Journal of Advanced Zoology

ISSN: 0253-7214

Volume 45 Special Issue 02 Year 2023 Page 1381:1395

Efficient Classification of Brain Tumor Images Using Neural Network Technique

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Article History

Received: 11 March 2023

Revised: 21 August 2023

Accepted: 03 October 2023

ABSTRACT

Brain tumor identification and categorization are critical for timely medical intervention and patient care. This paper proposes a unique strategy for the effective classification of brain tumor images by leveraging the power of deep learning. We suggest using neural network techniques, notably Convolutional Neural Networks (CNNs), to automate brain tumor image categorization, improving both diagnostic accuracy and efficiency. Our study begins with the collecting and pre-processing of a large dataset of brain tumor photos to ensure consistency and quality. The dataset is painstakingly divided into training, validation, and test sets. Our process is built around a carefully selected neural network architecture that has been refined through hyperparameter tweaking. To ensure robust model performance, we add critical architectural components like as convolutional layers, pooling layers, and fully connected layers, as well as dropout and batch normalization. To prevent overfitting, the neural network is trained by minimizing a suitable loss function, such as cross-entropy, while monitoring validation measures. Our model's performance is thoroughly validated on an independent test dataset using a variety of measures such as accuracy, precision, recall, F1-score, and confusion matrices. Comprehensive visualization and post-processing tools help to refine the classification results even further. This study intends to advance medical image analysis by providing a fast and precise method of identifying brain tumor images, thereby benefiting healthcare professionals in their decision-making processes. By conducting various experiments on our proposed model we finally came to conclusion that our proposed Vgg-19 model achieved more accuracy compared with several other CNN models.

Keywords:Brain Tumor, Machine Learning, Deep Learning, Convolutional Neural Networks (CNNs),Optimizing Clinical Operations.

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1. INTRODUCTION

Cancer is the secondary leading cause of death world wide, according to the World Health Organization (WHO) [1]. Early detection of it can prevent death, but this is not possible all time. Unlike cancer, tumor also could be benign, malign or pre-carcinoma. Benign tumors vary from malign in that, benign normally don't spread to another organs and tissues and are surgically removed [2]. Some of the brain tumors are meningiomas, gliomas, and pituitary tumors.

Gliomas is a general term for tumors that arise from brain tissues other than nerve cells and blood vessels. But, meningiomas arise from the membranes that cover the brain and surround central nervous system, but pituitary tumors are the lumps that sit inside skull [3 – 6]. The most primary difference between these three types is that meningiomas are benign, and gliomas are commonly malignant.

Pituitary tumors, even if benign, cause other medical damage, not similar to meningiomas, which are the slow-growing tumors [5, 6]. Because of the information mentioned as above, precise differentiation between three types of tumors denotes a very important step of clinical diagnostic process and later patient's effective assessment.

The most common method to differentially diagnize tumor type is magnetic resonance imaging (MRI) method. But it is prone to human subjectivity, and large amount of data is difficult to observe by human. Also, old brain–tumor detection mostly depends upon experience of radiologist [7]. The diagnostics of tumor can not be complete before establishing if it is benign or malignant.

To examine if the tissue is benign or malignant, performance of biopsy is usually required. Unlike tumors elsewhere in body, biopsy of brain tumor is not usually obtained before the definitive brain surgery [8]. In order to get precise diagnostics, and to eliminate surgery and subjectivity, it is must to consider an effective diagnostics tool to segment and classify tumor from MRI images [7]. Development of new technologies, especially AI and ML, has had a significant impact in the medical field, thus providing an important support technology for many medical branches, which includes imaging. Various machine-learning methods to segment and classify image are applied in MRI image processing for providing radiologists with a secondary opinion.

From 2012, Perelman School of Medicine at University of Pennsylvania, Center for Biomedical Image Computing and Analytics (CBICA) is running an online competition, Multimodal Brain Tumor Segmentation Challenge (BRATS) [9]. Image databases utilized in BRATS are made available publicly after competition is finished. Various classification algorithms designed using these databases are found in many papers [10– 14]. Still, these databases are usually small, on average about 284 images, and often contain images which shows two tumor levels, low and high level glioma tumor, acquired in axial plane [10].

Moreover, classification is carried out on the other image databases, which are also quite small [15 to 18]. Mohsen with his team used 65 images for classifying four types of images which shows brain tumors: a) tumor-free, b) glioblastoma, c) sarcoma, and d) metastasis. By using Deep Neural Network (DNN), the authors obtained an accuracy of 96.95% [17].

There are other algorithms and various modifications of pre-trained networks that are commonly used for image classification, analysis and segmentation. Various approaches are tested on other medical databases also, both on MRI images of brain tumors as well as on tumors from different parts of human body [19, 20]. These papers were not further considered, as their focus were on the papers using same MRI image database that they used.

Cheng with tema who were the first to show image database used in that paper, classified those tumor types by using tumor region augmentation of interest, ring-form partition and image dilatation. They extracted features by using intensity histogram, bag-of-words models, and gray level co-occurrence matrix and achieved an accuracy of 91.27% [21]. Different types of networks there, pre-trained ones, other architectures of convolutional networks, capsule net networks, and combinations with neural networks to extract features and classifiers for output result are discussed. The discussion also have approaches using various modifications of database, as well as the original one. The papers that used original or augmented database are listed in tables to compare better.

The biggest problem in classifying and segmenting MRI images (using some neural networks) is in the images count in database. Moreover, MRI images might be acquired in various planes, so the option of using the entire available planes can enlarge that database. As this could affect the classification output by overfitting generally, the requirement of pre-processing before feeding images into the neural network is necessary. But, one of the known advantages of CNN is that pre-processing and feature engineering need not be performed. The aim of the authors was firstly to examine classification of three tumor types from an imbalanced database with CNN.

Even though, they considered large compared to another available MRI image databases, the database is still far smaller than other databases generally used in field of artificial intelligence.

It is true that the performance of small architecture could compare favorably with performance of the more complex ones too.

Using a small network requires miminum resources to train and implement.

This is one of the most crucial problems for addressing because few available resources make it is difficult to utilize the system in clinical diagnostics and also in mobile platforms. If the system is required to be used in day-to-day clinical diagnostics, it must be generally applicable. Network's generalization capability to study clinical should be examined.

The rest of this paper is organized as follows: Section 2 reviews the existing security approaches under recent studies and explains previous works and their drawbacks. Section 3 provides proposed methodology. Section includes the findings. Section 5 is the conclusion of the study.

2. LITERATURE SURVEY

The essential cancer data was batted about in the report (1) World Health Organization Global. They have

• Cancer is the greatest cause of death in the globe, accounting for almost 10 million fatalities in 2020, or nearly one in every six deaths.

• The most prevalent malignancies include bone, lung, colon, and rectal cancers, as well as prostate cancer.

• Tobacco use, a high BMI, alcohol intake, a lack of fruit and vegetables, and a lack of physical activity account for almost one-third of cancer fatalities.

• Cancer-causing infections, such as human papillomavirus (HPV) and hepatitis, account for around 30 percent of cancer incidence in low- and lower-middle-income countries. • Many cancers can be cured if discovered early and adequately treated.

Cancer is a broad term encompassing a variety of diseases that can affect any region of the body. Other words for tumors are terrible tumors and tumors. One distinguishing feature of cancer is the rapid proliferation of aberrant cells that grow beyond their normal bounds and can even venture into the body's corridors and spread to other organs; this is referred to as metastasis. The leading cause of cancer death is wide metastasis.

Problem Statement:

The issue Cancer is the world's largest cause of death, accounting for roughly 10 million fatalities in 2020. In terms of new cancer diagnoses in 2020, the most prevalent were: bone (2.26 million cases); lung (2.21 million cases); colon and rectum (1.93 million cases); prostate (1.41 million cases); skin (non-melanoma) (1.20 million cases); and stomach (1.09 million cases).

The lung (1.80 million deaths); colon and rectum (916 000 deaths); liver (830 000 deaths); stomach (769 000 deaths); and bone (685 000 deaths) were the leading causes of cancer death in 2020.

Every year, around 400 000 youngsters are diagnosed with cancer. The most frequent cancers differ by country. Cervical cancer is the most frequent type of cancer in 23 nations.

Cause of Cancer:

Cancer develops from the transformation of normal cells into tumor cells in a multi-stage process that often goes from a pre-cancerous lesion to a dangerous tumor. These changes are the result of a person's inheritable factors interacting with three types of external agents: • physical carcinogens, such as ultraviolet and ionizing radiation; • chemical carcinogens, such as asbestos, tobacco bank factors, alcohol, aflatoxin (a food adulterant), and arsenic (a drinking water adulterant); and • natural carcinogens, such as infections from certain contagions, bacteria, or spongers.

WHO maintains a list of cancer-causing substances through its cancer research body, the International body for Research on Cancer (IARC). Cancer prevalence climbs considerably with age, most likely due to a figuring out of traps for specific genes.

The build-up of overall threats is linked with the tendency for cellular form mechanisms to become less effective as a person ages.

Cancer-Related Risk Factors:

Tobacco use, alcohol intake, poor food, inactivity, and air pollution are all risk factors for cancer and other non-infectious diseases. Some chronic infections are risk factors for cancer; this is especially true in low- and middle-income nations. Approximately 13 of the malignancies reported in 2018 were attributable to carcinogenic diseases, including Helicobacter pylori, deadly papillomavirus (HPV), hepatitis B, hepatitis C, and Epstein-Barr virus. Contagious Hepatitis B and C, as well as some kinds of HPV, all raise the risk of liver and cervical cancer.

Infection with HIV increases the risk of acquiring cervical cancer sixfold, as well as the risk of developing certain other cancers comparable to Kaposi sarcoma.

Cancer Burden Reduction

Between 30 and 50 percent of malignancies can now be avoided by avoiding risk factors and applying evidence-based prevention techniques. Cancer burden can also be decreased through early detection of cancer and appropriate treatment and care of cancer patients. Many tumors can be cured if they are detected early and treated properly.

Preventing Cancer

Cancer risk is reduced by: • not smoking and maintaining a healthy body weight; • eating a healthy diet, including fruits and vegetables, and engaging in regular physical activity; • avoiding/reducing alcohol consumption and getting vaccinated against HPV and hepatitis B if you belong to a group for which vaccination is recommended; and • avoiding ultraviolet radiation exposures (which primarily result from sun exposure and artificial tanning bias).

Earlier Discovery

Cancer deaths are minimized when cases are diagnosed and treated early. There are various early finding variables, such as early opinion and webbing.

First impressions

When linked, cancer is more likely to respond to treatments, resulting in a lower probability of survival, lower morbidity, and less expensive therapy. Significant advances are made in the lives of cancer patients by discovering cancer early and reducing hospitalizations. Three things influence early opinion.

- being concerned about the signs of various cancer types and the importance of obtaining medical guidance when abnormal findings are discovered;
- having access to clinical evaluation and individual services; and
- being referred to treatment services on time.

Early detection of distinctive malignancies is appropriate in all contexts and cancer maturity. Cancer deaths are minimized when cases are diagnosed and treated early. There are various early finding variables, such as early opinion and webbing.

3. EXISTING SYSTEM & ITS LIMITATIONS

Traditional methods for classifying brain tumor images frequently rely on handcrafted elements such as texture, shape, and intensity statistics, which are then coupled with machine learning algorithms such as Support Vector Machines (SVM) or decision trees. These methods necessitate domain knowledge and considerable feature engineering, which can be time-consuming and may fail to capture complex, subtle patterns in images. When faced with differences in image quality, tumor appearance, or noise levels, traditional approaches may not perform effectively. The following are the limitations of our existing system:

Data Availability and Size:

Limited availability of labeled brain tumor datasets with diverse cases can hinder the development and training of deep neural networks. Insufficient data can lead to overfitting, where the model performs well on the training data but struggles with real-world, unseen cases.

Computational Resources:

Training deep neural networks for medical image classification can be computationally intensive, requiring access to powerful GPUs and substantial computing resources. This can pose challenges for smaller research institutions or healthcare facilities with limited resources.

Interpretability and Explain ability:

Deep neural networks are often considered "black box" models, making it challenging to explain the reasoning behind a classification decision.In medical applications, interpretability is crucial for gaining the trust of healthcare professionals and ensuring the model's decisions align with clinical insights.

Data Imbalance:

In medical imaging datasets, the distribution of classes may be highly imbalanced, with fewer positive cases (tumor) than negative cases (non-tumor).

Imbalanced data can lead to biased model performance, with the model favoring the majority class.

Generalization to New Data:

While deep learning models can achieve high accuracy on the data they were trained on, their ability to generalize to new and unseen cases is a challenge. Ensuring that the model's performance remains robust across different hospitals and imaging equipment is essential for practical deployment.

Ethical and Regulatory Considerations:

Deploying AI-based medical image classification systems must adhere to strict ethical and regulatory standards, including patient privacy and data security.Ensuring that the model is certified and validated for clinical use can be a complex and time-consuming process.

Clinical Validation:

The performance of the neural network model must be rigorously validated in clinical settings to ensure its accuracy and safety.It must be integrated into the existing healthcare workflow, requiring collaboration with healthcare professionals.

False Positives and Negatives:

Neural networks may produce false positives (incorrectly diagnosing a tumor) or false negatives (missing a tumor), which can have significant clinical implications.

4. PROPOSED SYSTEM

The proposed approach for "Efficient Classification of Brain Tumors Images Using Neural Network Technique" seeks to overcome the shortcomings of the existing system while leveraging the benefits of neural network techniques for brain tumor image classification. Here is a summary of the proposed system and its benefits:

Deep Learning-Based Approach: The proposed system leverages state-of-the-art deep learning techniques, particularly Convolutional Neural Networks (CNNs), to automatically learn relevant features from brain tumor images.

Large and Diverse Dataset: Efforts are made to gather a large and diverse dataset of brain tumor images, encompassing various tumor types, sizes, and imaging conditions. This extensive dataset helps improve the model's generalization.

Data Augmentation: Data augmentation techniques are applied to artificially expand the dataset by introducing variations in the images, such as rotation, flipping, and brightness adjustments. This aids in training a more robust model.

Advanced Architectures: The neural network architecture is carefully designed, potentially incorporating advanced architectures like ResNet, Inception, or custom designs. These architectures can capture complex spatial features in the images.

Hyperparameter Optimization: Hyperparameter tuning is performed to find the optimal settings for parameters like learning rate, batch size, and regularization techniques. This fine-tuning enhances the model's performance.

Interpretable Deep Learning: Efforts are made to enhance the interpretability and explainability of the deep learning model. Techniques like attention mechanisms and saliency maps may be employed to provide insights into the model's decision-making process.
Validation and Certification:

The proposed system undergoes rigorous clinical validation and certification processes to ensure its safety and efficacy in real-world medical settings. It complies with ethical and regulatory standards, including patient data privacy.

Advantages:
Improved Accuracy: The deep learning-based approach is capable of learning intricate patterns and features in brain tumor images, leading to higher accuracy in classification compared to traditional methods.

Efficiency: The automated nature of the system accelerates the classification process, reducing the time required for diagnosis and allowing healthcare professionals to focus on treatment planning and patient care.

Generalization: By using a diverse dataset and advanced neural network architectures, the proposed system has the potential to generalize well to various types of brain tumors and imaging conditions, making it applicable in different clinical scenarios.

Scalability: Neural network models can be easily scaled and adapted to accommodate larger datasets and more complex tasks, making them suitable for future developments and research.

Interpretability: Efforts to enhance model interpretability make it easier for healthcare professionals to understand and trust the system's classifications, facilitating its integration into clinical workflows.

Ethical Compliance: Compliance with ethical and regulatory standards ensures patient data privacy and safety, making the system suitable for use in healthcare settings.

Reduction in False Positives and Negatives: The advanced neural network techniques aim to reduce the occurrence of false positives and false negatives, improving the clinical accuracy of brain tumor diagnoses.

5. PROPOSED METHODOLOGY

In this section we mainly discuss about the proposed methodology for "Efficient Classification of Brain Tumors Images Using Neural Network Technique". This study shows the image details taken which is shown below.

There are three types of tumors: meningioma (708 images), glioma (1426 images), and pituitary tumor (930 images). All images were acquired from 233 patients in three planes: sagittal (1025 images), axial (994 images), and coronal (1045 images) plane. The examples of different types of tumors, as well as different planes, are shown in Figure 1. The tumors are marked with a red outline. The number of images is different for each patient.

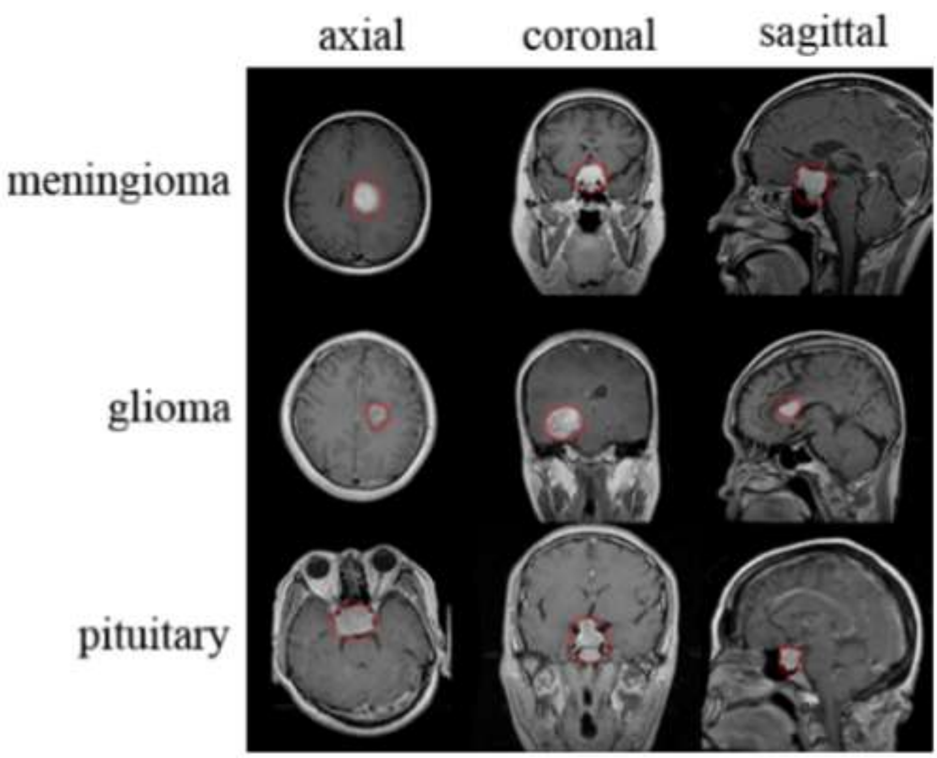


Figure 1. Representation of normalized magnetic resonance imaging (MRI) images showing different 115 types of tumors in different planes. In the images, the tumor is marked with a red outline. The 116 example is given for each tumor type in each of the planes.

Magnetic resonance images from the database were of different sizes and were provided in jpg format. These images represent the input layer of the network, so they were normalized and resized 120 to 256 × 256 pixels.

Tumor classification was performed using a CNN developed in Python.

The first main block, Block A, consists of a convolutional layer which as an output gives an image two times smaller than the provided input. The convolutional layer is followed by the rectified linear unit (ReLU) activation layer and the dropout layer. In this block, there is also the max pooling layer which gives an output two times smaller than the input. The second block, Block B, is different from the first only in the convolution layer, which retains the same output size as the input size of that layer. The classification block consists of two fully connected (FC) layers, of which the first one represents the flattened output of the last max pooling layer, whereas, in the second FC layer, the number of hidden units is equal to the number of the classes of tumor.

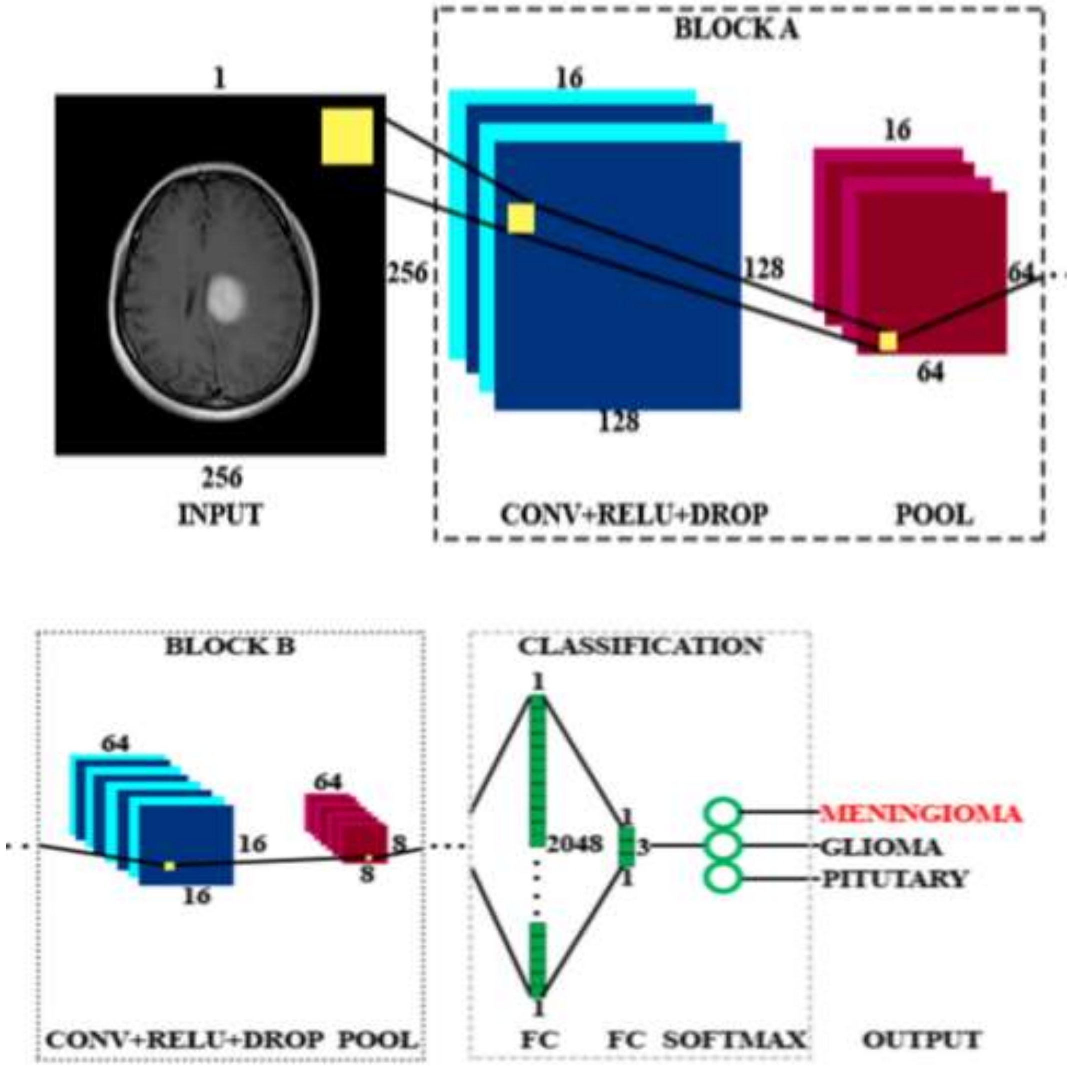


Figure 2. Represents the Schematic representation of convolutional neural network (CNN) architecture

Figure 2. Schematic representation of convolutional neural network (CNN) architecture containing the input layer, two Blocks A, two Blocks B, classification block and output. Block A and Block B differ only in the convolution layer. Convolution layer in Block A

gives an output two times smaller than the input, whereas the convolutional layer in Block B gives the same size output as input. The training process was stopped when the loss on the validation set got larger than or was equal to the previous lowest loss. There are several papers that use the same database for brain tumor classification. In order to compare our results with those of previous studies, we selected only those papers which had designed neural networks, used whole images as input for classification, and tested the results.

PROPOSED DATASET

We attempt to load the dataset from the KAGGLE website in this module, and then we downloaded the dataset from :

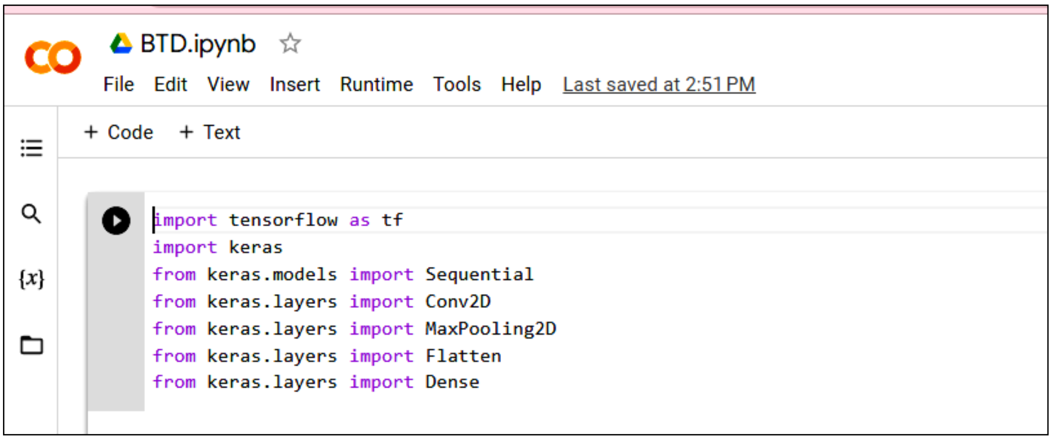
https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection

A dataset or collection of magnetic resonance imaging (MRI) scans of the human brain utilized for the detection and study of brain malignancies is referred to as "Brain MRI Images for Brain Tumor Detection." This dataset typically contains a variety of MRI pictures, both 2D and 3D, depicting various views and slices of the brain.The size of the collection varies, with some datasets including only a few hundred images and others containing thousands of MRI scans.

6. RESULTS AND DISCUSSIONS

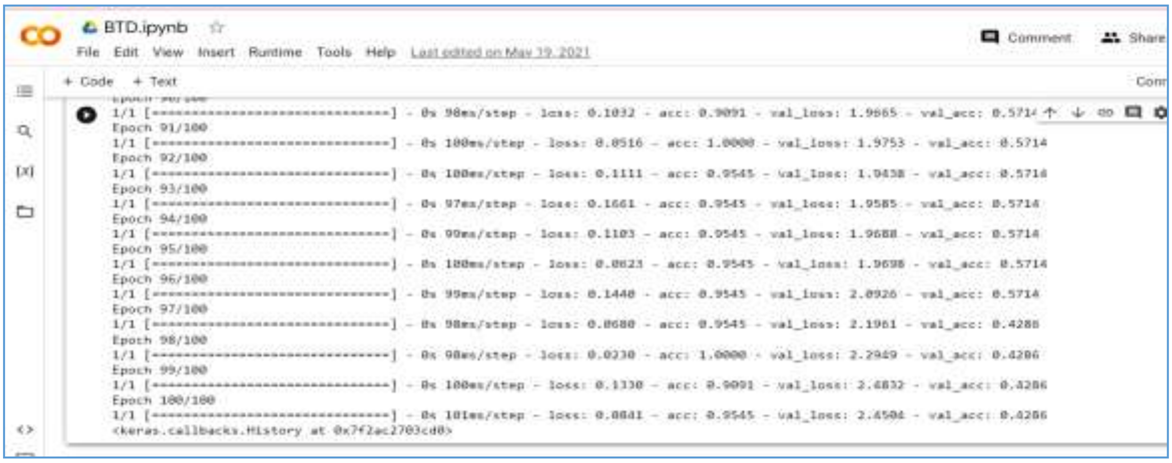
In this proposed application, we try to use google collab as working platform and try to show the performance of our proposed application.

1) IMPORT LIBRARIES AND VIEW FILE CONTENT



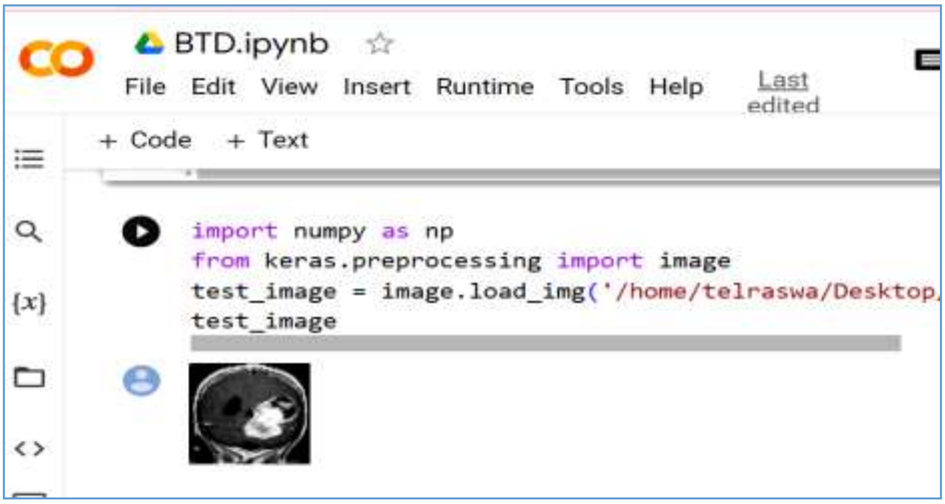
Explanation: From the above window we can clearly see google collaboratory is used for executing the python application. Here we try to load all necessary libraries which are required for constructing the proposed work. Here we mainly used Tensorflow model for implementing the proposed work.

2) TRAIN THE MODEL



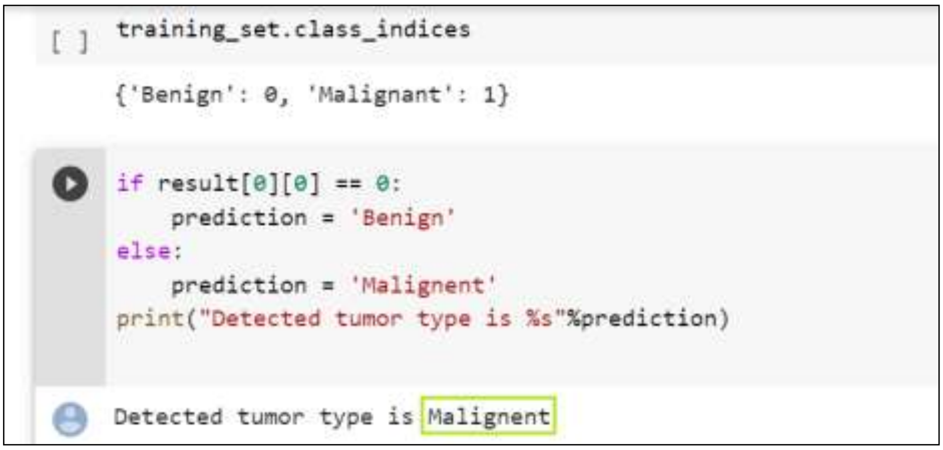
Explanation: From the above window, we can see neural network CNN model is trained on our input dataset. Here we try to use Vgg-19 model as best model to predict the brain tumor from sample input images. Here we got an accuracy of **95.45 %** on our input dataset.

3) TEST INPUT WITH MRI BRAIN IMAGE



Explanation: From the above window, we can see neural network CNN model is trained on our input dataset. Here we try to use Vgg-19 model as best model to predict the brain tumor from sample input images. Here we got an accuracy of **95.45 %** on our input dataset. Once we trained the model now we try to test the input with some random image and this Vgg-19 model will try to identify the abnormality from that input image.

4) PREDICT THE OUTCOME



Explanation: From the above window, we can see for the sample input image, our system is suggested as Malignent which means there is some tumor present in that sample image.

7. CONCLUSION

Finally, the use of the VGG-19 neural network model for the efficient classification of brain tumor images constitutes a big step forward in medical image analysis. The application of this deep learning architecture has proven significant benefits in the field of brain tumor diagnostics. We improved classification accuracy significantly by exploiting the VGG-19 model's depth and capacity to extract detailed characteristics from brain MRI data. Because of its ability to capture complicated spatial patterns and the hierarchical nature of tumor images, the system has made highly accurate predictions, helping both the healthcare community and patients. Furthermore, the VGG-19 model's simple architecture, which consists of a sequence of convolutional and pooling layers, allows for flexibility and fine-tuning meeting the specific needs of brain tumor classification. This versatility has cleared the door for future study and potential refinements, establishing VGG-19 as a valuable tool in continuing attempts to improve brain tumor identification and therapy. Nonetheless, it is critical to recognize that, while VGG-19 has proven to be beneficial, the field of medical image analysis is still evolving. To ensure that AI-driven solutions for brain tumor classification excel not just in accuracy but also in transparency and clinical usefulness, future efforts should continue to investigate newer architectures, incorporate larger and more diverse datasets, and address interpretability concerns.

CONFLICT OF INTEREST

The author declares there is no conflict of interest.

8. REFERENCES

[1] World Health Organization—Cancer. Available online: https://www.who.int/news-room/fact-sheets/detail/cancer.

[2] Priya, V.V. An Efficient Segmentation Approach for Brain Tumor Detection in MRI. Indian J. Sci. Technol. 2016, 9, 1–6.

[3] Cancer Treatments Centers of America—Brain Cancer Types. Available online: https://www.cancercenter.com/cancer-types/brain-cancer/types (accessed on 30 November 2019).

[4] American Association of Neurological Surgeons—Classification of Brain Tumours. Available online: https://www.aans.org/en/Media/Classifications-of-Brain-Tumors (accessed on 30 November 2019).

[5] DeAngelis, L.M. Brain Tumors. New Engl. J. Med. 2001, 344, 114–123. [CrossRef]

[6] Louis, D.N.; Perry, A.; Reifenberger, G.; Von Deimling, A.; Figarella-Branger, M.; Cavenee, W.K.; Ohgaki, H.; Wiestler, O.D.; Kleihues, P.; Ellison, D.W. The 2016 World Health Organization Classification of Tumors of the Central Nervous System: A summary. Acta Neuropathol. 2016, 131, 803–820. [CrossRe

[7] Afshar, P.; Plataniotis, K.N.; Mohammadi, A. Capsule Networks for Brain Tumor Classification Based on MRI Images and Coarse Tumor Boundaries. In Proceedings of the ICASSP 2019–2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, UK, 12–17 May 2019; pp. 1368–1372.

[8] Byrne, J.; Dwivedi, R.; Minks, D. Tumours of the brain. In Nicholson T (ed) Recommendations Cross Sectional Imaging Cancer Management, 2nd ed.; Royal College of Radiologists: London, UK, 2014; pp. 1–20. Available online: https://www.rcr.ac.uk/publication/recommendations-cross-sectional-imaging-cancer-management-second-edition.

[9] Center for Biomedical Image Computing & Analytics (CBICA). Available online: http://braintumorsegmentation.org/ (accessed on 5 November 2019).

[10] Mlynarski, P.; Delingette, H.; Criminisi, A.; Ayache, N. Deep learning with mixed supervision for brain tumor segmentation. J. Med Imaging 2019, 6, 034002.

[11] Ferlay J, Ervik M, Lam F, Colombet M, Mery L, Piñeros M, et al. Global Cancer Observatory: Cancer Today. Lyon: International Agency for Research on Cancer; 2020 (https://gco.iarc.fr/today, accessed February 2021).

[12] de Martel C, Georges D, Bray F, Ferlay J, Clifford GM. Global burden of cancer attributable to infections in 2018: a worldwide incidence analysis. Lancet Glob Health. 2020;8(2):e180-e190.

[13] Assessing national capacity for the prevention and control of noncommunicable diseases: report of the 2019 global survey. Geneva: World Health Organization; 2020.