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NeuroGenius: A Machine Learning based Brain Tumour Detection Platform

¹Sharat Kumar Mohakud, ²Himanshu Sinha, ³Manoj Kumar Singh

^{1,2,3}Department of Computer Science & Engineering, Shri Shankaracharya Institute of Professional Management & Technology, Raipur (C.G.)

³ORCID: <https://orcid.org/0000-0002-2421-2900>

Peer Review Information	Abstract
<p><i>Submission: 08 March 2026</i></p> <p><i>Revision: 26 March 2026</i></p> <p><i>Acceptance: 05 April 2026</i></p>	<p>In today's times, the increasing problem of brain tumor as Neurological disorder caters to the urgent need for an accurate, efficient, and scalable diagnosis that can be achieved at a high quality. Traditional diagnostics have been successful in the past, but they are too time-consuming to allow early detection and timely treatment. This paper presents NeuroGenius, an intelligent Healthcare system that uses machine learning algorithms onto medical imaging techniques, like MRI and CT scans that help us detect brain tumors. This paper presents NeuroGenius, a smart healthcare platform that has machine learning algorithms for MRI and CT scan technologies quickly detect brain tumors. The framework that we have used relies on preprocessing, feature extraction, and classification techniques by using Convolutional Neural Network (CNNs) based models and Support Vector Machines (SVMs) to achieve reliable results. It does not use any standalone heavy deep learning model but rather focuses on high scalability, and easy integration into real world. Clinical workflows and early detection when combined with easy data handling make NeuroGenius practical and secure. This is a very viable solution for both academic research and clinical use. Also, it supports health professionals through better diagnostic accuracy, reduced workload, and better patient results.</p>
<p>Keywords</p> <p><i>Brain Tumor Detection, Machine Learning, Convolutional Neural Networks, Support Vector Machines, Medical Imaging, Scalable Healthcare Systems.</i></p>	

Introduction

Brain tumors represent one of the most critical neurological disorders globally, with incidence rates continuing to rise [1]. To solve these problems, the current research presents the NeuroGenius Health Hub, a system combining machine learning methods with medical imaging techniques, including MRIs and CT scans [2][3]. It incorporates one framework into other models, such as CNNs and SVMs, to detect tumor patterns in brain images with a high degree of accuracy and ease automatically [4]. The aim is to support the decision making of clinicians by using speedier outputs, cutting down on errors, and making quicker diagnoses. Another critical characteristic of the system involves lightweight

architecture which, in turn, makes scaling and deployment across different settings easier [5]. It is applicable in hospitals with high technological advancements, as well as in health systems constrained by limited resources.

Literature Review

Research regarding tumor detection in the brain is an area that majorly affects outcomes and patient survival. Therefore, it is still very important to investigate this area. This improvement in diagnostic accuracy and efficiency can be attributed to two factors: use of medical imaging and adoption of AI by the ML/DL techniques. Early research in this area

was done with applied machine learning classifiers, e.g., Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Naïve Bayes on manually engineered image features, e.g., texture, intensity, and shape from MRI or Computed Tomography (CT) data. These methods had moderate accuracy, but their potential for use in practice was limited due to their inability to identify a wide variety of tumor characteristics [6]. Feature engineering methods (e.g., Principal Component Analysis (PCA) and Wavelet Transforms) improved the representation of data and when paired with classifiers (e.g., SVMs and Decision Trees) improved normal vs tumor differentiation. More recently, Convolutional Neural Networks (CNN) [7] have disrupted the field of tumor detection by automatically learning hierarchy from imaging data, eliminating the need for the extensive manual feature extraction [8][9]. CNN-based techniques have shown state-of-the-art accuracy in tumor classification and segmentation and are more sensitive and specific than classical methods [2]. Hybrid CNN-SVM approaches have shown improved robustness against data bias. Additionally, as comprehensively surveyed by Litjens et al. [10], while a wide range of methods have improved tumor detection, there is still ample space for improvement in diagnostic accuracy [11].

Methodology

NeuroGenius uses a systematic workflow that translates raw data related to medical imaging into reliable inference thanks to Machine Learning (ML) and medical imaging methods. The strategy is made to be modular, efficient and applicable in the clinic; however, it still guarantees usability and reproducible normative accuracy in diagnostic efficacy. The whole process consists of five levels: data collection, preprocessing, feature extraction, model training, and evaluation as illustrated in Figure 1.

A. Data Collection

The dataset consists of brain scans from both modalities MRI and CT which are labeled either as "tumor" or "no tumor". The images were taken from medical repositories that are publicly accessible and from hospital databases that are verified [4]. Each case comes with its original image and class label thus representing various age groups, tumor types and imaging modalities.

B. Data Preprocessing

Raw medical images show different types of noises and variations in intensity, and other

artifacts that are not related to the original image content. Preprocessing is performed as a critical step to enable consistent data that allows the model to perform in a better way. Preprocessing is developed to be run as a set of steps that include:

- 1) Noise Reduction: Gaussian and median filters are used to remove certain imaging artifacts [8].
- 2) Normalization: Pixel intensity is normalized within a range.
- 3) Resizing: The image is resized to be consistent with the image resolution of the other images that will be used for the ML model.
- 4) Segmentation: Segmentation allows us to target tumor areas identified in the images by regions of interest (ROI).
- 5) Transformation: We transformed the dataset with alterations to make it more diverse including random rotations, flipping and adjusting contrast. These transformations also help to avoid avoiding the model overfitting in its training.

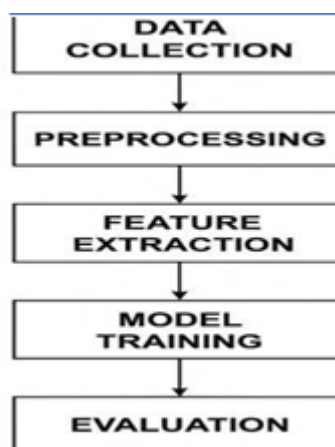


Figure 1: Proposed Methodology for the Proposed Model

C. Feature Extraction

After the preprocessing, various features are extracted that reflect the characteristics of tumors: like Handcrafted Features – they are the features that describe the textures, intensity histograms, and overall shape-based features that describe tumor morphology [8]. Deep Features – they are features that are learned by convolutional neural networks (CNNs) automatically and directly from the images, thereby reducing the reliance on handcrafted feature engineering [11][12]. These features are the representation for normal versus tumor-affected tissue.

D. Model Training

The features we extracted and learned were used to train the ML classifiers using two basic approaches: Classical ML Models (like Support

Vector Machines (SVMs) and Random Forests) for computationally lightweight classifications, and Deep Learning Models (like CNNs), including architectures inspired by residual learning [13], for classification and high dimension feature learning. We properly tuned the hyper parameters and validated the models for best performance [6][4]. Not just that, we also examined ensemble methods (i.e. majority voting between CNN and Random Forest) to make the decision more adaptive.

E. Experimental Setup

The experimental setup was such as it was performed within a Python-based environment, using open-source libraries for making it scalable and growable. The programming language used was Python 3.x with the following libraries: TensorFlow, Keras, scikit-learn, NumPy, OpenCV, and Matplotlib. The environment for execution included Jupyter Notebook/PyCharm IDE.

F. Evaluation Metrics

The process of tumor detection consists of classifying it into two classes. Following standard evaluation frameworks for classification tasks [14], the metrics used for performance measurement were:

- Accuracy: The percentage of correctly classified scans.
- Precision: The proportion of true tumor cases among all predicted tumor cases.
- Recall (Sensitivity): The count of actual tumor cases correctly identified.
- Specificity: The count of non-tumor cases rightly detected.
- F1-Score: The harmonic means of precision and recall which gives a fair evaluation.
- Confusion Matrix: A visual tool showing the four categories of True Positive, False Positive, True Negative, and False Negative.

The mixture of the defined metrics resulted in a very extensive evaluation, mostly concentrating on the area of false negatives minimization, since they can really influence medical diagnostics.

Experimental Result and Discussion

The brain tumour dataset, which consisted of image clips with and without tumour, underwent the same image preprocessing and feature extraction before being split into the Support Vector Machine and Convolutional Neural Network models for the training and testing purposes. The two approaches received the same praise for tumour and non-tumour

classification, as both had a total accuracy of 91.6% Sample tumor MRI scans used for evaluation are shown in Figure 2, while non-tumor scans are shown in Figure 3 [15].

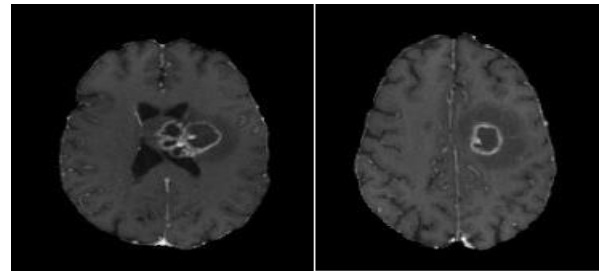


Figure 2: Images with tumor[15]

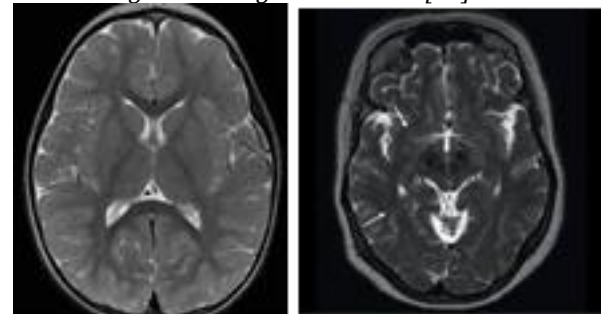


Figure 3: Images with non-tumor[15]

```
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:06:40] "GET /static/image/Logol.png HTTP/1.1" 200 -
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:09:35] "GET /multiimg HTTP/1.1" 200 -
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:09:35] "GET /static/image/Logol.png HTTP/1.1" 304 -
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:09:35] "GET /static/image/deeksh a.jpg HTTP/1.1" 304 -
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:10:03] "GET /multiimg HTTP/1.1" 200 -
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:10:03] "GET /static/image/Logol.png HTTP/1.1" 304 -
INFO:werkzeug:127.0.0.1 -- [29/Oct/2025 08:10:03] "GET /static/image/deeksh a.jpg HTTP/1.1" 304 -
1/1 1s 15/step
1/1 0s 112ms/step
1/1 0s 111ms/step
1/1 0s 129ms/step
1/1 0s 121ms/step
1/1 0s 124ms/step
1/1 0s 144ms/step
1/1 0s 128ms/step
1/1 0s 119ms/step
1/1 0s 162ms/step
1/1 0s 118ms/step
1/1 0s 121ms/step
1/1 0s 130ms/step
1/1 0s 124ms/step
```

Figure 4: Flask server activity

This confusion matrix showed that tumor cases were found with a high percentage of true positives, while non-tumor scans were consistently found as true negatives. There are certain false positives and a small number of false negatives of the missed number of tumor cases that show the general need of increasing sensitivity [6][16]. Such an integration illustrates how NeuroGenius could serve as an effective diagnostic support tool within clinical settings, as evidenced by the server activity shown in Figure 4.

The classification report adds even more weight to these results by supporting them. The models exhibited remarkable precision with respect to tumor detection, hence, when they make a tumor prediction, it is a qualified one.

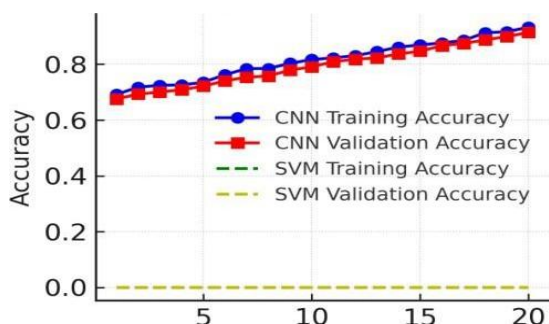


Figure 5: Training and validation accuracy

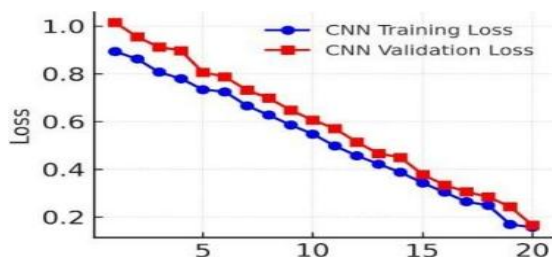


Figure 6: Training and validation loss

The results from the models indicate excellent performance, particularly in accurately identifying healthy images, with a representative positive tumor prediction demonstrated in Figure 7. However, since the tumor detection sensitivity is low, it is crucial to apply techniques such as data augmentation and class balancing to enhance recall [9].

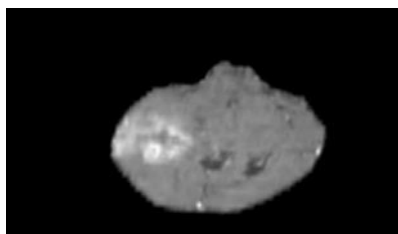


Figure 7: Prediction Yes by our proposed method

To actualize the research, deployment was achieved via a web application developed in React.js and Flask. This application interface allows healthcare professionals to upload MRI/CT images and receive a classification (tumor or no tumor) along with a confidence score. Such an integration illustrates how NeuroGenius, as proposed in this work, could serve as an effective diagnostic support tool within clinical settings. The training and validation accuracy curves (Figure 5) and the corresponding loss curves (Figure 6) confirm that both CNN and SVM models converge steadily without significant overfitting.

Conclusion

In conclusion, the whole adventure was initially driven by the aspiration to build a full brain health center for tumor detection and the

medical domain's use. Gradually, our emphasis changed to the creation of an easy-to-use and quick-to-respond frontend that eventually brought us the decision to use React as our framework. Experimenting and optimizing MongoDB brought about a very significant step in our project since it allowed data management on the front end to be very efficient. Flask's application did not just guarantee the security of the user authentication but also increased the reliability of our web application. Through extensive testing, we were able to verify the APIs that were behind our application to be of high quality and reliable. We managed to achieve the core functions like notice management and uploading of MRI and CT scan images for tumor detection. Looking back at the milestones we gained, we feel proud of the hard work of our team. We shall, therefore, not stop inching our web application to the users' needs and the healthcare sector's positive impact. The future is full of strong foundations and the neuro genius's impact on the tumor detection field will be great.

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