**ECONOMICAL IMPACT ON ADVANCE HEALTHCARE A COMPARATIVE ANALYSIS OF**

**BRAIN TUMOR DETECTION USING CNN AND VGG-19**

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**ABSTRACT**

**AIM** This paper analyzed the economic potential of using deep learning to detect brain tumors in healthcare. Diagnosing brain tumors is critical for effective treatment. Deep learning algorithms present a significant opportunity to make real improvements. **METHODOLOGY** Data: A dataset was used that contained brain MRI scans. It included healthy scans as well as scans with brain tumors. Models: Two deep learning models were employed. The first model was a Convolutional Neural Network (CNN). The second model was VGG-19, which is a pre-trained model already known for having good results in image recognition. Evaluation: To avoid overfitting, and to ensure model generalizability we employed five-fold cross-validation. This approach calculates model performance on different data splits, which provides a more robust evaluation. **RESULTS** Accuracy: The model VGG-19 performed better. It had an accuracy of around 91.67%. The CNN’s accuracy was approximately 90.96%. The economic impact of a higher level of accuracy in this prediction task is important. A better sensitivity and specificity in brain tumor detection can: Reduce unnecessary procedures: By minimizing false positives, invasive and expensive procedures may be avoided. Improve treatment efficacy: Detecting a problem earlier may increase the number of effective treatment options available. This may equate to better patient outcomes and less expensive healthcare in the long run. Increase productivity: As mentioned above, earlier detection could get patients back to work. It also contributes to economic activity in general. **CONCLUSION** This paper demonstrated that deep learning can have economic impacts. The improved accuracy of the learned model VGG-19 (over a basic CNN model) suggests that there is money to be saved, and improvement in patient outcomes for the healthcare system. Further research with larger datasets, and even implementation in a real world system could further solidify the economic impact of this technology.  
  
**KEYWORDS**

Deep learning, Brain tumor detection, Healthcare, Convolutional Neural Network (CNN), VGG-19, dataset, MRI scans, five-fold cross-validation, accuracy, sensitivity, specificity, economic impact, treatment efficacy, productivity, patient outcomes, healthcare system, real-world implementation, larger datasets, improved accuracy.

**INTRODUCTION**

The development of healthcare through cutting-edge technology is now illustrated on the field of brain tumor detection. Early detection that is both accurate and reliable is crucial for improving patient outcomes and reducing the burden of illness. In this study, we explore the potential of the architecture called VGG-19 and Convolutional Neural Networks (CNN) in changing the way that brain tumor detection works[1] . We will also compare their effects on helping doctors make better diagnoses.

Traditional methodologies depend on manual interpretation of medical images by neurologists. This is a subjective and labor-intensive practice. By mimicking the human visual cortex, CNN has invented a new computerized method to read medical photos. It is much faster and retains objectivity unparalleled in any other form of automated photo analysis[2].

Because CNN can discern intricate features directly from raw data, it shows great potential for the efficient and accurate detection of brain tumors. With an additional high number of convolution layers, the VGG-19 produces an especially good effect in some types of fine patterns and spatial dependencies: which is well embodied by medical images[3]. Consequently, as we will explain in this paper, it achieves a higher accuracy in finding tumors.

The combination of CNN and the VGG-19 architecture harnesses the strength of both models, which will arrive at unparalleled accuracy and reliability in neuroimaging diagnostics. Early detection of tumors is a crucial step toward timely medical intervention and treatment strategies tailored to individual needs, optimizing treatment success while minimizing harm to patients[4].

An added advantage of the CNN and VGG-19 models is that they can accurately distinguish between malignant and benign lesions, providing doctors with a great deal of help in diagnosis and treatment planning. Moreover, these models can identify specific tumor features such as classification, grade, and molecular markers important for therapeutic decision-making and prognostication.

Building CNN and VGG-19 models into clinical practice offers the promise of enhancing the availability of medical services while at the same time reducing disparities in diagnosis. With these advanced computational tools performing brain tumor detection all on their own, image interpretation is automated and healthcare efficiency rises. This in turn lefts a weight off the shoulders of medical professionals.

Obstacles remain, such as the need for healthcare staff and regulatory bodies to understand model decisions and conduct comprehensive validation studies[5]. Future studies should attempt to introduce multimodal imaging data that will further refine diagnostic capabilities and enable comprehensive characterization of brain tumors.

To sum up, the comparison study of brain ACT detection using CNN and VGG-19 suggests that the two methods can help to push the development of health industry[6]. From the point of view of accuracy, VGG-19 achieves 91.67% and CNN 90.96%. Exemplifying a paradigm shift towards more precise, efficient neuroimaging diagnostics these models stand to benefit both patients and their outcome.

**MATERIALS AND METHODS**

Comparative analysis by Saveetha School of Engineering at SIMATS in the field of brain tumor detection involved using convolutional neural networks (CNN) and VGG-19 architecture. Under the VGG-19 system, Group 1 managed to achieve an amazing 95.86% accuracy through its deep convolutional layers and advanced features. Group 2 hit anaccuracy of 90.96% using a basic CNN model, demonstrating that even simple methods can work admirably well in tumor detection. These results reveal the potential for deep learning techniques to revolutionize diagnosis of brain tumors. By using advanced computational models, combined with clinical data that is easy to obtain from patients and thanks in power amount, healthcare providers can now both enable early detection of ill health diseases such as cancer and improve patient outcomes. In the future deeper research into different technical approaches for doing non brain imaging diagnostics will be essentialMoving forward, efforts must focus on pushing these technologies out into a clinical setting. They should strive to meet the requirements of routine healthcare systems and work towards progress in the detection and treatment of brain tumors.

**PSEUDOCODE 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

**PSEUDOCODE FOR VGG-19**

**Step 1:** Begin

Step 2: Import Required Libraries

- Import necessary libraries such as os, cv2, matplotlib.pyplot, keras, and tensorflow.keras.

**Step 3:** Load and Preprocess Data

- Define the path to the dataset.

- Use ImageDataGenerator to preprocess and augment the images.

- Split the dataset into training and testing sets.

**Step 4:** Define Model Architecture

- Load the VGG19 pre-trained model without the top layers.

- Add custom layers for binary classification on top of the VGG19 base.

- Compile the model with the Adam optimizer and binary cross-entropy loss.

**Step 5:** Train Model

- Train the compiled model using the training set and validate on the testing set.

- Monitor training performance using the history object.

**Step 6:** Visualize Training History

- Plot training and validation accuracy over epochs.

- Plot training and validation loss over epochs.

**Step 7:** Evaluate Model

- Evaluate the trained model on the testing set.

- Print the test accuracy.

**Step 8:** End

**RESULT**

In Table 1, the overall performance of both VGG-19 and CNN models in the field of brain tumor detection were displayed.VGG-19 surpassed the CNN model by 0.71 in its presicion rate, while at the same time showing how pertinent these models are when it comes to improving chance identification within an image.

According to Table 2, precision is divided into three categories: micro, macro and weightedVGG-19 got a higher rating than the CNN model in terms of precision. It registered 91.67%, whereas the latter scored 90.96%.Now further research into standard deviation and error margins is needed. Moreover these results point out just how reliable VGG-19 is as compared with the CNN model for gains inaccuracy, so long as they affect plain tumors. This will certainly improve health care results for our people.

**CONCLUSION**

We tried to use advanced machine learning models such as Convolutional Neural Networks (CNN) and VGG-19 to improve brain tumor detection accuracy. If successful, early identification and treatment of brain tumors becomes more possible- and is no longer a rare procedure to be attempted out of desperation on an individual who has already suffered long term damage from living with this kind of disease without knowing exactly where else in her body large tumors lie. Our research showed that VGG-19 model achieved a better resuit than the equivalent of a simplified CNN--reaching 91.67% against 90.96%. It confirms the greater power of determining presence in medical images is endowed by VGG-19 and demonstrates real benefits for health care workers who need to make that snap call between doing nothing or slicing up some patient. Using VGG-19, we can raise the accuracy of brain tumor diagnostics, which will give patients better responses and lives. Ultimately, this will contribute to better health care and much less human suffering as a result.

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**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-19 Algorithm with various iterations

|  |  |  |
| --- | --- | --- |
| **Iteration** | **CNN(BASIC)** | **VGG-19** |
| 1 | 76.12 | 93.01 |
| 2 | 90.06 | 93.89 |
| 3 | 90.03 | 93.89 |
| 4 | 92.07 | 92.07 |
| 5 | 94.03 | 94.76 |
| 6 | 91.04 | 95.2 |
| 7 | 89.04 | 94.76 |
| 8 | 88.09 | 93.01 |
| 9 | 93.06 | 94.76 |
| 10 | 97.92 | 96.96 |

**TABLE 2:** Presenting group statistics results for CNN(Basic) and VGG-19 algorithms

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Mean Accuracy** | **Standard Deviation** | **Minimum Accuracy** | **Maximum Accuracy** |
| **CNN(BASIC)** | 90.35 | 2.4231 | 76.12 | 97.92 |
| **VGG-19** | 91.67 | 2.4231 | 64.63 | 96.94 |

**GRAPH:**

A graph of a graph with blue and orange lines

Description automatically generated

**ACCURACY GRAPH FOR CNN(BASIC)**

A graph with blue and orange lines

Description automatically generated

**ACCURACY GRAPH FOR VGG-19**