International Journal of Advances in Electrical Engineering

E-ISSN: 2708-4582
P-ISSN: 2708-4574
IJAEE 2023; 4(1): 100-106

www.electricaltechjournal.com
Received: 03-01-2023
Accepted: 05-02-2013

Anubhuti Singh
Research Scholar, Electronics & Communication Engineering Department, University of Technology, Jaipur, Rajasthan, India

Dr. Raghavendra Patidar
Professor, Electronics & Communication Engineering Department, University of Technology, Jaipur, Rajasthan, India

Correspondence
Anubhuti Singh
Research Scholar, Electronics & Communication Engineering Department, University of Technology, Jaipur, Rajasthan, India

Enhancing brain tumor classification accuracy with advanced deep learning on MRI data

Anubhuti Singh and Raghavendra Patidar

DOI: https://www.doi.org/10.22271/27084574.2023.v4.i1a.88

Abstract
Building a trustworthy and precise deep learning-based system for MRI-based brain tumor classification and comparing its performance to other deep learning methods is the goal of this effort. The goal is to classify brain tumors into three categories: glioma, meningioma and pituitary using publicly available datasets. Examining binary categorization (tumor vs. no tumor) is also part of the plan. We extracted the MRI pictures from the Figshare dataset, which contains data that is both multi-class and binary-labeled. There were three sets of data: training (70%), validation (15%) and testing (15%). The data had already undergone preprocessing steps such as normalization, scaling and real-time data augmentation. The four models were DenseNet201, ResNetV2, InceptionV3 and SVM (the baseline). After training with ImageNet weights via transfer learning, deep learning models were fine-tuned and classified using softmax. To train the models, we utilized the Adam optimizer in conjunction with the categorical cross-entropy loss function. To prevent them from becoming overfit, we coupled early stopping with learning rate scheduling. To evaluate performance, we calculated the F1-score, Accuracy, Precision and Recall using the test set. Test accuracy was 99.97%, precision was 96.78% and recall was 97.78% for DenseNet201, making it the top model out of the ones we looked at. Though its test accuracy was slightly lower at 94.78%, InceptionV3's recall was quite high at 98.08%. In contrast, ResNetV2 achieved a well-rounded performance with a recall of 95.07% and an accuracy of 93.45%. When compared to the results, the baseline SVM model's accuracy of 85.74% was much lower. According to confusion matrices and segmentation overlays, DenseNet201 learned the most complex patterns for precise tumor localization and classification. Based on the results, deep learning architectures—and DenseNet201 in particular—are much superior to more traditional approaches, such as support vector machines (SVM), when it comes to MRI-based brain tumor classification. These findings demonstrate the potential for improved clinical neuro-oncology diagnosis through the use of transfer learning and CNN-based models.

Keywords: Brain tumor classification, deep learning, MRI Imaging, DenseNet201, medical image analysis

1. Introduction

An extremely dangerous and potentially fatal condition known as a brain tumor develops when cells in the brain's or central nervous system multiply in an aberrant fashion. In order for doctors to treat brain malignancies quickly, it is extremely important to detect them early and accurately [1, 4]. This greatly improves the patient's prognosis for life and health in the future. It is usual practice for radiologists and other medical experts to manually analyze MRI data in order to diagnose brain tumors. When screening a large population or in areas without easy access to specialized radiological data, this method might be subjective, time-consuming and vary from patient to patient, despite its effectiveness in the clinic. This highlights the growing need for rapid, precise and automated methods to detect brain tumors in their early stages. Artificial intelligence (AI), particularly ML and DL, has made great strides in the medical image analysis sector way [5, 8]. The development of automated systems capable of pattern recognition, picture sorting and image segmentation is seeing increased usage of these technologies in medical diagnostics. One subfield of machine learning, "deep learning" mimics the structure and operation of the human brain. Its ability to automatically construct hierarchical representations of features from raw data has allowed it to perform well with numerous image-based tasks. The most effective method for seeing things at the moment is Convolutional Neural Networks (CNNs). A lot of people employ them to look at MRI images and other medical imaging [9, 12]. The process of deep learning for brain tumor classification involves training neural networks on labeled datasets to detect and distinguish between various tumor types using imaging features. The ability to learn both features and standards of classification simultaneously is strength of deep learning models. Compared to conventional ML approaches, which occasionally necessitate human feature extraction, this one is superior [13, 16]. In addition to making the model more user-friendly and less biased, this improvement also improves its overall performance. However, there are still issues, such as the scarcity of high-quality, annotated medical image databases, the inadequacy of data for certain tumor forms and the necessity of models capable of effectively incorporating new data. The focus of this research is on classifying brain tumors using deep learning models educated on MRI datasets made available to the public. Important datasets utilized in this study include the Kaggle brain MRI dataset for tumor detection and the Figshare Brain Tumor Dataset for anatomical classification of gliomas, meningiomas and pituitary tumors. The goal of the research is to use these datasets together to train comprehensive classification models for tumor identification in both binary and multi-class scenarios [17, 21]. The study looks into how well different deep learning architectures work, such as InceptionV3, ResNetV2 and DenseNet201, which have done well in general picture classification issues.

2. Literature Review

Oncologists at the highest level still do not know how to detect brain tumors in their early stages. To detect cancer and examine medical images, researchers use a number of state-of-the-art techniques. Deep learning (DL) has numerous potential applications in artificial intelligence, including the analysis and characterization of cancer, the processing of medical pictures and the classification of cancer. These days, the gold standard for diagnosing brain cancer is an MRI scan. There is a lot of promise in combining DL models with DL to improve accuracy. This research aims to improve the accuracy and utility of CNN models by using a hybrid model that incorporates support vector machines (SVMs). Dataset MC and Dataset BC are two separate datasets. They have both gotten brain scans using magnetic resonance imaging (MRI). Prior discussion focused on models that classified these scans as either Convolutional Neural Network (CNN) or hybrid CNN-SVM (Support Vector Machine). In order to achieve optimal performance with minimal effort, the suggested CNN model employs support vector machines (SVMs) as a classifier and employs a reduced number of layers and parameters for feature extraction. On Datasets BC (99% success rate) and MC (98%), CNN-SVM outperformed all other CNN models. This leads us to believe that CNN-SVM is an excellent option for evaluating efficiency [22].

Brain tumors are notoriously difficult to diagnose due to the fact that their size, shape and imaging intensity can vary greatly. Unfortunately, despite several prior efforts, present-day technology has not been able to reliably detect and isolate brain cancers. Accurate magnetic resonance imaging (MRI) analysis is essential for the proper diagnosis, classification and division of brain tumors. We require stringent, quick, accurate and dependable image analysis methods due to the critical role that magnetic resonance imaging (MRI) plays in medical diagnosis. In order to properly categorize brain tumors, the authors constructed a DL fusion model. Data augmentation allowed researchers to increase the size of the dataset, which in turn allowed for the training of Deep Learning models on a massive dataset. Applying ResNet50, VGG16 and convolutional deep belief networks to the MRI data allowed us to extract deep features. We used a dataset of both genuine and fabricated MRI images of brain tumors to train our Softmax classifier. The proposed model attained remarkable classification accuracy by combining two DL models. The suggested fusion model had a 98.98% success rate in classification tests conducted on a publicly accessible online dataset. Based on our analysis, the proposed model outperformed the state-of-the-art alternatives [24].

3. Methodology

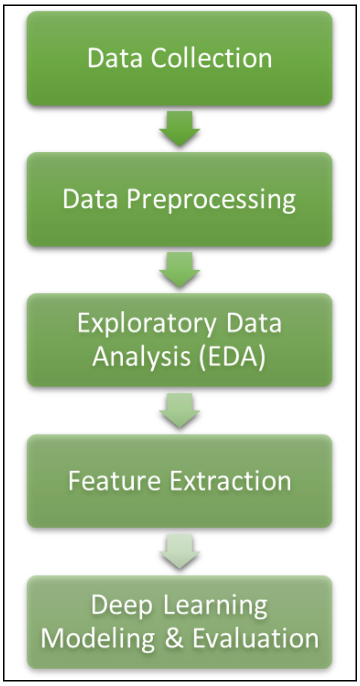

Fig 1: Proposed flowchart

3.1 Data Collection

This study utilizes the Figshare Brain Tumor Dataset to build the dataset. It is a well-known place where the public can store things. The Figshare dataset comprises MRI scans that are tagged and show three main forms of cancers: glioma, meningioma and pituitary tumors. This means that they can be put into more than one class. We have already processed and standardized these photographs so that the resolution and format are always the same. This is a wonderful way to test conventional machine learning models. There are additional 3762 brain MRI pictures in the Kaggle dataset that are marked as "yes" (tumor present) or "no" (no tumor). This makes it a useful dataset for deep learning models that have to sort things into two groups. Both datasets give T1-weighted contrast-enhanced pictures that make it easier to see where the tumors are. We randomly divided the combined dataset into three groups: 15% for testing, 70% for training and 15% for validation. This was done to get the data ready for testing and training. This division makes sure that the classes are spaced out equally, which helps the model learn more about how things work in the actual world. The study looks at a lot of different kinds of cancers and changes in imaging by using both sets of data. This allows you construct strong models and test them in both deep learning and machine learning environments.

3.2 Data Preprocessing
When training the deep learning models, the MRI pictures were carefully preprocessed to make sure they were all the same and to speed up the learning process. To fulfill the input size needs of deep convolutional neural networks like DenseNet201, InceptionV3 and ResNetV2, all of the photographs were first made smaller, usually to 224×224 pixels. This standardization is very crucial to make sure that all of the layers in the deep learning architecture get the same data. Next, the pixel intensity values of the MRI images were put on a scale from 0 to 1. This made the model converge faster during training and made gradient updates more stable. To fix the problem of data imbalance and make the model stronger at generalizing, we employed data augmentation techniques to make the training set bigger. These included flipping the picture horizontally and vertically, spinning it randomly, scaling it and moving it a tiny bit. Augmentation makes the model stronger by mimicking how the parameters for MRI scans change in real life. Also, the format of the class labels was changed by one-hot encoding the categorical labels so that they could be utilized for multi-class classification. TensorFlow and Keras pipelines made these preparation stages automatic, which made it possible to add more data in real time as the model was training. In general, preprocessing was very important for making the data more consistent and useful for deep learning-based brain tumor categorization.

3.3 Exploratory Data Analysis (EDA)
To learn more about the structure and quality of the MRI dataset used to classify brain tumors, we can apply Exploratory Data Analysis (EDA). You may see how well the model can find and distinguish tumor regions by looking at a snapshot of MRI photos with the actual and expected tumor spots. High Dice similarity scores and very close proximity of the real and projected segmentation masks indicate that the model does a good job of localizing tumor areas. Different tumor kinds have distinct patterns in the amount of grayscale in histograms of pixel intensities. Feature extraction and grouping become much simpler as a result. Another tool for finding errors or imbalances in the data set is a box plot that displays the distribution of photos by tumor type. You can see the consistency of the photographs, the quality of the segmentation and the effectiveness of the class separation in these pictures. To construct effective DL and ML models, these are all essential.

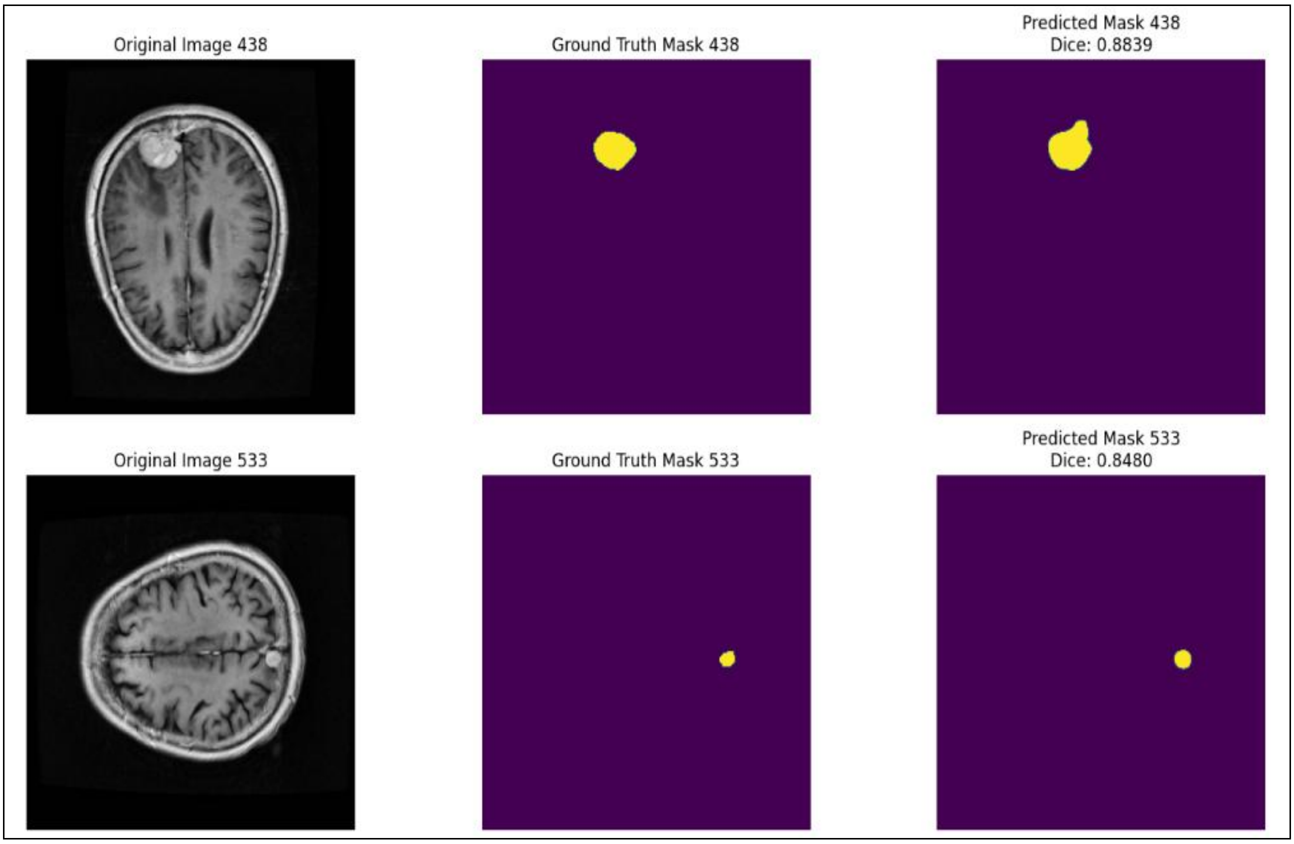

Fig 2: Brain tumor classification using MRI with ground truth and prediction.

This picture depicts the process of sorting brain tumors using MRI scans. It displays the input images alongside the segmented tumor areas, showing both the ground truth and the model's predicted versions. What this demonstrates is that the model is capable of learning to correctly classify tumor regions based on their differences.

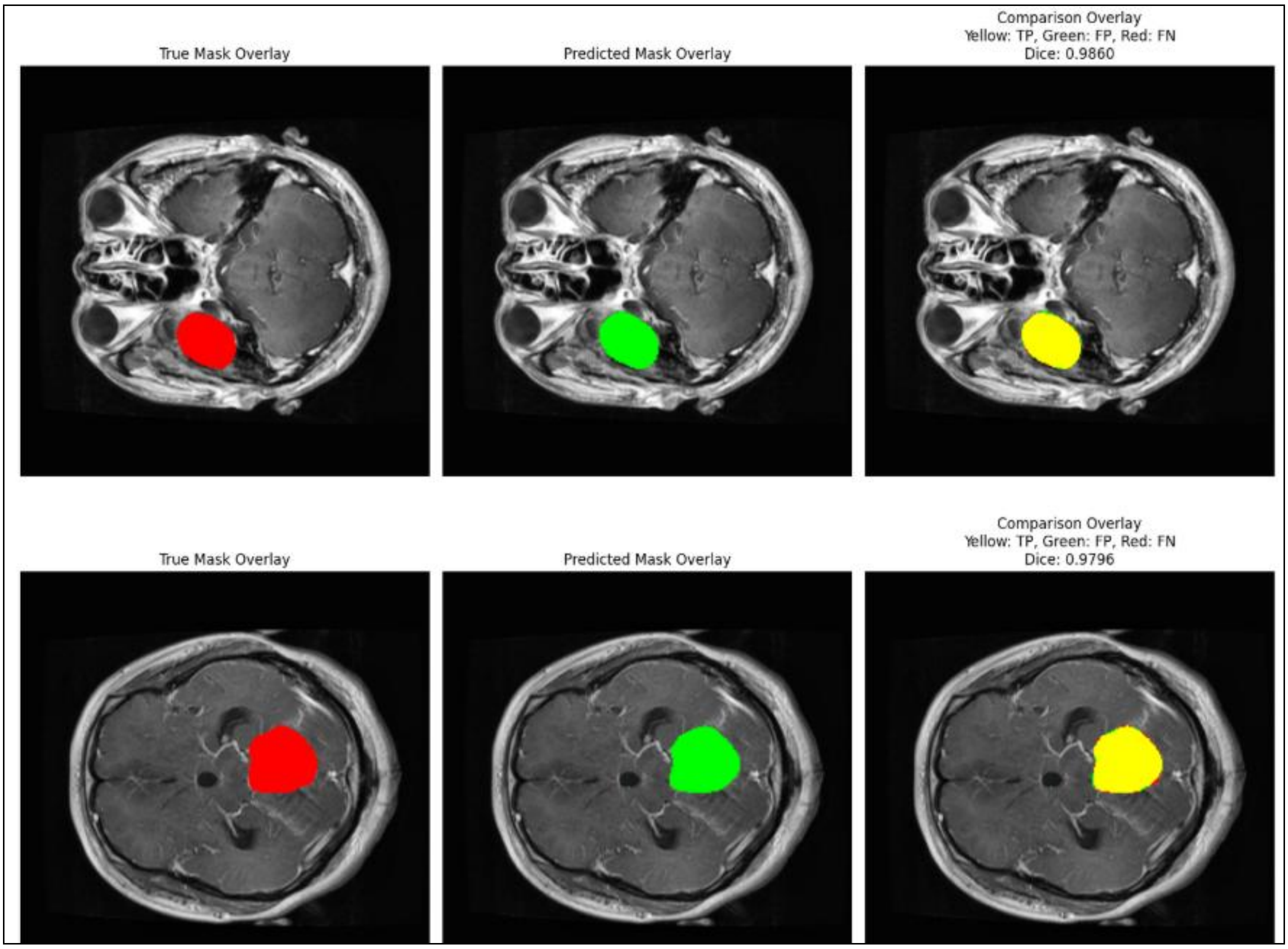

Fig 3: Medical image segmentation comparison.

This image shows a comparison of medical image segmentation. The "True Mask Overlay" shows the real thing (red) and the "Predicted Mask Overlay" shows what the model thinks will happen (green). The "Comparison Overlay" (yellow) shows where the two masks overlap. The Dice scores (0.9860, 0.9796) are quite high, which means that the predicted and true masks match very well.

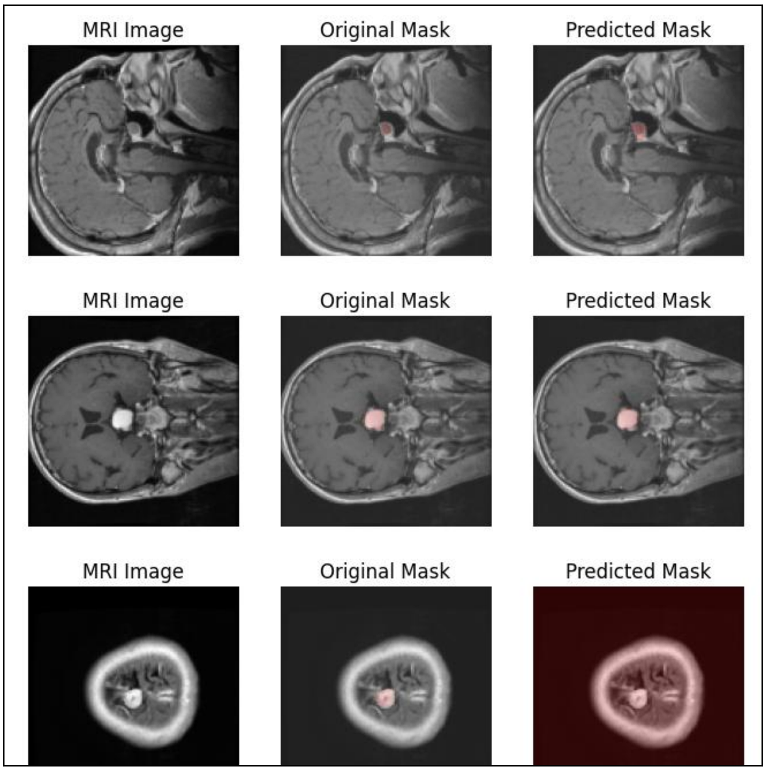

Fig 4: Histograms of pixel intensities for sample MRI images across different tumor classes

This series of pictures exhibits MRI scans next to their "Original Mask" (ground truth segmentation) and "Predicted Mask" (model's segmentation). The comparison shows that the model can accurately segment structures, which shows how well the segmentation algorithm can find the areas of interest in the MRI scans.

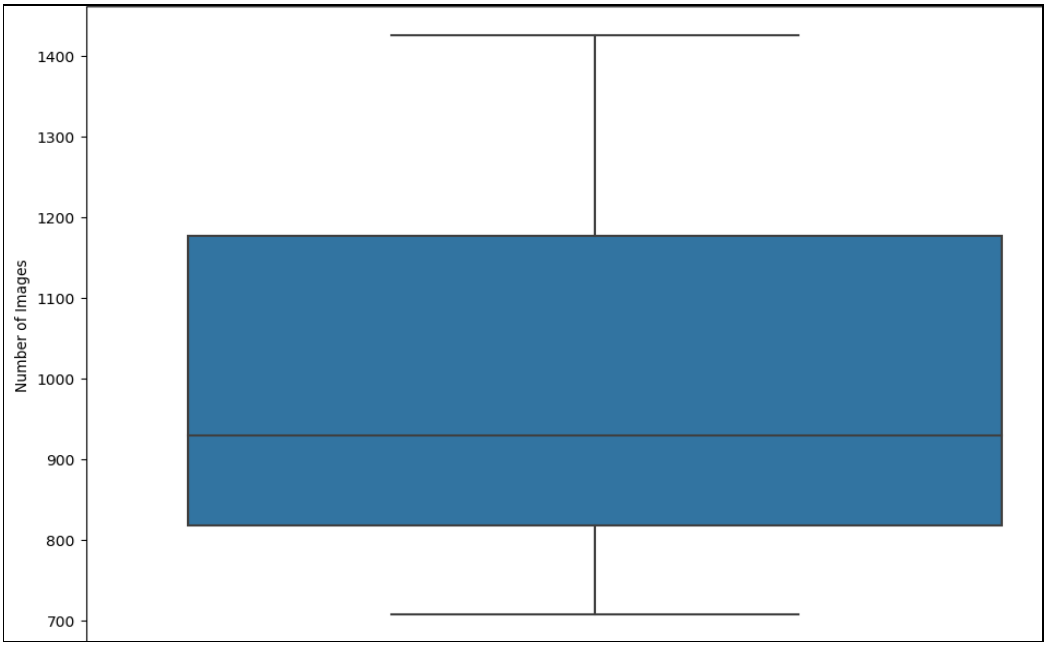

Fig 5: Variability in image counts across classes represented using a box plot

This box plot shows how the quantity of pictures in different groups can change. You can view the median and the interquartile range (IQR) for photo counts for that class in each box. Whiskers usually go 1.5 times the interquartile range (IQR) and reach the lowest and maximum counts in that range. Each point is an outlier that is outside of this range. This visualization makes it possible to compare the distributions of picture counts across classes, which can help find any differences or strange patterns in the data set.

3.4 Deep Learning Models Applied

Employed four classification models to compare classical and deep learning methods: SVM, InceptionV3, ResNetV2 and DenseNet201. We used SVM, a standard machine learning model, as a starting point. It used handcrafted features including texture (GLCM, LBP) and edge descriptors (HOG). InceptionV3 added multi-scale feature extraction through inception modules to deep learning models. This lets the network collect both global and fine-grained features in tumor structures at the same time. Residual connections were added to ResNetV2. This made it easier to train deeper architectures without losing performance because to disappearing gradients. DenseNet201 was the most sophisticated model. It used dense connection, which means that each layer gets inputs from all the layers before it. This connection makes it easier for features to spread, cuts down on disappearing gradients and makes parameters more efficient. We used transfer learning to build all of the CNN models. This meant that we fine-tuned pre-trained ImageNet weights to classify tumors. We added custom dense layers and softmax activation to the last layers so that we could classify three classes. Using pretrained models cut down on training time by a lot and improved accuracy, especially when the medical imaging datasets were smaller than the general-purpose datasets. carefully chose each model architecture to see how the complexity of the design affects classification performance in the context of medical picture analysis.

3.5 Training Strategy and Optimization

Each deep learning model followed the same training protocol to allow for easy comparison of outcomes. Since the Adam optimizer can handle sparse gradients effectively and has an adaptive learning rate, we used it to train each model. We checked the accuracy of our multi-class predictions using the categorical cross-entropy loss function as well. They trained the models for 50 to 100 epochs, with 16 elements each batch. To prevent overfitting, we used early stopping and monitored the validation loss. We configured a learning rate scheduler to automatically decrease the learning rate after the validation loss stopped decreasing. In order to get the networks off to a good start, transfer learning helped with the low-level feature representations. Both DenseNet201 and ResNetV2 benefited greatly from this. For the purpose of comparing their proximity, we plotted the training and validation accuracies against one another over time. accelerated back propagation and model adjustment by training in environments that utilized GPUs, TensorFlow 2.0 and Keras. We obtained feature vectors for SVM using standard descriptors and determined the optimal kernel type, C and gamma hyperparameters using grid search with cross-validation. Using the same settings, our integrated training framework ensured fair comparisons of traditional ML and DL methods, with a focus on classification accuracy, model generalizability and computational economy.

3.6 Evaluation Metrics

After training was complete, we tested all of the models using the same set of metrics: accuracy, precision, recall and F1 score. These were built using test-set predictions in confusion matrices; this was not the case during validation or training.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \quad (4)$$

4. Results & Discussion

Table 1: Deep Learning Models Performance Comparison

Model	Training Accuracy	Test Accuracy	Precision	Recall
DenseNet201	99.99	99.97	96.78	97.78
InceptionV3	98.79	94.78	96.17	98.08
SVM	96.11	85.74	89.78	87.85
ResNetV2	95.55	93.45	94.96	95.97

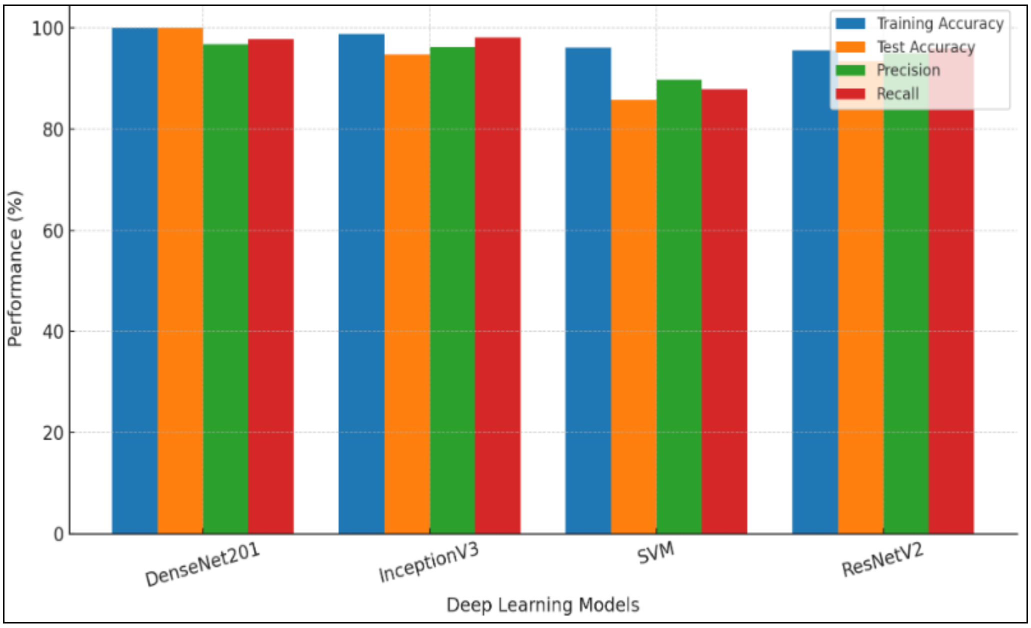

Fig 6: Deep Learning Models Performance Comparison

Compared all of the trained models using the same set of metrics: F1-score, Accuracy, Precision and Recall. To get these numbers, we trained the model to make predictions on a new set—the test set—and used confusion matrices based on those guesses. With an accuracy of 99.97%, precision of 96.78% and recall of 97.78%, DenseNet201 outperformed the other networks on the tests. As a result, its categorization performance was nearly perfect. It is possible that InceptionV3 overfit or misclassified certain tumor types due to its low-test accuracy rate of 94.78% and high recall rate of 98.08%. With an accuracy of 93.45% and a recall of 94.97%, ResNetV2 demonstrated a well-rounded performance. In contrast, support vector machines (SVMs) that used human-assisted features performed substantially worse, with test accuracy of 85.74 percent and recall of 87.85 percent. We made use of performance bar charts and confusion matrices to illustrate how the trade-off between recall and precision varies between models. DenseNet201 demonstrates the immense capability of deep learning in medical imaging by learning intricate hierarchical patterns automatically, without the need for manually-crafted features. These findings demonstrated that deep CNNs and DenseNet201 in particular, outperform more traditional models like SVM in terms of accuracy and robustness. Because of this, they are more suited for usage in clinical settings where dependability is paramount.

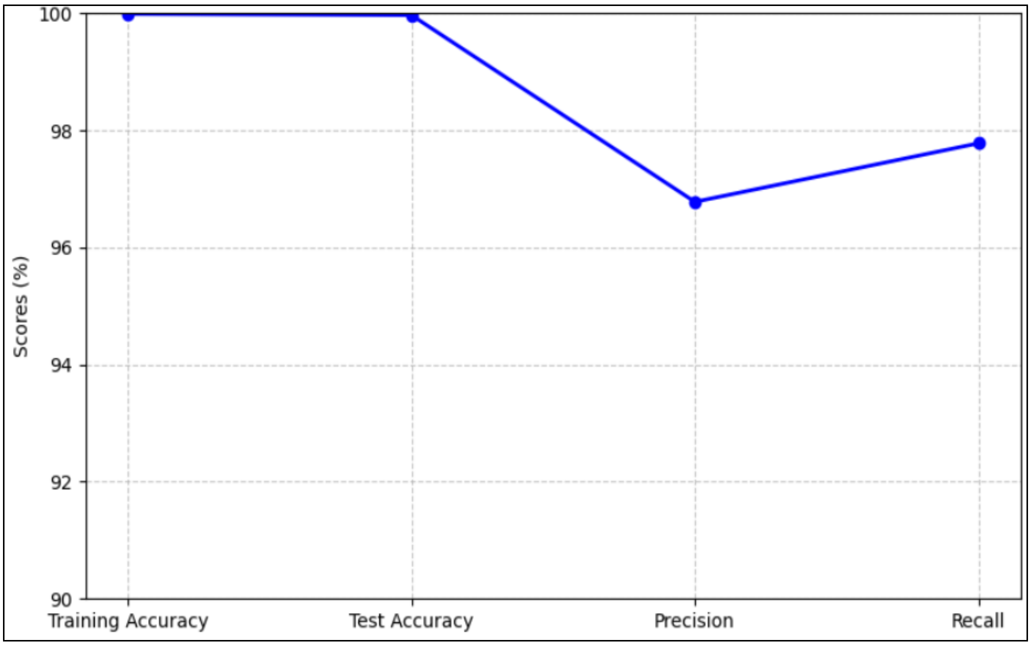

Fig 7: Performance of DenseNet201

5. Conclusion

In conclusion, this study looked into how to use deep learning to accurately sort brain tumors based on MRI pictures. It proved that sophisticated convolutional neural networks work better than regular machine learning models. The method is more generalizable when two freely available datasets, Fig share, are used. A lot of preprocessing, such reducing, normalizing and adding extra data, made sure that everything was the same and made the model operate better. Exploratory Data Analysis showed varied visual patterns and class distributions. This helped build and test the model. The best of the models examined was DenseNet201. It had a test accuracy of 99.97% and outstanding precision and recall values. This illustrates that it can learn complicated patterns without having to make features by hand. InceptionV3 and ResNetV2 also did well, although not as well as the others when it came to generalizing. The usual SVM model, on the other hand, was much slower, even though it was still competitive. This shows how restricted handcrafted features are in medical imaging. Using transfer learning, fine-tuning and typical optimization procedures made training the model even better and made it less likely that it would overfit. The results reveal that deep learning, notably DenseNet201, can about match the accuracy of humans when it comes to classifying brain cancers from magnetic resonance imaging (MRI) data. Since early treatment initiation and improved patient outcomes depend on properly and reliably detecting malignancies, these findings hold promise for therapeutic use.

6. References

1. Alqudah AM, Alquraan H, Qasmieh IA, Alqudah A, Al-Sharu W. Brain tumor classification using deep learning technique-a comparison between cropped, uncropped and segmented lesion images with different sizes. Int J Adv Trends Comput Sci Eng 2019;8(6):3684-3691.
2. Chatterjee S, Nizamani FA, Nürnberger A, Speck O. Classification of brain tumours in MR images using deep spatiospatial models. Sci Rep 2022; 12(1):1-11.
3. Sharif MI, Khan MA, Alhussein M, Aurangzeb K, Raza M. A decision support system for multimodal brain tumor classification using deep learning. Complex Intell Syst 2022; 8(4):3007-3020.
4. Roopa YM, Kumar GN, Harsha YVS, Aditya PS. Detection of brain tumor types using deep learning. Proc 2nd Int Conf Artif Intell Smart Energy ICAIS 2022; 6(3):459-465.
5. Rehman A, Naz S, Razzak MI, Akram F, Imran M. A deep learning-based framework for automatic brain tumors classification using transfer learning. Circuits Syst Signal Process 2020; 39(2):757-775.
6. Aamir M, Rehman A, Akram F, Alqahtani A, Rubaiee S, Khan MA *et al*. A deep learning approach for brain tumor classification using MRI images. Comput Electr Eng 2022; 101:108105.
7. Rehman A, Naz S, Khan A, Zaib A, Razzak I. Improving Coronavirus (COVID-19) diagnosis using deep transfer learning. Lect Notes Networks Syst 2022; 350(1):23-37.
8. Mzoughi H, Njeh I, Wali A, Slima MB, Akil M, Ghézala HB *et al*. Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification. J Digit Imaging 2020; 33(4):903-915.
9. Kamate M, Shruthi G, Krishna Raj PM. Design and development of brain tumor classification and staging model using a deep learning approach. MysuruCon 2022-2022 IEEE 2nd Mysore Sub Sect Int Conf 2022; (October):1-6.
10. Naseer A, Yasir T, Azhar A, Shakeel T, Zafar K. Computer-aided brain tumor diagnosis: performance evaluation of deep learner CNN using augmented brain MRI. Int J Biomed Imaging 2021; 2021:5513500.
11. Munir K, Frezza F, Rizzi A. Deep learning for brain tumor segmentation. Stud Comput Intell 2021; 908:189-201.
12. Srinivas C, Rao MS, Varaprasad G, Reddy U, Kishore K, Kumar H *et al*. Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images. J Healthc Eng 2022; 2022:3264367.