside organs using radio waves and powerful magnetic fields. Since it gives accurate information about the interior architecture, it is more effective than CT or EEG scans because it offers accurate details regarding the inner composition.

The success of the sophisticated image creation models previously discussed serves as the inspiration for our approach. In order to create captions, we use a deep convolutional neural network to create a vector form of an image, which is subsequently input into an LSTM network. Our approach's general structure is shown in Figure 1. Which illustrates all the structure of our method.

Preventing the model from overfitting to the training data is one of the primary issues in image captioning. This is because even the largest datasets, such as the Microsoft Common Objects in Context (MSCOCO) dataset, solely have 170,500 labeled examples. For the specific purpose of creating captions for the MSCOCO dataset, any top-down architecture needs to learn how to derive a strong image representation and a solid hidden state. LSTM to capture the image's semantics & language modeling to ensure the captions are syntactically correct.

The MRI scan is used in brain imaging for diagnosis, and monitoring the progression of malignant tumors is common. This information is crucial for various diagnostic and treatment decisions. MRI scans provide detailed insights into the brain's structure and can reveal the presence of earlier undetected brain tissue. Researchers have developed several automated processes for detecting brain tumors and cataloging them using scanned MRI since the advent of computer-aided medical imaging.

However, in recent years, the most successful algorithms have been developed using neural networks (NN) as well as vector support machines (SVM). With very few nodes, external frameworks such as Vector Support Machine (SVM) and K-Nearest Neighbor (KNN) can capture complex connections. [2] As a result, they have advanced into state-of-the-art technologies that outperform other domains of health information, such as biological data analysis, expertise in medicine, and medical imaging evaluation.

II. ASSOCIATED ACTIVITIES

Brain cancers are frequently detected and tracked with magnetic resonance imaging (MRI). Both diagnosis and treatment frequently make use of this information. MRI scans can show intricate patterns of brain tissue and provide comprehensive insights on the structure of the brain. Researchers have created a number of automated techniques over time for classifying and detecting brain cancers from MRI data. In the meantime, the most accurate models in recent years have been created using artificial neural networks & support vector machine. With fewer nodes, these techniques may precisely depict complex relationships (SVM). With an accuracy of 83 percent and 92 percent in place of the number of features (k), this method has effectively finished the majority of assignments.

For brain cancers to be successfully treated, early and correct identification is essential. In addition to aiding in the development of novel drugs, early detection, if caught in time, can save lives. Neuro-oncologists have benefited immensely from the development of biomedical informatics and computer-aided diagnosis in many ways. Machine learning algorithms are currently used to assess medical photos and data, as opposed to the time-consuming and error-prone manual detection of malignancies. Automated diagnostic systems outperform traditional methods in medical imaging analysis. This superior performance is typically achieved through the combination of a fully connected network for classification purposes and a convolutional neural network (CNN) for extracting relevant features. The proposed approach employs a CNN-based model and deep neural network methodology to categorize MRI scans as either "TUMOR DETECTED" or "TUMOR NOT DETECTED." In testing, this model demonstrated impressive results, achieving an average accuracy of 96.19 percent and an f-score of 96.5.

The creation of automatic machine learning (AutoML) methods that leverage deep analyzing algorithms has been the subject of recent research. Using T1-weighted magnetic resonance imaging, this work aims to develop an open-source online application driven by deep learning for the detection and identification of brain

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cancers, such as gliomas, meningiomas, and pituitary tumors. This application's deep learning strategy is built with the help of the Python-based Keras package. The results of these experiments show that this program can detect and diagnose three different kinds of brain cancers. Both Turkish and English versions of this web application are available to the general audience. Previous developments in deep learning for different domains have shown that the accuracy of the application may improve with the amount of data collected [8]. In order to differentiate between various kinds of brain tumors, the program makes use of pre-trained convolutional neural network (CNN) models that use transfer learning.

Additionally, the program makes use of deep reading techniques from reference sources for data augmentation and classification. Textbooks usually employ a learning curve to show how effective class separation is. Examples of models that are commonly used in textbooks that have been earlier trained on large datasets, such as ImageNet, are VGG-19, ResNet-101, and Inception.v1.

The optimal strategy for radiology research and testing is to construct layers that are appropriately connected according to data labels. Freezing layers is also the ideal option if the database is small in order to remove any limitations. They can't properly train themselves without transferring learning, thus they need expensive specialized processors (GPUs) with a lot of processing power [9]. The requirement to change the image capture size to match the earlier trained model's input size presents another difficulty for transfer learning. As a result, the collection of brain MRI images we could use for our research was quite limited.

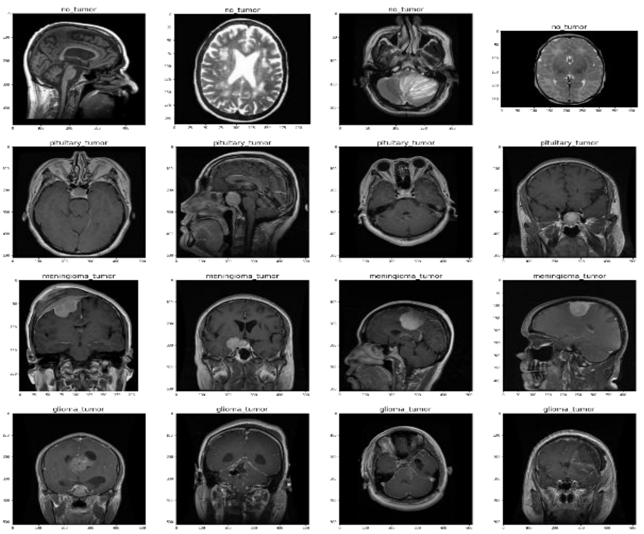

Fig1: Throughout the MRI, different kinds of tumor are discovered is depicted above.

After employing an image processing and data enhancement technique, we promptly trained the Convolutional Neural Networks model on the enhanced image data to determine whether the MRI picture contained a tumor. Lastly, we compared the diagnostic and computational performance of our model to that of the VGG-19 and ResNet models. Further studies are completed in [10] through [18]. Meningiomas, pituitary gliomas, and no tumor were all incorporated in the neurological model proposed by Ref. [19] for MRI scan analysis. The three distinct classification kinds have been defined in this work.

III. DESIGNED FRAMEWORK

The neural network's structure and functionality are depicted using a number of pictures of the distinct brain. Neural networks are the most often used model for tasks such as task generation and division, data collection, pattern matching, and vector measurement. Based on their connections, neural networks are divided into three categories. Feed, universal network, and feedback are the three categories. Currently, feed forward neural networks come in two varieties: One layer and a complicated layer. The input and output layers are the only layers present when there is only one layer; the concealed layer is invisible and hidden. In contrast, complicated layer consists of three tiers: hidden, o/p, and i/p. A continuous network is referred to as a feedback loop network.

An image cannot normally be resized by a neural network. An image can be transformed using a neural convolutional network from a three-dimensional input volume to a three-dimension output volume with length, width, and height. The layers that comprise a convolutional neural network are input, modification, integrated, unit fixed layer (ReLU), and lastly a completely combined layer. Within each sub-region, there are subclasses of the convolution layer. On the ReLU layer, the activation element function is finished. Which blending layer is utilized is up to us. We either use it or ignore it. Alternatively, poor-quality samples are commonly produced using the composite layer.

The data from the convolutional neural network of different brains has been split into two sets: training and testing.

Additionally, brain images linked to tumors are categorized based on the condition they depict. In order

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to develop a prediction-based model, the training procedure discusses preliminary analysis, feature billing, and segmentation losses. After that, the training photo series is labelled. The size of the preview image is decreased.[13]

Lastly, a convolutional neural network is used to segregate spontaneous brain activity. An image network is used to generate a set of brain images. The previously stated picture network is one of them.

IV. CNN-BASED LABELING METHODOLOGY

Stage 1: Apply the convolution filter from the starting layer.

Stage 2: Reduce the reactivity of the convolution filters by reducing the sample size.

Stage 3: The signal flow between layers is controlled by the opening layer.

Stage 4: Expand your training by using a modified line unit.
(ReLU).

Stage 5: Each neuron in the continuous layer is connected to every other neuron in the layer below.

Stage 6: In order to provide input to the neural network during training, a layer of damage is added at the end.

1) *Manipulation of Image*

Initially, we employed open-source computer vision (CV) Kenny's edge detection tech to remove dark edges from images & isolate the relevant brain regions in MRI scans. After identifying the actual brain edges using Kenny Edges' method, the exclusive brain region of the image is extracted.

2) *Data enhancement*

The intentional process of making pre-existing data more extensive and complicated is known as data augmentation. We know that it takes a lot of data to fine-tune the constraint in a deep neural network.

Nevertheless, due to the small size of our dataset, we employed data augmentation techniques to improve our training dataset by making little changes to our photos, like lightness, spinning, or turning.

Our training dataset shall expand as a result of our model learning to stage photos more skillfully by treating each of these minor alterations as a new image. [14] The shows several enhanced images from a single image.

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For the extraction of enhanced MRI image data, we provide a naive CNN model with an input size of 250 x 250 pixels and a batch size of 33. First, a single 19-filter convolutional layer with a filter size of 35 percent was

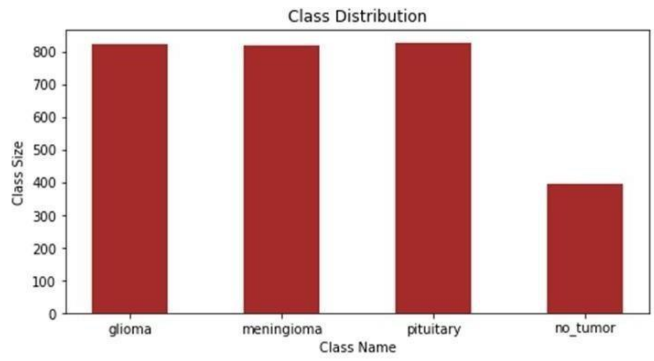

Fig.2. Distribution of classes for four brain tumor categories in the figure

employed. A limited set of filters was used to detect lines, vertices, and boundaries [6]. To obtain the largest summation of the image, we first added a max pooling operation with a 19 filter. We then expanded the number of filters and convolutional layers to 56,128, and 256—35% of the overall size-all using the same filter. It uses these tiny patterns as a set of filters to identify bigger structures, like a rectangle, round, and so forth.

We positioned max pooling operation over the convolutional layers to increase their effectiveness. We finally developed a completely linked dense layer of 512 neurons with a softmax output layer that classifies the final decision label in the input MRI image as either Does Not Contain Cancer or Is Cancer after calculating the likelihood score for each class. For the design of our proposed CNN architecture, a yes or no is displayed.

V. OUTCOMES AND INSIGHTS

Neural networks are constructed and function using models of various imaging of the central nervous system. Neural networks are the most often used model for activities that include task formulation and division, data collection, pattern matching, and vector measurement. Based on their connections, neural networks are divided into three categories. Input ,

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overall framework, and output signal are the three categories.

Currently, forward-propagation neural networks come in two varieties: one-layer and composite-layer. The input and output layers are the only layers present when there is only one layer; the concealed layer is invisible and hidden. The input, hidden, and output layers are the three layers that comprise a multilayer.

TABLE I

	precision	recall	f1-score	support
glioma_tumor	0.9	0.82	0.86	84
meningioma_tumor	0.84	0.81	8.82	89
no_tumor	0.84	0.97	0.9	38
pituitary_tumor	0.93	0.97	0.95	76
accuracy			0.88	287
macro avg	0.87	0.89	0.88	287
weighted avg	0.88	0.88	0.88	287

Fig.3 Comparison of brain tumor classification across four categories.

A closed-loop response network is a continuous network. Using the feature value, the class determination calculates the outcome and determines its validity. The Support Vector Machine model takes a lot of computing time and has a comparatively poor degree of precision.

Since the neural network can manage everything on its own, we do not need generalized characteristic collection processes in our convolutional neural network-based categorization. An illustration of a tumor or non-tumor serves as a representation of our findings. [16] The reduction of complexity and the reduction of computing time lead to an increase in accuracy.

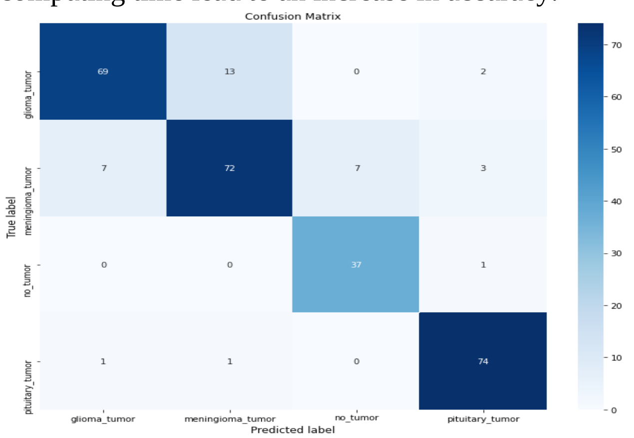

Fig.4. Evaluation of the confusion matrix during processing

The results of the classification precision are shown in Figure 4. Lastly, the probability score value has been used to identify whether or not the brain tumor is malignant. When compared with imaging of a properly functioning brain, the likelihood score for brain cancer is high.

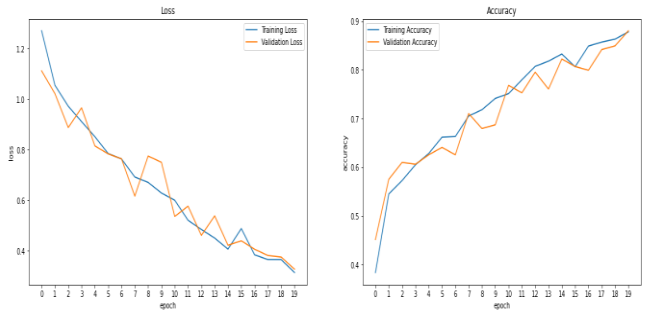

Fig.5. No dropout for the Core CNN architecture with Matrix expansion & Data manipulation.

VI . CONCLUSION

This project's primary goal is to create an automated approach for classifying brain tumors that is quick, extremely reliable, and user-friendly. SVM and DNN-based classification takes a lot of time and gives poor calculation while detecting tumor and non-tumor. To achieve an accuracy rate of up to 98%, we use convolutional neural networks as compared to other neural networks. CNN doesn't require a separate feature extraction. Classification results are then isolated from the images of the cancerous and healthy brains.

The ImageNet database is used for classification. Pre-training has been done on this model. Only the final layer is thus taught. The CNN retrieves the height, width, and depth characteristic values in addition to the raw pixel information. Lastly, to obtain higher precision, a loss function based on batch gradient descent is used. Calculations are made for training exactness, validation exactness, and validation loss. Similarly, the accuracy of training is 97.2% usually; the validation accuracy is effective with minimal reduction.

VII . CONFLICT OF INTEREST

According to the authors, there were no business or financial ties that would've prompted concerns about possible conflicts of interest throughout the study.

REFERENCES

– D.N. Louis, A. Perry, G. Reifenberger, A. Von Deimling, D. Figarella-Branger, W.K. Cavenee, H. Ohgaki, O.D. Wiestler, P. Kleihues, D.W. Ellison The 2016 world health organization classification of tumors of the central nervous system: a summary Acta Neuropathol, 131 (6) (2016), pp. 803-820

– Gudigar A, Raghavendra U, San T, Ciaccio E, Acharya U. Application of multiresolution analysis for automated detection of brain abnormality using mr images: A comparative study. Future Gener Comput Syst 2019;90:359–67.

– D.N. Louis, A. Perry, G. Reifenberger, A. Von Deimling, D. Figarella-Branger, W.K. Cavenee, H. Ohgaki, O.D. Wiestler, P. Kleihues, D.W. Ellison The 2016 world health organization classification of tumors of the central nervous system: a summary Acta Neuropathol, 131 (6) (2016), pp. 803-820

– M.A. Khan, H. Arshad, W. Nisar, M.Y. Javed and M. Sharif, "An integrated design of fuzzy C-means and NCA-based multi-properties feature reduction for brain tumor recognition" in Signal and Image Processing Techniques for the Development of Intelligent Healthcare Systems, Berlin/Heidelberg, Germany: Springer, pp. 1-28, 2021.

– S. Pereira, A. Pinto, V. Alves and C.A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images", IEEE Trans. Med. Imaging, vol. 35, pp. 1240-1251, 2016.

– Y Pan, W Huang, Z Lin, W Zhu, J Zhou, J Wong et al., "Brain tumor grading based on neural networks and convolutional neural networks", 37th annual international conference of the IEEE, pp. 699e702, 2015.

– Sindhumol S, Kumar A, Balakrishnan K. Spectral clustering independent component analysis for tissue classification from brain MRI. Biomed Signal Process Control. (2013) 8:667–74. 10.1016/j.bspc.2013.06.007

– Hemanth G, Janardhan M, Sujihelen L. Design and implementing brain tumor detection using machine learning approach. In: 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI). Tirunelveli: IEEE; (2019). p. 1289–94.

– Upadhyay M, Rawat J, Maji S. Skin cancer image classification using deep neural network models. In: Evolution in Computational Intelligence: Proceedings of the 9th International Conference on Frontiers in Intelligent Computing: Theory and Applications (FICTA 2021). Vol. 267. Singapore: Springer Nature; (2022). p. 451

– Islami F., Ward E.M., Sung H., Cronin K.A., Tangka F.K.L., Sherman R.L., Zhao J.X., Anderson R.N., Henley S.J., Yabroff K.R., et al. Annual report to the nation on the status of cancer, part 1: National cancer statistics. JNCI J. Natl. Cancer Inst. 2021;113:1648–1669. doi: 10.1093/jnci/djab131.

– Zaccagna F., Grist J.T., Quartuccio N., Riemer F., Fraioli F., Caracò C., Halsey R., Aldalilah Y., Cunningham C.H., Massoud T.F., et al. Imaging and treatment of brain tumors through molecular targeting: Recent clinical advances. Eur. J. Radiol. 2021;142:109842. doi: 10.1016/j.ejrad.2021.109842.

– Yeung M., Sala E., Schönlieb C.B., Rundo L. Focus U-Net: A novel dual attention gated CNN for polyp segmentation during colonoscopy. Comput. Biol. Med. 2021;137:104815. doi: 10.1016/j.compbiomed.2021.104815.

– Yasaka K., Akai H., Kunimatsu A., Kiryu S., Abe O. Deep learning with convolutional neural network in radiology. Jpn. J. Radiol. 2018;36:257–272. doi: 10.1007/s11604-018-0726-3

– Arabahmadi M., Farahbakhsh R., Rezazadeh J. Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging. Sensors. 2022;22:1960. doi: 10.3390/s22051960.

– Deepak S., Ameer P.M. Brain tumor classification using deep CNN features via transfer learning. Comput. Biol. Med. 2019;111:103345. doi: 10.1016/j.compbiomed.2019.103345.

– Swati, Z. N. K. et al. Brain tumor classification for MR images using transfer learning and fine-tuning. Comput. Med. Imaging Graph. 75, 3446 (2019)