Deep Learning-Based Brain Tumor Classification Using MRI Images: A DenseNet 201 and SVM Approach

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**Abstract.** The brain is a vital organ in the human body, primarily responsible for processing sensory information, generating motor responses, and enabling complex cognitive functions. Brain tumors, which arise from abnormal tissue growth within brain cells, are among the most common brain disorders. According to the International Agency for Research on Cancer, over 124,000 individuals worldwide were diagnosed with brain tumors in 2014, with more than 97,000 fatalities recorded. Presently, Magnetic Resonance Imaging (MRI) remains the preferred approach for detecting brain tumors. Given the high mortality risk associated with brain tumors, extensive MRI image datasets of brain tumors were analyzed in this study to facilitate detection through deep learning. The approach employed here involved the DenseNet 201 model combined with Support Vector Machines (SVM) to classify three tumor types: glioma, meningioma, and pituitary tumors. The highest accuracy achieved in this study was 99.65%, using an 80% training and 20% testing data split, with oversampling applied through the SMOTE method.

**Keywords:** Brain, Tumor; MRI, DenseNet, SVM, CNN

# INTRODUCTION

The brain is a vital organ in the human body, playing a central role in daily functions, much like other organs. With a volume around 1,350cc, it contains over 100 million nerve cells that manage all human activities. The cerebral cortex, the brain's outer layer, is responsible for processing sensory input and coordinating motor actions, as well as enabling complex cognitive functions [1]. Consequently, the brain is essential for sustaining life. If brain function ceases, nerve cells are unable to operate correctly, ultimately leading to the individual's death.

A brain tumor, the most prevalent brain disorder, occurs due to the growth of abnormal tissue in the brain. Glioma, also known as astrocytoma, is one of the most frequent types affecting both children and adults [2]. Brain tumors are categorized into two types based on their origin: primary and secondary [3]. Primary brain tumors originate from the brain tissue itself, while secondary brain tumors develop when cancer from other body organs spreads to the brain. Although the exact cause of genetic mutations leading to brain tumors remains unknown, certain factors—such as age, heredity, and prior radiotherapy—can increase the likelihood of tumor development. Among primary brain tumors, glioma is one of the most deadly types, especially in adults [4].

According to 2014 data from the International Agency for Research on Cancer, over 124,000 individuals are affected by brain tumors, resulting in more than 97,000 deaths (Sabbih Hamoud & Ghazali, 2014). This highlights the serious threat this condition poses to the lives of those affected.

Currently, technology plays a crucial role in supporting disease diagnoses, aiding medical professionals in performing highly accurate examinations thanks to rapid technological advances. Among the tools used to diagnose brain cancer, Magnetic Resonance Imaging (MRI) stands out as one of the most powerful and flexible imaging techniques in clinical medicine. MRI works by capturing detailed images of internal organs using strong magnetic fields around the patient's body. Over the past 30 years, significant advancements in MRI have enabled it to provide functional and quantitative insights, including data on microstructures and blood flow within tissues. MRI is particularly useful in diagnosing brain tumors, offering a safer alternative to CT scans, especially for sensitive patients. Additionally, the quality of MRI images has continued to improve, supporting earlier diagnosis of such conditions. With increased availability of MRI images online, researchers in this study have been motivated to develop tools that aid medical professionals in their work [5].

In the diagnostic process for brain tumor patients, paramedics often face delays in decision-making and reaching conclusions. This is problematic because brain tumor treatment typically requires swift action [2]. Consequently, the availability of numerous MRI images of brain tumor cases has motivated researchers to develop classification systems for brain tumors. Machine learning and deep learning techniques have become instrumental in creating these classification systems, allowing MRI images to be processed efficiently for accurate and timely diagnosis. Common machine learning methods used include K-Nearest Neighbors (KNN), Neural Networks, Support Vector Machines (SVM), and Random Forests. Among deep learning approaches, the Convolutional Neural Network (CNN) is widely favored.

Recent studies have focused extensively on classifying brain tumors using MRI images from patients. Over the past five years, research has consistently shown that MRI technology can efficiently categorize brain tumors, offering quicker diagnostic results. A study titled "Multi-Classification of Brain Tumor Images Using Deep Neural Network" reported high accuracy levels in classification. This research, led by Hossam H. Sultan and colleagues in 2019, applied the CNN algorithm and tested two scenarios using distinct dataset structures [6]. The first scenario used data collected from Nanfang Hospital and General Hospital of Tianjin Medical University in China between 2005 and 2010. This dataset included three types of brain tumors: meningioma, glioma, and pituitary, with the model achieving an average accuracy of 96.13%. In the second scenario, a dataset classifying glioma brain tumors across grades I to IV was taken from The Cancer Imaging Archive (TCIA), specifically from the Repository of Molecular Brain Neoplasm Data (REMBRANDT). This model achieved 98.7% accuracy, distinguishing meningioma, glioma, and pituitary tumor types.

A study by Abdu Gumaei and colleagues, titled "A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification" (2019), explored brain tumor classification using MRI images from a dataset developed by Jun Cheng. The dataset included 3064 MRI images, categorized as 1426 meningioma, 708 glioma, and 930 pituitary images. This study employed the Regularized Extreme Learning Machine (RELM) approach, achieving an accuracy rate of 94.23% [7].

In 2019, S. Deepak and colleagues conducted a notable third study on brain tumor analysis, achieving impressive accuracy. Their research, titled "Brain Tumor Classification Utilizing Deep CNN Features via Transfer Learning" [8], reached 98% accuracy by using a pre-trained CNN model. They employed GoogleNet for feature extraction from MRI brain tumor images, with Support Vector Machines (SVM) for MRI image classification. The dataset used in this research was developed by Jun Cheng and is available on Figshare [8].

A study by Zar Nawab Khan Swati et al., titled "Brain Tumor Classification for MR Images Utilizing Transfer Learning and Fine-tuning" [9], explores the use of transfer learning, specifically with the VGG19 model, to classify MRI brain tumor images, achieving a top accuracy of 94.82%. This study uses a dataset developed by Jun Cheng, comprising 3064 images from 233 patients with brain tumors [9].

Similarly, research in 2020 by Neelum Noreen et al., titled "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor" [10], applies a dataset created by Jun Cheng and employs models such as InceptionV3 and DenseNet201. This approach reaches high accuracies of 99.34% and 99.51%, respectively [10].

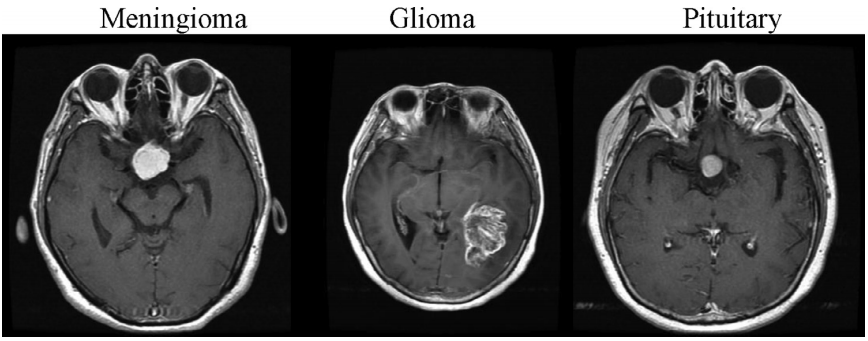
Building on findings from past studies that emphasize the need for method refinement to improve accuracy, recent research using InceptionV3 and DenseNet201 has shown accuracy exceeding 99%, significantly surpassing previous results. Given these advancements, the authors of this study seek to develop a model for classifying brain tumors by analyzing Magnetic Resonance Imaging (MRI) images. This model will employ deep learning for feature extraction, specifically utilizing DenseNet201, which distinguishes this study from earlier ones by achieving superior accuracy on the selected dataset. The goal of this research is to create a model with high accuracy and precision in tumor classification.

# METHODS

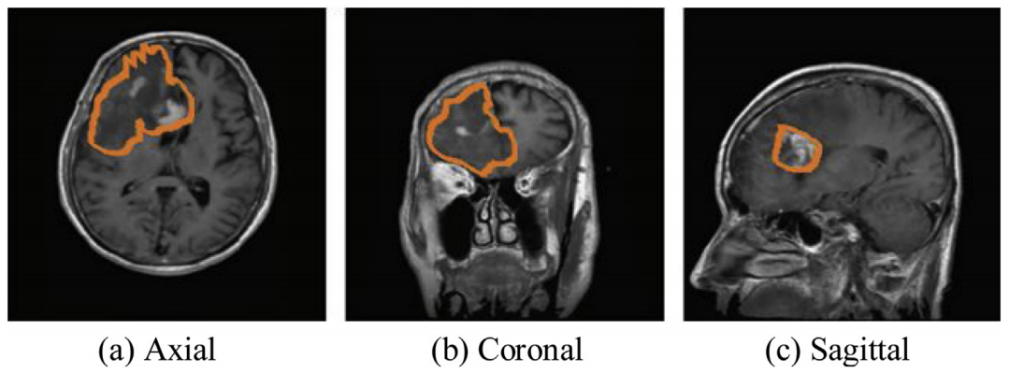
## DATASET

The dataset utilized in this study comprises MRI brain images collected from 233 patients diagnosed with brain tumors, originally compiled by Jun Cheng. Data collection occurred between 2005 and 2010 at Nanfang Hospital in Guangzhou and the General Hospital of Tianjin Medical University, both in China [9]. MRI images in this dataset were acquired using three sampling methods—axial, sagittal, and coronal—each capturing images at different angles, resulting in varied perspectives of the tumors. **FIGURE 1** displays an example, showing the full MRI image resolution of 512x512 pixels. The dataset includes three types of tumors: meningioma, glioma, and pituitary, as illustrated in **FIGURE 2**, with approximately 1426 images of meningioma, 708 images of glioma, and 930 images of pituitary tumors. Due to the distribution of images, this dataset from Jun Cheng is classified as imbalanced.

The dataset processing in this study is kept minimal, with an emphasis on test scenarios that vary based on the model and dataset type. The original dataset, sized at 512x512 pixels, is resized to 224x224 pixels to improve performance and speed up computation. The resized dataset is then split into two segments, with 80% allocated for training and 20% for testing. During this split, random selection functions from the sklearn library are used, setting the random\_state to 21 for consistency.



**FIGURE 1.** Sample images of 3 different tumor types [11]



**FIGURE 2**. Samples of differences in brain tumor MRI imaging techniques (a) Axial, (b) Coronal, (c) Sagittal [9]

The dataset undergoing conversion will initially be processed through the DenseNet 201 model, which identifies the optimal weight for each pixel in the image. This weight acts as a parameter to help classify the MRI image of a brain tumor. Following extraction, each image will then possess a new parameter with a value of 94,080.

## SMOTE

The dataset utilized in this research is considered imbalanced due to a notable discrepancy in data quantity across its three classes. To address the imbalance issue, some studies have employed oversampling techniques, which involve increasing the data in underrepresented classes to match the size of the most prevalent class. One approach for this is SMOTE, introduced by Chawla in 2002, which generates synthetic data for the minority class by leveraging the K-nearest neighbors algorithm [12].

## PROPOSED MODEL

### DenseNet 201

DenseNet 201 is a technique in transfer learning within deep learning that reuses pretrained models from previous tasks to address current problems [13]. There are various types of pre-trained models available for CNNs, including AlexNet, VGGNet, LeNet, and DenseNet [13]. This study specifically utilizes the pretrained DenseNet201 model to extract features from MRI images of the brain.

In the DenseNet 201 method for brain tumor datasets, data extraction was performed on both the lower and upper dense blocks. This approach involved four dense block levels, each defined by the specific number of layers within each block [10].

1. Convolution Layer

In a CNN, the convolution layer serves as the initial layer, linking the input with the filter, structured as a cubic block of neurons.

1. Max-poling Layer

This layer's purpose is to decompose the dataset, selecting the maximum value for each pixel within four newly created elements. It helps reduce the required parameters and accelerates the computation process [6].

1. Fully Connected Layer

The final layer of the CNN, which serves as the classifier, determines the class label of the tested data through the fully connected layer.

1. Support Vector Machine (SVM)

Support Vector Machines (SVM) are a popular method in supervised learning, widely used for both classification and regression tasks. Compared to other classification techniques, SVM provides an improved approach to handling both linear and non-linear issues effectively [14].

In this research, SVM was selected as in prior studies. The SVM classifier was combined with Deep CNN for feature extraction to achieve high accuracy [8].

# RESULTS AND DISCUSSION

At this point, four tests were carried out, each highlighting key differences across proposed scenarios involving two distinct classifiers. The first and second scenarios employed imbalanced datasets, while balanced datasets were used in the third and fourth scenarios. Additionally, adjustments to model parameters for both the DenseNet and SVM classifiers were made to optimize model performance.

## 1ST TESTING

The initial test scenario involves classifying an imbalanced MRI brain tumor dataset, which was extracted using the DenseNet 201 model and then classified with a Support Vector Machine (SVM) model. The dataset includes 1,143 samples of the glioma class, 740 of the pituitary class, and 568 of the meningioma class for training purposes. Model performance is assessed using test data, with each class having a 20% split for testing. The SVM classifier uses an rbf kernel with a C parameter of 10.

The SVM model developed showed promising results in this first scenario. Test data served as validation across all scenarios. As shown in Figure 7, the model’s overall performance is satisfactory, though the meningioma class has a relatively lower precision compared to the glioma and pituitary classes.

## 2ND TESTING

In this second testing scenario, the dataset used is similar to the one in the first scenario. The DenseNet 201 model is modified by adjusting the last dense layer.

The training process for this DenseNet 201 model involves 200 epochs, using the Adam optimizer with a learning rate of 0.0001 and a decay rate of 0.0001/16, a batch size of 16, a softmax activation function at the final layer, and categorical crossentropy for the loss function.

The highest accuracy reached during training in this scenario is 98.04%. However, when the final model is tested on the test dataset, the accuracy drops slightly to 97.22%.

The classification report from this second test scenario indicates that the best performance achieved in the first test was not surpassed. A reduction in precision, recall, and f1-score for the meningioma class impacted the validation model’s performance, leading to a lower outcome than in the first scenario. However, the validation accuracy during model training still managed to reach 98.04%.

## 3RD TESTING

The third test scenario was conducted in a similar way to the first one, with the key difference being the use of a dataset that was initially imbalanced. This dataset was adjusted using the SMOTE method to create an equal amount of data between the minor and major classes. The SVM model's parameters were kept consistent with those in the first scenario to ensure clearer comparative results. Upon testing the trained model with the test data, a maximum accuracy of 99.18% was achieved. Improvements in precision, recall, and F1-score across all classes indicate that the balanced dataset in the third scenario enhances performance over the previous two scenarios.

## 4TH TESTING

In the final test scenario, the DenseNet 201 model was applied similarly to the second test setup. The originally imbalanced dataset was modified through oversampling to ensure an equal distribution of data across all classes.

The model was trained under specific conditions: 200 epochs, Adam optimizer, a learning rate of 0.0001 with a decay rate of 0.0001/16, batch size of 16, categorical cross-entropy loss, and softmax activation in the final layer. During training and testing, this balanced dataset scenario showed superior performance compared to earlier scenarios. The model, initially set for 200 epochs, was stopped early through a callback function as it reached the targeted accuracy quickly. The highest accuracy achieved was 99.65%, halting training at 59 epochs.

## EVALUATION of TEST RESULTS

The study proposes utilizing transfer learning techniques to analyze MRI images of brain tumors by guiding the model's performance through feature extraction derived from the DenseNet 201 model. The dataset, known as the Jun Cheng dataset, comprises information from 233 brain tumor patients treated between 2005 and 2010, with data collected from Nanfang Hospital in Guangzhou, China, and the general hospital of Taijin Medical University, China. This dataset is categorized into three tumor classes: meningiomas, gliomas, and pituitary tumors. Notably, the data distribution across classes is imbalanced, with 1,426 images for meningiomas, 708 for gliomas, and 930 for pituitary tumors.

Previous studies have also employed the Jun Cheng dataset, achieving commendable accuracy rates. For instance, Abdu Gumaei and colleagues' research, titled “A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification,” reported an accuracy rate of 94.23% [7]. In previous studies, the best results achieved reached 99.51%. Notably, this result was from research conducted by Neelum Noren and colleagues, titled "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor" [10]. This research employs the DenseNet 201 model, configured with 100 epochs, a learning rate of 0.0001, a batch size of 20, the Adam optimizer, and categorical cross-entropy as the loss function. The data split used in this study follows a similar pattern to prior research, with 80% of the data designated for training and 20% for testing. In the fourth test scenario, where the datasets were balanced through oversampling, the DenseNet 201 model achieved a peak accuracy of 99.65%. TABLE 1 presents the testing outcomes across all scenarios.

In this study, the highest performance was achieved in the fourth test scenario by applying the DenseNet 201 model along with a balanced dataset. TABLE 2 shows a comparison of model performance with previous research. The prior research that achieved the best results was titled "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor" by Neelum Noren, et al. [10]. The DenseNet 201 model implemented here reached an accuracy of 99.51%. The primary distinction between this study’s DenseNet 201 model and that in the previous work is the modification of the final dense layer and the use of balanced datasets generated via the SMOTE method. The author chose the DenseNet 201 model due to its superior performance capabilities over models utilized in other studies.

**TABLE 1** Performance comparison of the proposed model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Scenario** | **Class / Label** | **SMOTE** | **(%) Precision** | **(%) Recall** | **(%)F1-Score** | **(%) Average accuracy** |
| Scenario 1 | glioma | Not | 93 | 97 | 95 | 97.55 |
| Meningiomas | 100 | 97 | 98 |
| Pituitary | 98 | 99 | 99 |
| Scenario 2 | glioma | Not | 92 | 96 | 94 | 97.22 |
| Meningiomas | 99 | 97 | 98 |
| Pituitary | 98 | 98 | 98 |
| Scenario 3 | glioma | Yes | 98 | 99 | 99 | 99.18 |
| Meningiomas | 100 | 98 | 99 |
| Pituitary | 100 | 100 | 100 |
| Scenario 4 | glioma | Yes | 100 | 99 | 99 | 99.65 |
| Meningiomas | 99 | 100 | 100 |
| Pituitary | 100 | 100 | 100 |

**TABLE 2** Comparison of model performance with previous studies

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No** | **Authors** | **Dataset** | **Method** | **Accuracy** |
| 1 | Abdu Gumaei, et al [7] | Jun Cheng Dataset | Regularized Extreme Learning Machine (RELM) | 94.23 |
| 2 | Neelum Noreen, et al [10] | Jun Cheng Dataset | DenseNet 201 | 99.51 |
| 3 | S. Deepak, et al [8] | Jun Cheng Dataset | GoogleNet Feature Extraction  &  SVM Classifier | 98 |
| 4 | Zar Nawab Khan Swati, et al [9] | Jun Cheng Dataset | VGG19 | 94.82 |
| 5 | Hossam H. Sultan, et al [6] | Jun Cheng Dataset | CNN | 96.13 |
| **6** | **Proposed method** | **Jun Cheng Dataset** | **DenseNet 201 + SMOTE** | **99.65** |

# CONCLUSIONS

The results from all test scenarios indicate that the DenseNet 201 model can classify brain tumor MRI images with high accuracy. By leveraging the DenseNet 201 model for feature extraction from MRI images and pairing it with an SVM classifier, the model shows strong performance. This outcome aligns with findings from prior research by Neelum Noreen and colleagues, titled "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor" [10].

In this research, the maximum accuracy achieved was 99.51% using the DenseNet 201 model. The same model and dataset were applied in this study, but adjustments were made by employing the SMOTE method to transform the imbalanced dataset into a balanced one. Additionally, the final dense layer was modified to enhance model performance. With the balanced dataset and DenseNet 201, this study attained a top accuracy of 99.65%, surpassing the results from the previous study that used an imbalanced dataset.

Therefore, based on all scenarios in this research, it can be concluded that balancing the dataset yields better outcomes compared to prior studies using the DenseNet 201 model, as balancing each class positively impacts model performance in the classification process.

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