**EDUCATIONAL IMPACT OF ADVANCE DIAGNOSTICS A STUDY ON**

**BRAIN TUMOR DETECTION USING CNN AND U-NET**

**SUNIL SHURAJ N, SIVAGAMI S**

**SUNIL SHURAJ N**

Department of Artificial Intelligence And Data Science,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University,Chennai,Tamil Nadu,Pincode:602105,

[sunilshurajn4019.sse@saveetha.com](mailto:sunilshurajn4019.sse@saveetha.com)

**SIVAGAMI S**

Associate Professor, Corresponding Author,

Department of Data Vista,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, Pincode:602105,

sivagamis.sse@saveetha.com

**Abstract**

**AIM:** This study, for example, aims to explore the long-term educational effect of advanced diagnosis techniques, using brain tumor detection as an example. Early, correctly diagnosing brain tumors is essential for the well-being of patients. Anyone who sees a doctor about mental symptoms of any kind should have a check-up examination! In this area of medicine, deep learning algorithms hold great promise. **Methodology** Data: Our basis for this paper is a brain MRI scan dataset that includes both healthy and affected samples. Models: The study used two deep learning models CNN (Convolutional Neural Network): A mature and widely known architecture for image analysis. U-Net: A special architecture that is effective in image segmentation. Evaluation: We performed the five-fold cross-validation in order to ensure model's generalizability and prevent overfitting phenomenon. **Results** Accuracy: In detecting the presence of brain tumors from MRI scanned images within 91.50% model attacked they had better results than combining lines of CNN (90.96%). Educational outcomes: This study offers educators and healthcare professionals important insights: Deep learning strengths: It is a clever use of powerful deep-learning techniques for the analysis of medical images, particularly brain-tumor diagnosis. Comparative analysis: By contrasting CNN with U-Net,the study shows the strengths and potential advantages of specialized architectures like U-Net for segmentation tasks. Improved Diagnostic Education: These findings can be utilized in medical teaching, providing knowledge to future health professionals of advanced diagnostic tools. **Conclusion** Our research suggests that deep learning can be a valuable pedagogical tool in brain tumor detection. The higher accuracy of U-Net, compared to a simple CNN model, shows potential for improved diagnostic education and future advancements in this field. With further exploration of deeper learning architectures in brain-tumor detection, as well as the richer datasets that come from larger studies, we can continue to refine these capabilities.

**Keywords:**

Educational effect, Advanced diagnosis techniques, Brain tumor detection, Deep learning algorithms, MRI scan dataset, CNN, U-Net, Five-fold cross-validation, aAccuracy, Comparative analysis, Improved diagnostic education, Pedagogical tool, Future advancements.

**INTRODUCTION**

But in modern medical practice, it is critical to detect brain tumors on time. Timely diagnosis and precise identification are crucial to saving patients' lives and alleviating the symptoms of their diseases. The aim of our research project is to use Convolutional Neural Networks (CNNs.) and U-Net architecture created a sophisticated brain tumor detection system of unmatched refinement.

Due to brain tumors, cells inside the brain began to abnormally grow, and as a result diagnosing them is a formidable challenge. This requires advanced screening techniques ahead of detection and research into fine computational models to prevent mistakes from the machine. Through deep learning technologies such as CNN and U-Net, major advances have been made in medical image analysis. This means better diagnosis and care for patients.

Of course, traditional brain tumor detection utilizes comprehensive judgement of medical images by neurologists, a subjective and time-consuming process. CNN is inspired by the human visual cortex and gives an automatic approach similar to the brain's processing of visual information. Learning subtle patterns directly from raw data, CNNs have powerful capabilities in identifying brain tumors from radiological images efficiently.

U-Net architecture with its deep convolution layers is well-versed in extracting high-quality features and so satisfies the demands of medical image analysis. With its increased depth and convolution layers specifically-designed to capture fine details and spatial relationships from medical images, U-Net heightens accuracy and stability in identifying brain tumors.

The fusion of CNN and U-Net forms a system that draws on the advantages of both models to provide unsurpassed accuracy and reliability in neuroimaging diagnostics. Early detection of tumors is crucial to positive treatment outcome and prognosis. Medical image analysis using subject CNN and U-Net models provide the means to identify tiny anomalies that could suggest the onset of a tumor, leading timeously to intervention and tailoring therapeutic strategies.

CNN and U-Net models have an important advantage in that they can accurately distinguish malignant from benign lesions. By examining multiple parameters of imaging characteristics-classifying a lesion's size, shape, texture, and mode of enhancement-these models help to make precise diagnoses that guide tumor treatment strategies.

What's more, when these advanced tools are introduced, automated brain tumor detection will be brought to the mainstream of healthcare. By quickening the interpretation of radiological images, they lighten the load on healthcare personnel and improve efficiency by providing diagnostic services to resource-limited regions where healthcare infrastructure is still meager down-to-earth.

The challenges faced include the need for medical personnel and regulators to understand the decisions made by CNNs or U-Net models. Comprehensive validation studies and clinical trials are crucial in determining real-world performance across many patient populations and different healthcare settings for such models.

Future research should work on integrating multimodal imaging data-magnetic-resonance imaging, computed tomography (CT), and positron emission tomography (PET)-to further enhance the diagnostic capabilities of CNN and U-Net systems. By constantly refining and validating them, diagnostic systems based on CNN and U-Net hold out the promise of revolutionizing brain tumor detection and improving patient outcomes on a global scale.

**MATERIALS AND METHODS**

Saveetha Engineering College was involved in a challenging research operation that used the most current techniques in deep learning for recognizing brain tumors. Harnessing deep learning techniques such as Convolutional Neural Networks (CNNs) within the present VGG-16 architecture, the study realized promising results. From its deep convolutional layers and advanced feature extraction capability Group 1, utilizing VGG-16, achieved a truly formidable accuracy rate of 95.86%.Group 2, on the other hand, achieved a credible accuracy of 90.96% using a basic CNN model indicating its effectiveness in tumor detection.These findings illustrate the potential of deep learning techniques to enhance brain tumor diagnosis. Future research institutions should focus on further refining the models known as CNN and VGG-16, and putting them into clinical use so that patients might actually benefit. The cumulative impact of this research in education is considerable; it points to the potential of modern diagnostics to transform the way we manage brain tumors and ultimately improve patient outcomes.

**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 U-NET**

**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 U-Net.

**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 U-Net model.

- Configure encoding and decoding paths including convolutional layers, max-pooling layers, and transpose convolution layers.

**Step 6:** Data Splitting

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

**Step 7:** Model Training

- Train the U-Net 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 Intersection-Over-Union (IoU).

**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.

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**Step 13:** End

**RESULT**

**Table 1: Evaluation of CNN and U-Net Models for Brain Tumor Detection**

| **Model** | **Accuracy** | **Precision** |
| --- | --- | --- |
| CNN | 90.96% | 0.533 |
| U-Net | 91.50% | 0.615 |

**Table 2: Precision Metrics for CNN and U-Net Models**

| **Model** | **Precision** |
| --- | --- |
| CNN | 90.96% |
| U-Net | 91.50% |

Table 1 provides an overview of the performance of CNN and U-Net models in advancing healthcare through brain tumor detection. While both models demonstrated high accuracy, Table 2 offers a detailed summary of precision metrics. The U-Net model exhibited superior precision of 91.50%, compared to CNN's slightly lower precision of 90.96%. Further analysis regarding standard deviation and common errors is pending. These results underscore the reliable and commendable performance of U-Net, highlighting its superiority in achieving enhanced accuracy over the CNN model in the domain of brain tumor detection, thus contributing to improved healthcare outcomes.

**CONCLUSION**

In conclusion our aim is to improve the accuracy of brain tumor detection, using the most advanced machine learning model to date Convolutional Neural Network (CNN) and U-Net. The ultimate aim of this research was to improve brain tumor detection at an early stage so that surgery is not necessary and patients will have less pain. Results showed that when predicting medical images of brain tumor diseases, the U-Net model of prediction accuracy was highest--at 91.50%. A simple CNN model scored 90.96%. This means that U-Net has the best model performance of all in identifying brain image of tumor out from a set of images taken at random from medical records instead for example tables or descriptions in text form

The use of U-Net offers significant potential to help patients with brain tumors achieve more accurate diagnoses and receive better medical services. Through these advanced diagnostic techniques, patients benefit in terms of both medical care and their quality of life as a whole. In the future, integration of U-net into clinical practice will potentially redefine standards and procedures for neuroimaging testing among patients with brain tumors. The effect of this Our study such as advancing detection of tiny tumors in the brain by means of innovation or equipment upgrade may well be a guide for future research development on how to develop medical products fitting of mankinds talents and Times.

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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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**GRAPHS**

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

A graph of a graph

Description automatically generated

**(FIG 2) ACCURACY AND VALIDATION GRAPH FOR U-NET**

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