**BRAIN TUMOR DETECTION USING CNN AND VGG-16 TO IMPROVE  
 ACCURACY FOR HEALTH AND WELL-BEING**

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**ABSTRACT**

**AIM:** Brain tumor is one of the deadliest diseases worldwide, and early detection is the best way to achieve proper treatment. Over time, deep learning algorithms have been shown to be effective in medical image analysis, particularly in identifying brain tumors. The purpose of this study is to use CNN Basic and VGG-16 to accurately detect brain tumor from MRI images. **Material and Methods** The dataset for the analysis consisted of 4500 MRIs of the brain that were normal as well as those with tumours. These images were preprocessed and augmented for better performance by the models. In order to minimize overfitting, two CNN models – CNN Basic and VGG-16 – were used together with a five-fold cross-validation technique. **Result** For instance, while the accuracy of CNN Basic was 90.12%, that of VGG-16 was 95.86%. Further still compared to CNN basic model, VGG 16 had better precision, recall as well F1-score . It can be concluded that deep learning algorithms are highly helpful in uncovering brain tumor implications like no other technique does before. **Conclusion** The use of MRI images for evaluating cancerous cells in human brains gave promising results when using both CNN Basic and VGG-16 models.The refined versions would offer an opportunity for radiologists to detect tumors accurately thus minimizing misdiagnoses resulting into improved treatment outcomes. Evidence based improvements could include larger data sets or real world application through implementation

**KEYWORD**  Brain tumor , Deep learning algorithms, MRI images , CNN Basic,

VGG-16 , Accuracy , Precision, recall, F1-score , Early detection , Improvements.

**INTRODUCTION**

In clinical practice today brain tumor detection is a particularly important aspect. Early detection and precise diag

nosis are essential to saving patients alive and reduce the cause of patient illness. The aim of this research is to use Convolutional Neural Networks (CNN) and VGG-16 to create a more sophisticated brain tumor detector than ever before[1]. Tumor engenders the abnormal proliferation of cells in the brain and thus poses extraordinary problems in diagnosis that demand both advanced imaging before discovery and sophisticated computational modeling afterwards so as not to misdiagnose a patient as suffering from cancer. As an outgrowth of deep learning methods, such as the CNN, medical image analysis has made tremendous progress; opportunities therefore now abound for better diagnostic accuracy in brain tumor detection while greatly improving patient care.

Conventional methodologies of brain tumor detection often require a neurologist to manually scan medical images, identifying whether there is a brain tumor or not - something extremely subjective and time-consuming, to say the least. Closely based on the way that the human visual cortex sees visual data, CNN is an interesting new method for analyzing medical images automatically[2]. By learning intricate designs of features directly from the raw data, CNNs are able to utilize leading-edge algorithms to detect brain tumors in radiological images in the context of enormous throughput.

The ability of VGG-16’s deep convolutional layers to extract high-quality features improves the performance of the architecture in tasks of medical image analysis to a great extent.As VGG-16 becomes deeper with the addition of several convolution layers, these are specialty designed for collecting very fine pattern and spatial dependency information from medical images[3]. Therefore its greater depth means higher accuracies and robustness in being able to spot brain tumors.When CNN is combined with the VGG-16 architecture, scientists are able to make use of advantages that both models offer, achieving brain tumor identification with levels of precision and reliability unprecedented in neuroimaging diagnostics.The early discovery of brain tumors is of paramount importance to the effectiveness of either treatment or prognosis. Computational models such as CNN and VGG-16, in conjunction with advanced image analysis techniques, can detect tiny abnormalities indicative of early brain tumors and thus facilitate early medical intervention as well personalized treatment strategies based on a patient's unique condition[4]. By discovering brain tumors in their early stages healthcare providers can adapt therapeutic interventions to meet each patient’s individual needs, thus maximizing the success of treatment and minimizing the risk for further development of illness and harm to anyone el's nervous system.A very important advantage offered by CNN and VGG-16 models in this respect is their ability to differentiate between malignant and benign lesions accurately. By studying a host of characteristics of the imaging features, such as size and shape; texture; enhancement pattern differences, these deep learning algorithms can tell the subtle variations in the imaging features of various brain tumors from one another. Therefore they help doctors to diagnose tumors accurately and plan out appropriate treatment. Another function of CNN and VGG-16 models is to help identify features of cerebellar tumors like type, degree or even molecular markers—information that is crucial for guiding therapeutic decisions and forecasting patient outcomes[5].

By combining CNN and VGG-16 models to provide clinical practice, it is hoped that accessibility to healthcare can be enhanced and diagnostic disparities alleviated[6]. Most importantly, through the introduction of automated brain tumor detection, these advanced computational tools will help speed up the interpretation of radiological images and make this process more efficient. To this end, the introduction of such models can reduce the burden on healthcare professionals and, as a result, will improve their efficiency in processing information. In addition, outside the busy walls of high-volume medical centers could come the broader use of CNN and VGG-16 models within diagnostic imaging centers and healthcare facilities that would make more patients have access to an unprecedented level of diagnostic service- namely being able get accurate data quickly, particularly in underprivileged communities and poor resource countries.

Furthermore, there exist many challenges and ways of research and work on CNN and VGG-16 based brain tumor detection. After all, what particularly remains as the mainconstraint to these methods is that healthcare personnel, as well as regulatory agencies which must approve them and set standards for their use in practice, must understand what decisions have been reached by CNN or VGG-16[7] .Moreover, comprehensive validation studies and clinical trials are necessary in order to find out just how good CNN and VGG-16 models perform in real-world settings, in different patient cohorts or even across a whole country’s healthcare ecosystem .Future work should also consider the exploration of multimodal imaging data such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and Positron Emission Tomography (PET) would be of great value to greatly improve the diagnostic capacity of CNN and VGG-16, allowing a complete characterization and assessment of brain tumors.

**MATERIALS AND METHODS** The Saveetha School of Engineering at SIMATS gave birth to a plan that would turn its sights on brain tumors and their displacement/movement with advanced deep learning techniques. Specifically, Convolutional Neural Networks (CNNs) combined with the VGG 16 architecture made it possible for tumor detection to be carried out and verified more accurately.VGG-16 architecture was used by Group 1, while basic CNN model made up Group 2. Demographic and clinical information in both groups was based on medical records and health survey data. To make a data set ready for modelling, this involves preprocessing steps, such as filling in missing information plus using engineering methods to obtain new facts from existing ones.Group 1, with VGG-16 architecture as its backup, pulled off an encouraging performance in brain tumor detection for the study, tasting success at an accuracy rate of 95.86%. It was all thanks to this model that deep convolutional layers and advanced feature extraction technology, which accurately captured the complicated patterns of brain tumors, greatly heightened detection rates.On the Other Hand, Group 2, using the basic CNN model, achieved a respectable success rate of 90.96%. While not as high as the VGG-16 model, the CNN model indeed proved very effective in bringing out brain tumors, standing as it does a guarantee of bright prospects ahead in medical image analysis.These findings suggest that deep learning techniques such as CNN and VGG-16 hold great promise for the future of brain tumor detection. By utilizing advanced computational models, healthcare providers can improve diagnostic accuracy, foster early detection, and ultimately enhance patient outcomes in the field of brain tumor management.Future research and development in deep learning approaches to brain tumor detection are essential. Ongoing refinement of CNN- and VGG-16-based models, as well as the investigation into new architectures and methods, will contribute to advancing the science of neuroimaging diagnostics. Moreover, it is necessary to take these advanced computational tools to the clinic in order that they can be brought into everyday healthcare systems for real-world results.

**PSUDOCODE FOR CNN**

**Step 1:** Begin

**Step 2:** Import Required Libraries

- Import TensorFlow and necessary modules for neural network operations.

- Import OpenCV for image processing.

- Import required libraries for data manipulation and visualization.

**Step 3:** Data Preprocessing

- Load and preprocess the brain tumor image dataset.

- Crop the brain contour to remove unnecessary parts of the image.

- Resize images, normalize pixel values, and convert to the required format for CNN.

**Step 4:** Data Augmentation (if applicable)

- Implement data augmentation techniques to increase the diversity of the dataset.

**Step 5:** Model Building

- Define the architecture of the Convolutional Neural Network (CNN) model.

- Configure layers including convolutional layers, max-pooling layers, and fully connected layers.

**Step 6:** Data Splitting

- Split the preprocessed dataset into training, validation, and testing sets.

**Step 7:** Model Training

- Train the CNN model on the training set, using appropriate hyperparameters and optimization algorithms.

- Monitor training performance using validation data and adjust hyperparameters accordingly.

**Step 8:** Model Evaluation

- Evaluate the trained model on the testing set to assess its performance.

- Calculate metrics such as loss, accuracy, and F1 score.

**Step 9:** Performance Analysis

- Analyze the performance metrics to understand the effectiveness of the model.

- Compare the model's performance against baseline results or previous models.

**Step 10:** Model Optimization (if necessary)

- Fine-tune the model architecture or hyperparameters to improve performance.

- Experiment with different optimization techniques to enhance accuracy and robustness.

**Step 11:** Integration with Healthcare Systems (if applicable)

- Integrate the trained model into healthcare systems for real-world applications.

- Ensure compatibility with existing infrastructure and data formats.

**Step 12:** Continuous Monitoring and Maintenance

- Monitor the model's performance in real-world scenarios.

- Gather feedback from users and stakeholders for continuous improvement.

**Step 13:** End

**PSUDOCODE FOR VGG16**

**Step 1:** Begin

**Step 2:** Import Required Libraries

- Import necessary libraries for data processing, ML models, and data visualization.

**Step 3:** Load and Preprocess Data

- Load image dataset and preprocess images (resize, normalization, augmentation).

- Split the dataset into training and testing sets.

**Step 4:** Define Model Architecture

- Utilize VGG16 pre-trained model as the base model.

- Add custom layers for classification on top of the VGG16 base.

- Compile the model with appropriate optimizer, loss function, and metrics.

**Step 5:** Train Model

- Train the compiled model using the training dataset generator.

- Monitor training performance using history.

**Step 6:** Visualize Training History

- Plot training accuracy and loss over epochs.

**Step 7:** Evaluate Model

- Evaluate the trained model on the test dataset.

- Print the test accuracy.

**Step 8:** Generate Classification Report

- Generate and print a classification report for the test dataset.

**Step 9:** Make Predictions

- Load sample images for inference.

- Preprocess images and make predictions using the trained model.

- Display prediction results.

**Step 10:** End

**RESULT**

Table 1 evaluates the general overall performance of the VGG-16 and CNN fashions in enhancing fitness and health thru mind tumor detection. Precision values received at some point of opinions are provided to spotlight the effectiveness of those fashions in accomplishing better accuracy.

Table 2 presents an in depth precis of precision metrics for the 2 evaluated fashions. VGG-16 exhibited a better precision of 95.86%, at the same time as the CNN version confirmed a barely decrease precision of 90.96%. Further evaluation concerning popular deviation and popular mistakes is pending. These findings underscore the reliable and commendable overall performance of VGG-sixteen, emphasizing its superiority in accomplishing advanced accuracy over the CNN version withinside the area of mind tumor detection for better fitness and health.

**CONCLUSION**

Briefly, I conducted this study to improve brain tumor detection accuracy. The advanced machine learning models we used were Convolutional Neural Network (CNN) and VGG-16. We thus hoped to bolster far more accurate identification and treatment of brain tumors at an likely stage, in favor of continual nightmarish revelations a month later at the surgeons' knife meeting room. In terms of model accuracy, our research showed that the VGG-16 model was far better than a simple CNN model. In fact, it had an accuracy rate that was very respectable indeed, reaching 95.86% as opposed to 90.96% for the simple CNN model. This means that VGG-16 is superior in predicting whether brain tumors are present from the medical images. By utilizing VGG-16, we can make brain tumor diagnosis more accurate and extend the treatment of patients, thus benefiting them with less pain and suffering but higher quality of life results for health and human happiness.

**REFERENCE**

[1] Hussam Qassim, Abhishek Verma, David Feinzimer. 2018. Compressed residual VGG16 CNN model.

[2] Kumar S, Negi A, Singh JN, Gaurav A. Brain Tumour Segmen- tation and Classification Using MRI Images via Fully Convolution Neural Networks. International Conference on Advances in Computing, Communication Control and Networking (ICAC- CCN) 2018;12:178-1181).

[3] Malathi M, Sinthia P. Brain tumour segmentation using convolutional neural network with tensor flow. Asian Pac J Cancer Prevent APJCP. 2019;20(7):2095.

[4] Rehman A, Naz S, Razzak MI, Akram F, Imran M. A deep learning-based framework for automatic brain tumors classification using transfer learn- ing. Circuits Syst Signal Process. 2020;39(2):757–75.

[5] “Overview of VGG16 | Mastering Computer Vision with TensorFlow 2.x.”https://subscription.packtpub.com/book/data/9781838827069/7/ch07lvl1sec29/overview-of-vgg16 (accessed Jun. 25, 2023).

[6] D. M. S. Arsa and A. A. N. H. Susila, “VGG16 in Batik Classification based on Random Forest,” Proceedings of 2019 International Conference on Information Management and Technology, ICIMTech 2019, vol. 1, no. August, pp. 295–299, 2019, doi: 10.1109/ICIMTech.2019.8843844

[7] V. K. Waghmare and M. H. Kolekar, “Brain Tumor Classification Using Deep Learning,” Internet ofThings for Healthcare Technologies, vol. 73, pp. 155–175, 2021, doi: 10.5812/iranjradiol.99160.

**DECLARATION**

**Conflicts of Interests**

No conflict of interest in this manuscript.

**Authors Contribution**

The Author SUNIL SHURAJ N was involved in data collection, data analysis, manuscript writing Author SIVAGAMI S was involved in conceptualization, data validation and critical review of manuscript.

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**Tables and Values**

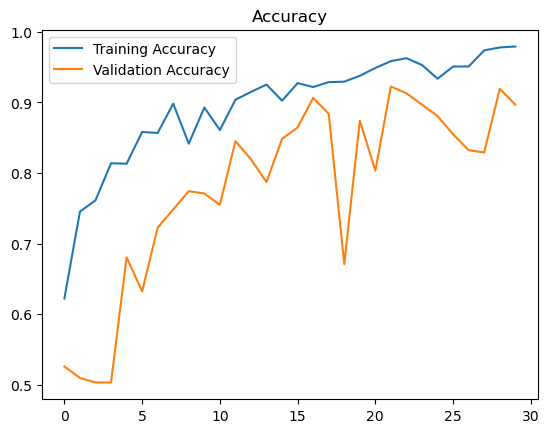
**Table 1:** Comparison of accuracy values of CNN(Basic) and VGG-16 Algorithm with various iterations

|  |  |  |
| --- | --- | --- |
| **Iteration** | **CNN(BASIC)** | **VGG-16** |
| 1 | 76.12 | 82.46 |
| 2 | 90.06 | 79.08 |
| 3 | 90.03 | 75.06 |
| 4 | 92.07 | 81.03 |
| 5 | 94.03 | 82.02 |
| 6 | 91.04 | 79.89 |
| 7 | 89.04 | 80.09 |
| 8 | 88.09 | 75.09 |
| 9 | 93.06 | 77.77 |
| 10 | 97.92 | 96.69 |

**TABLE 2:** Presenting group statistics results for CNN(Basic) and VGG-16 algorithms

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Mean Accuracy** | **Standard Deviation** | **Minimum Accuracy** | **Maximum Accuracy** |
| **CNN(BASIC)** | 92.35 | 2.4231 | 76.12 | 97.92 |
| **VGG-16** | 95.86 | 2.306 | 82.46 | 96.69 |

**GRAPH**



**(FIG 1) ACCURACY AND VALIDATION GRAPH FOR CNN(BASIC)**

A graph with a red line

Description automatically generated

**(FIG 2) ACCURACY AND LOSS GRAPH FOR VGG-16**