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Research Article

Artificial Intelligence (AI) for Brain Tumor Detection: Automating MRI Image Analysis for Enhanced Accuracy

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Abstract

Accurately diagnosing and planning for the treatment of brain tumors is crucial in clinical practice. Brain tumor detection and diagnosis rely heavily on artificial intelligence (AI) systems that mainly employ medical imaging modalities like MRI. This study employs cutting-edge DL and image processing techniques to intelligently forecast the brain tumor using AI. The complicated and varied nature of brain tumors frequently presents challenges to deep learning models, despite their promising performance in this task. In order to overcome this obstacle, we present the InceptionV3 architecture, which is based on CNNs and uses 5-fold cross-validation to classify brain tumors from MRI images. A training, validation, and testing of a model were conducted using a publically accessible MRI dataset that included 7023 greyscale brain MRI pictures. These images were classified into four types of tumors: gliomas, meningiomas, no tumors, and pituitary. To enhance diversity of a training dataset, the photos were preprocessed by scaling, greyscale conversion, and labeling. Afterward, data augmentation techniques were applied. A model's performance was assessed using 5-fold cross-validation, yielding an F1-score of 99.98%, an average accuracy of 97.12%, precision of 97.97%, and recall of 96.59%. Other Artificial Intelligent models that were compared included InceptionV3, VGG19, CNN, and DenseNet and the results indicated that the InceptionV3 gave better results overall. These results demonstrate that deep learning can accurately and efficiently detect brain tumors utilizing MRI pictures.

Keywords: *Brain tumor detection, Magnetic Resonance Imaging (MRI), Artificial Intelligence (AI), Deep learning, CNN, InceptionV3, Preprocessing.*

1. Introduction

There is no more important or intricate organ in the human body than the brain, which regulates the complicated neurological system. The most deadly brain tumor is brought on by the brain's cells growing erratically and uncontrollably [1]. Brain tumors and their investigation have recently attracted a great deal of attention due to the rapid development of medical image processing. According to the NBTF summary, improvements in patient diagnosis and a death rate from brain tumors are outpacing previous years' findings worldwide [2][3]. It is critical to check for brain tumors early on in order to promote easytreatment and healthy living using modern clinical imaging techniques [4][5]. PET, MRI, and CT are the most frequently used modalities for tumor analysis in the brain [6][7].

MRI has better spatial resolution and contrast between soft tissues than any of the other methods now used to diagnose brain diseases[8][9].

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Brain tumors and other neurological problems can be non-invasively detected using MRI [10][11]. However, only highly skilled radiologists should attempt to decipher MRI scans due to the complexity of the endeavor [12][13]. Variability in tumor appearance, as well as human limitations like weariness and subjectivity, make this work prone to errors [14][15]. Furthermore, in places with a shortage of specialists, access to correct and prompt diagnoses can be limited, delaying treatment commencement and negatively impacting patient outcomes [16].

Brain tumor detection and diagnosis rely heavily on AI systems that mainly employ medical imaging modalities like MRI. Medical image analysis[17][18], including tasks like identification, detection, and segmentation, faces challenges in feature extraction, particularly with traditional ML methods that rely on hand-crafted features and prior knowledge[19][20][21]. With the proliferation of brain tumor datasets comes the pressing need for improved feature extraction methods, particularly for MRI datasets that contain unbalanced images of brain abnormalities [22][23]. CNNs, a type of DL approach, have become particularly effective tools for MRI categorization because they can immediately learn pertinent features from image data, doing away with the need for manual feature engineekj nring and increasing classification accuracy [24][25]. CNNs [26] Have demonstrated efficacy in tasks like as tumor identification, segmentation, and classification; they offer trustworthy second opinions and assist in prioritizing urgent patients, freeing up doctors to concentrate on more difficult tasks[27][28]. The objective of this study was to enhance medical diagnosis and patient outcomes by creating a CNN-based image classifier that could detect brain tumors in MRI scans. The project's use of a publicly available MRI dataset necessitated data preprocessing to guarantee consistent and high-quality images, followed by the development of a custom CNN architecture for brain tumor diagnosis, hyperparameter optimization, and the achievement of optimal model performance.

Motivation and Contribution

The goal of this effort is to use AI to analyze MRI images more efficiently and accurately in order to detect brain tumors. Traditional approaches to brain tumour detection rely mostly on laborious and error-prone manual interpretation, despite the critical need for early and accurate detection for prompt medical action. This study intends to automate the classification of brain tumors from MRI scans by utilizing DL models, specifically InceptionV3, with the goal of relieving healthcare personnel of some of their workload while simultaneously improving the accuracy of diagnostics. The end goal is to create a system that is scalable, dependable, and quick so that doctors can make better decisions for their patients.

The following are the primary benefits of this paper:

This study shows that the InceptionV3 model can effectively detect and categorize several forms of brain tumors by MRI scans using a DL-based method.

The study emphasizes the importance of preprocessing steps, along with data augmentation techniques, which improve model performance and help address data imbalance issues.

By employing 5-fold cross-validation, the research ensures a robust evaluation of the model's generalizability, enhancing the reliability of the results and preventing overfitting on a single training dataset.

The work achieves remarkable performance metrics (accuracy, precision, recall, and an F1-score) for multi-class brain tumor classification using the pre-trained InceptionV3 model, demonstrating the model's appropriateness for medical image classification tasks.

The study examines the relative merits of various DL models for brain tumor identification, comparing InceptionV3, VGG19, CNN, and DenseNet; the results show that InceptionV3 is the best model.

Structure of the paper

Here is the structure of the study: Section **II** presents relevant work on brain tumour detection. A flowchart and discussion of the proposed procedure are included in Section **III.** The experimental results of the suggested system are detailed in Section **IV,** along with comparison data. Section **V** concludes the investigation and provides limitations for future work.

Literature Review

This section discusses the surveys and reviews articles on brain tumor detection based on artificial intelligence algorithms in the healthcare sector.

Dipu, Shohan and Salam (2021), provide two DL-based approaches to brain tumor identification and classification: one incorporates the cutting-edge object detection framework YOLO while the other makes use of the DL library Fast Ai. A portion of the BRATS 2018 dataset was used to conduct an analysis of 1,992 brain MRI images. The Fast Ai classification model attained 95.78 percent accuracy, while the YOLOv5 model reached 85.95 percent[29].

N.Cinar et al. (2022), this section discusses the five CNNs that are most often utilized for the classification of brain tumors. CNN models that were utilized include VGG19, DenseNet169, AlexNet, InceptionV3, and ResNet101. It was using these models and their default hyperparameters that MR images that had previously been processed and stored in the same way were trained. On top of that, the VGG19 model achieved an impressive 97.2% accuracy. A few more models have somewhat lower accuracy rates: InceptionV3 94.3%, DenseNet169 92.8%, and AlexNet 89.5%[30].

M. Harahap et al. (2022) investigated classified brain tumors using Transfer Learning (TL) using a CNN algorithm and five DL models. An accuracy of 93.23% was achieved using the ResNet50 and DenseNet121 models. But among the models, VGG16 had the highest accuracy at 97.08%, MobileNetV2 came in second at 97.02, and DenseNet121 was last with 92.86%[31].

M. C. S. Tang and S. S. Teoh (2023), MRI from Kaggle has not yet been thoroughly examined using pre-trained models like ResNet18, while DL models like GoogLeNet and CapsNet have been suggested. Experiment results show that the model got a precision of 0.8966, sensitivity of 0.8667, specificity of 0.9000, and accuracy of 0.8833[32].

K. Pikulkaew et al. (2023), introduce a method that uses DL to diagnose brain tumours from MRI scans. Using Grad-CAM to display data in the region of brain tumors and a DCNN architecture for accurate detection and classification of brain malignancies, our technique achieves remarkable results. They evaluate our method, which achieved a high level of accuracy (97%) and outstanding precision, employing a Kaggle dataset that contains 2114 brain MRI images [33].

R. Pillai et al. (2023), After applying fine-tuned layers to three distinct deep transfer learning models, a dataset consisting of 251 MRI images is utilized for the purpose of detecting brain tumours. They employ ResNet50, VGG16, and InceptionV3 as our TL models, tweaking them with layers of Flatten, Dense, and Dropout. The VGG16 model earned the best accuracy, coming in at 91.58%. Therefore, brain tumour detection using DL models is successful and saves time and resources.

Table 1 summarizes the methods, data, key results, advantages, limitations, and suggested future work for each of the studies mentioned for brain tumor detection.

Table 1 Summary of these related works for brain tumor classification using various techniques

Reference	Methods	Data	Key Results	Advantages	Limitations	Future Work
Dipu, Shohan, and Salam (2021)	YOLO (You Only Look Once), Fast Ai classification model	BRATS 2018 dataset (1,992 MRI scans)	YOLOv5 model: 85.95% accuracy, Fast Ai model: 95.78% accuracy	High accuracy, real-time brain tumor detection, early diagnosis of brain cancer	Limited dataset size, only focused on two models	Expanding the dataset, testing additional models for enhanced accuracy
Cinar et al. (2022)	VGG19, DenseNet169, AlexNet, InceptionV3, ResNet101 (CNN architectures)	MR images with same preprocessing	VGG19: 97.2% accuracy, InceptionV3: 94.3%, DenseNet169: 92.8%, AlexNet: 89.5%	High accuracy with VGG19, comparison of multiple CNN architectures	Lower accuracy in other models, unsuitable architectures for MR images	Exploration of other deep learning models, enhancing preprocessing methods
Harahap et al. (2022)	CNN algorithm, Transfer Learning with five Deep Learning models	MRI data (no specific dataset mentioned)	VGG16: 97.08%, MobileNetV2: 97.02%, ResNet50 and DenseNet121: 93.23%, DenseNet121: 92.86%	High accuracy with VGG16, Transfer Learning improves model performance	Limited dataset details, performance variations across models	Investigating more transfer learning models, large-scale dataset testing
Tang and Teoh (2023)	ResNet18, GoogLeNet, CapsNet (deep learning models)	Kaggle dataset (public dataset)	ResNet18: 88.33% accuracy, Sensitivity: 86.67%, Specificity: 90.00%, Precision: 89.66%	Outperforms previous models in accuracy, specificity, and precision	Limited comparison with other models, sensitivity could be improved	Further investigation into fine-tuning and exploring other pre-trained models
Pikulkaew (2023)	Deep Convolutional Neural Network (DCNN), Grad-CAM for visualization	Kaggle dataset (2114 MRI images)	97% accuracy, high precision, Grad-CAM visualization for tumor detection	High accuracy, precise tumor classification, and visualization with Grad-CAM	Needs further validation with different datasets, Grad-CAM may not work well for all cases	Expanding dataset, refining Grad-CAM visualization for broader application
Pillai et al. (2023)	Transfer Learning with VGG16, InceptionV3, ResNet50 (fine-tuned layers)	MRI dataset (251 scans)	VGG16: 91.58% accuracy	High accuracy with VGG16, efficient use of transfer learning without excessive resource consumption	Limited dataset size, fine-tuned layers may not always improve results across different models	Exploring additional models, testing with larger datasets, optimizing fine-tuning layers

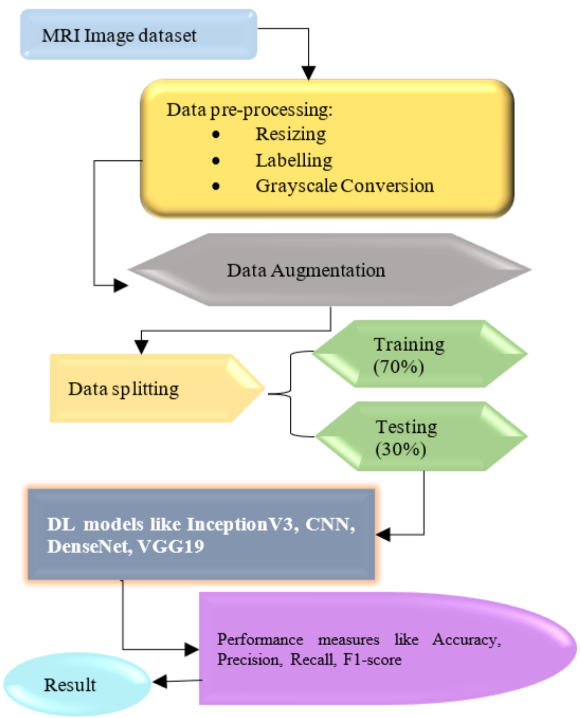

Fig.1 Proposed flowchart for brain tumor detection using MRI images

Methodology

An open-source MRI dataset comprised of 7023 greyscale brain MRI pictures labeled as glioma, meningioma, no tumor, or pituitary is the first stage in the suggested approach for brain tumor classification. The images undergo preprocessing, including resizing to 224x224 pixels, grayscale conversion, and labeling for each class to guide the classification process. Data augmentation techniques, such as rotating,zooming/scaling, and brightness adjustments, enhance the model's robustness and diversify the training data. The dataset is split into training (70%) and testing (30%) sets, with 5-fold cross-validation employed to assess model performance across multiple data splits. The classification is done using the InceptionV3 DL model, which is fine-tuned for multi-class classification and uses a pre-trained version that was learned on the ImageNet dataset. To measure how well the model can identify and categorize different kinds of brain tumors, we calculate performance measures, including recall,accuracy, precision, and F1-score. The whole process of mythology is shown in Figure 1, and each phase discussed below:

Data collection

The MRI dataset by the Kaggle repository was utilised for training, validation, and testing the model and several DL-based techniques in this work. The human brain is shown in 7023 greyscale and JPG MRI images from various categories in this collection. Glioma (1321 training and 300 testing images), Meningioma (1339training and 306testing images), No-tumor (with 1595training and405), and Pituitary (1457training and 300testing images) are the four categories of brain tumors displayed in the dataset. The validation job used 80% of the photos while the remaining 20% were not utilised.

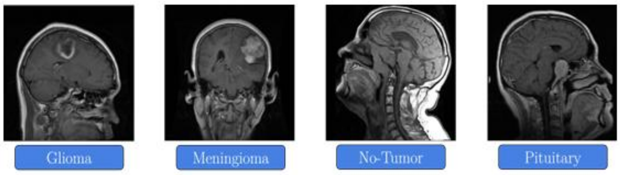

Fig.2 Sample images from the MRIs in the dataset.

Data preprocessing

To make the raw MRI pictures more usable by humans or machines, this is done to improve their quality [34][35]. The preprocessing techniques discussed for MRI image analysis involve a series of steps aimed at preparing the dataset for effective training of CNN models. These steps, including Resizing, Grayscale Conversion, Labeling, and augmentation (Rotation, Zoom/Scaling, and brightness), are crucial for improving model performance.

- Resizing ensures that all images are scaled to a uniform size, necessary for deep neural networks. The image's dimensions and shape are adjusted to 224*224.
- Grayscale Conversion: The images are normalized from BGR to grayscale format for less processing and emphasize on the most important features of an image.
- Labeling involves assigning specific labels to each class (Glioma(0), Meningioma(1), No-tumor(3), Pituitary(4)) to guide the classification process, shown in Figure 3, data distribution of image labels.

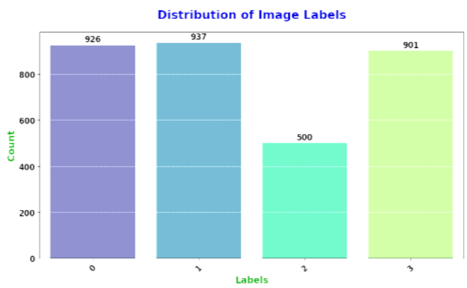

Fig.3 Data distribution of image labels

Data augmentation

To address issues such as data scarcity and imbalance, in addition to increasing the model's ability to generalize, random rotations, zoom and scale transformations, and variations in brightness levels are applied to the training data. These transformations are performed using TensorFlow's ImageDataGenerator() function, which includes parameters such as rotation_range, horizontal_flip, shear_range, zoom_range, and brightness_range. These augmentation techniques mimic different orientations, sizes, and lighting and, therefore, make the model more powerful. The rescale parameter (1.0/255) normalizes pixel values, ensuring consistency across images, while other parameters like rotation_range (10 degrees), horizontal_flip (True), and zoom_range (0.1) help introduce variability to the dataset.

Data splitting

The data were divided into training and test sets. The training information set was applied to model training, and the test information set was used to evaluate models. The data utilised for testing is 30% of the total, while 70% is devoted to training.

K-Fold Cross Validation (5 Folds)

When deciding on how well a model performs, then the K-Fold CV can be applied since it divides the dataset into subgroups or the folds [9]. Through training and validation on many folds, the model's generalisability to new data is assessed. 5-Fold Cross Validation has five equal-sized folds in the dataset.

Classification with InceptionV3 model

Neuroimaging brain picture categorization using 5-fold cross-validation with Inceptionv3, a CNN-based model. The Inceptionv3 DNN is one of many in the Inception family [36][37]. It is the outcome of improvements made to the initial Inception design. Its configuration of few links makes it a deeper network [38]. It mostly consists of several Inception modules. The input from the previous module is passed on to each subsequent module. The design may be changed, but it has 48layers and an input size of 299 × 299 [39]. One thousand unique objects may be classified using the provided pre-trained Inceptionv3 model, which was trained on an ImageNetdatabase. Figure 4 shows the most basic layout of its architecture.

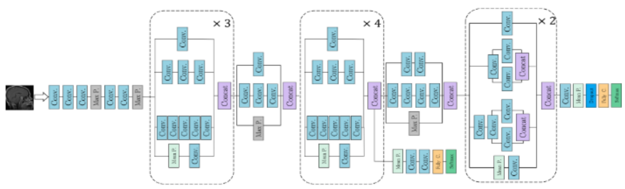

Fig.4 A basic representation of pre-trained InceptionV3 architecture

In the brain tumor classification model using InceptionV3, ReLU activation introduces non-linearity, while an initial learning rate 0.0001 ensures stable convergence. The SGD optimizer helps update weights efficiently, with a batch size of 16 to balance memory and stability. With a 70-30% train-test split and a dropout of 0.3-0.4, the model can be trained for 10 epochs without overfitting. For tumors that can be classified into more than one category, the output layer generates class probabilities using Softmax activation.

Performance metrics

The accuracy of brain tumor MRI scans is affected by the degree to which aberrant tissues are detected or not detected. The values of TP, FP, TN, and FN may be utilized to quantify these [40][41]. This study measures the system's accuracy, precision, recall, and f1-score using all of the photos in the database.

Accuracy

A ratio of properly categorized observations to total observations is shown by this most used performance metric. Equation (1) states how it is computed.

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + Fp + TN + FN}} \ldots\ldots(1)$$

Precision

The ratio of TP to the total of TP and FP is known as precision. It is used to assess a classifier's capacity to identify, from pictures, only relevant hot areas of malignant tumors. Eq. (2) illustrates the generic formula used for the same:

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

Recall

The ratio is defined as TP divided by the total of TP and FN. It goes by the name "sensitivity" as well. This metric is used to determine an image classifier's capacity to detect all relevant hot spots, whether they are benign or malignant, inside the pictures. Equation (3) for Recall is given below:

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

F1-score

This metric takes into account the relative importance of recall and precision. This demonstrates the classifier's capability to accurately identify the cancer kind and extract pertinent hot areas. The method of calculation is described in Equation (4).

$$F1 - Score = \frac{2(Precision * Recall)}{\mathrm{Precision + Recall}} \ldots\ldots(4)$$

TP refers to a number of expected positive situations that really turn out to be positive, as stated in the aforementioned formulae. As a measure, the True Negative (TN) takes into account just those occurrences that were expected to be negative. When something that should be negative turns out to be positive, this is called a false negative (FN) or a type two mistake. An example of a type one mistake is the number of false positives, or situations that were predicted to be positive but turned out to be negative.

Result Analysis and Discussion

Results and discussion of artificial intelligence models for brain tumour classification using MRI data are presented in this section. All experimental setup and results were done at Google Colab. The development environment that was used by the engineering team was Python and Jupyter Notebook. The InceptionV3 was built and trained with TensorFlow and Keras. The goal is amicable to determine the effectiveness of the InceptionV3 model, which has been suggested by proposing f1-score, loss, accuracy, recall, and precision metrics.

Table 2 InceptionV3 model Performance with 5 folds for brain tumor detection

Measures	InceptionV3					
K-folds	1	2	3	4	5	Average
Accuracy	97.17	97.27	97.14	97.02	97.03	97.12
Precision	97.88	98.18	98.01	97.88	97.91	97.97
Recall	96.66	96.71	96.67	96.46	96.47	96.59
F1-score	99.98	99.99	99.98	99.98	99.99	99.98

The InceptionV3 model performs very well in detecting brain tumors during 5-fold cross-validation. The value of the accuracy is between 97.02% and 97.27% with the average of 97.12%, which shows that the model has a high potential to predict tumor images. The precision is also fixed at a highly commendable 97.97%, indicative of the fact that the model correctly flags positive cases.

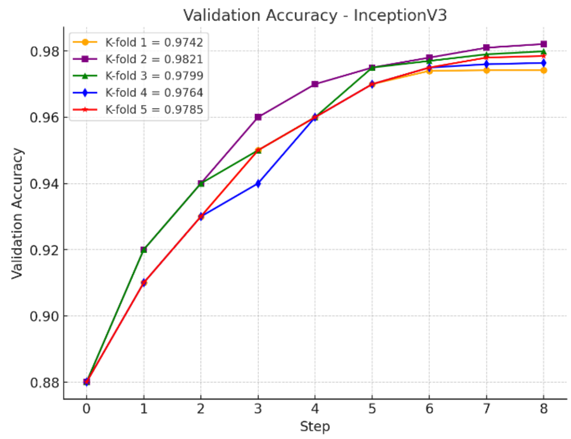

Fig.5 Validation accuracy for InceptionV3 model

The model's recall values, which range from around 96.46% to 96.71%, demonstrate its capacity to identify the majority of real tumor instances. Finally, there is a balance between recall and precision for each fold of the test for the model as shown by the F1-score of 99.98%.

Figure 5 displays the procedure of validating the InceptionV3 classification model used in this investigation. The figures expressed reflect the validation accuracy of InceptionV3 employed in this study. The number of k-folds utilised in this pattern. There is an average accuracy rate of 97.12%.

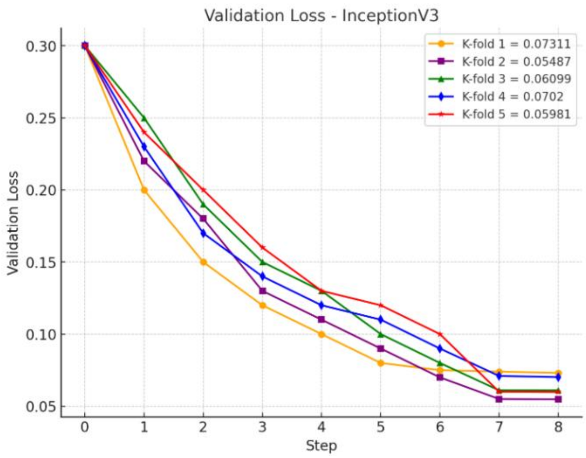

Fig.6 Validation Loss for InceptionV3 Model

Figure 6 displays the proportion of losses produced in every K-fold during a validation step of an InceptioV3 model. A loss of 6.3% was recorded on average while this model was being validated.

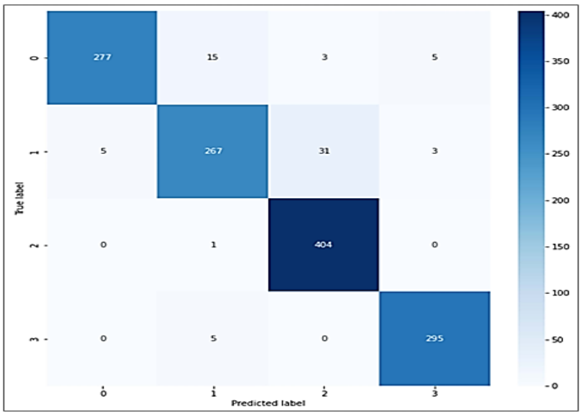

Fig.7 Confusion matrix for InceptionV3 model

Figure 7 displayed a confusion matrix, which shows how well a classification model works. The actual labels are shown in each row, while the anticipated labels are shown in each column. The diagonal entries (277, 267, 404, 295) indicate correctly classified instances for labels 0, 1, 2, and 3, respectively. Instances of off-diagonal values indicating misclassifications include 15 cases of label 0 being projected as label 1 and 31 cases of label 1 being forecasted as label 2. The color intensity visualizes the frequency, with darker shades representing higher counts. The model performs well overall, especially for label 2, with no misclassifications observed for this class.

Table 3 AI models comparison on the MRI image dataset for brain tumor detection

Models	Accuracy	Precision	Recall	F1-score
InceptionV3	97.12	97.97	96.59	99.98
VGG19[42]	95	88.79	98.25	93.28
CNN[43]	95.55	96	96	96
Dense Net[44]	94.4	94.6	94.7	94.6

The following table III presents the performance of ML and DL models across performance parameters. The comparison of model performance reveals that InceptionV3 outperforms all other models with the highest accuracy, 97.12%, and strong values for precision (97.97%), recall (96.59%), and F1-score (99.98%). CNN follows closely with an accuracy of 95.55% and equally high F1-score values (96%), recall (96%), and precision (96%). VGG19 shows slightly lower performance, with an accuracy95% and precision88.79, recall of 98.25, and F1 scores of 93.28%. DenseNet has the lowest overall performance, achieving 94.4% accuracy and relatively lower precision, recall, and F1 scores (94.6%, 94.7%, 94.6%), making it less effective compared to the other models for this task. InceptionV3 delivers the best overall performance for brain tumor detection.

The InceptionV3 model has good performance, but it has several limitations, such as the fact that it might overfit on short datasets and that better generalization would be possible with bigger, more varied datasets. Have achieved success despite the dataset's imbalanced classes and little number of images. The training dataset has been expanded and new characteristics that aid in model learning have been included via the use of data augmentation methods. The advancement of these methods may benefit medical professionals who focus on brain tumour early detection. Further investigation into alternative deep learning architectures, optimization of hyperparameters, and the incorporation of more sophisticated data augmentation methods might constitute a future studies. Further investigation into real-time testing in clinical settings might be undertaken to evaluate the model's applicability and resilience in real-life medical situations.

Conclusion And Future Work

Improved therapy outcomes and patient well-being depend on prompt and accurate detection of brain tumors. A CNN image classifier for MRI tumour detection in the brain was the primary goal of this study. In this work, the InceptionV3 model demonstrates exceptional performance for brain tumor detection, achieving an average accuracy of 97.12%, precision of 97.97%, recall of 96.59%, and an outstanding F1-score of 99.98 across 5-fold cross-validation. The results show that the model performs well when it comes to identifying and categorizing brain tumors. Analyzing the results it can be seen that the InceptionV3 model presents better accuracy and F1 score in comparison with other known architectures VGG19, CNN, DenseNet for this task. The efficiency of the model is also backed by the confusion matrix where high classification is achieved for label 2 with little confusion. The remaining graphs for validation loss and accuracy further confirm the stability of the proposed model in detecting tumors. The reliability and accuracy of diagnoses may be greatly improved with the use of deep learning methods, as shown by these data.

References

[1] P. B. Kanade and P. P. Gumaste, "Brain Tumor Detection Using MRI Images," *IJIREEICE*, 2015, doi: 10.17148/ijireeice.2015.3231.

[2] E. A. S. El-Dahshan, H. M. Mohsen, K. Revett, and A. B. M. Salem, "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm," *Expert Syst. Appl.*, 2014, doi: 10.1016/j.eswa.2014.01.021.

[3] S. Pandya, "A Systematic Review of Blockchain Technology Use in Protecting and Maintaining Electronic Health Records," *Int. J. Res. Anal. Rev.*, vol. 8, no. 4, 2021.

[4] M. T. Arora, Rajeev and Kumar, Shantanu and Jain, Nitin and Nafis, "Revolutionizing Healthcare with Cloud Computing: Superior Patient Care and Enhanced Service Efficiency," *SSRN*, 2022, doi: http://dx.doi.org/10.2139/ssrn.4957197.

[5] S. Pandya, "Predicting Diabetes Mellitus in Healthcare: A Comparative Analysis of Machine Learning Algorithms," *Int. J. Curr. Eng. Technol.*, vol. 13, no. 06, 2023, doi: https://doi.org/10.14741/ijcet/v.13.6.5.

[6] I. A. El Kader *et al.*, "Brain tumor detection and classification on mr images by a deep wavelet auto-encoder model," *Diagnostics*, 2021, doi: 10.3390/diagnostics11091589.

[7] G. Agrawal, G. Agrawal, M. Singh, and P. Kokardekar, "Brain Tumor Detection Using MRI Images," *Int. J. Next-Generation Comput.*, 2021, doi: 10.47164/ijngc.v12i5.460.

[8] H. S. Chandu, "A Survey of Semiconductor Wafer Fabrication Technologies: Advances and Future Trends," *Int. J. Res. Anal. Rev.*, vol. 10, no. 04, pp. 344–349, 2023.

[9] Abhishek Goyal, "Driving Continuous Improvement in Engineering Projects with AI-Enhanced Agile Testing and Machine Learning," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 3, no. 3, pp. 1320–1331, Jul. 2023, doi: 10.48175/IJARSCT-14000T.

[10] B. Kokila, M. S. Devadharshini, A. Anitha, and S. Abisheak Sankar, "Retraction: Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images," *Journal of Physics: Conference Series*. 2021. doi: 10.1088/1742-6596/1916/1/012226.

[11] K. Patel, "Quality Assurance In The Age Of Data Analytics: Innovations And Challenges," *Int. J. Creat. Res. Thoughts*, vol. 9, no. 12, pp. f573–f578, 2021.

[12] M. Gopalsamy, "Scalable Anomaly Detection Frameworks for Network Traffic Analysis in cybersecurity using Machine Learning Approaches," *Int. J. Curr. Eng. Technol.*, vol. 12, no. 6, 2022, doi: https://doi.org/10.14741/ijcet/v.12.6.9.

[13] S. Pandya, "A Machine Learning Framework for Enhanced Depression Detection in Mental Health Care Setting," *Int. J. Sci. Res. Sci. Eng. Technol.*, pp. 356–368, Oct. 2023, doi: 10.32628/IJSRSET2358715.

[14] A. Aleid, K. Alhussaini, R. Alanazi, M. Altwaimi, O. Altwijri, and A. S. Saad, "Artificial Intelligence Approach for Early Detection of Brain Tumors Using MRI Images," *Appl. Sci.*, 2023, doi: 10.3390/app13063808.

[15] A. P. A. Singh, "Best Practices for Creating and Maintaining Material Master Data in Industrial Systems," *Int. J. Res. Anal. Rev.*, vol. 10, no. 1, pp. 112–119, 2023.

[16] F. Khan *et al.*, "MRI-Based Effective Ensemble Frameworks for Predicting Human Brain Tumor," *J. Imaging*, 2023, doi: 10.3390/jimaging9080163.

[17] R. Hossain, R. B. Ibrahim, and H. B. Hashim, "Automated Brain Tumor Detection Using Machine Learning: A Bibliometric Review," *World Neurosurgery*. 2023. doi: 10.1016/j.wneu.2023.03.115.

[18] V. S. Lotlikar, N. Satpute, and A. Gupta, "Brain Tumor Detection Using Machine Learning and Deep Learning: A Review," *Curr. Med. Imaging Former. Curr. Med. Imaging Rev.*, 2021, doi: 10.2174/1573405617666210923144739.

[19] S. S. Singh, R. R. Kumar, and S. K. Punia, "Brain Tumor Detection Using Machine Learning," in *Lecture Notes in Networks and Systems*, 2023. doi: 10.1007/978-981-99-6568-7_4.

[20] M. R. S. and P. K. Vishwakarma, "An Efficient Machine Learning Based Solutions for Renewable Energy System," *Int. J. Res. Anal. Rev.*, vol. 9, no. 4, pp. 951–958, 2022.

[21] V. S. Thokala, "Integrating Machine Learning into Web Applications for Personalized Content Delivery using Python," *Int. J. Curr. Eng. Technol.*, vol. 11, no. 6, pp. 652–660, 2021, doi: https://doi.org/10.14741/ijcet/v.11.6.9.

[22] A. Chattopadhyay and M. Maitra, "MRI-based brain tumor image detection using CNN based deep learning method," *Smart Agricultural Technology*. 2022. doi: 10.1016/j.neuri.2022.100060.

[23] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," *BMC Med. Inform. Decis. Mak.*, vol. 23, no. 1, p. 16, Jan. 2023, doi: 10.1186/s12911-023-02114-6.

[24] M. Rizwan, A. Shabbir, A. R. Javed, M. Shabbir, T. Baker, and D. Al-Jumeily Obe, "Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network," *IEEE Access*, vol. 10, pp. 1–10, 2022, doi: 10.1109/ACCESS.2022.3153108.

[25] A. P. A. Singh, "STRATEGIC APPROACHES TO MATERIALS DATA COLLECTION AND INVENTORY MANAGEMENT," *Int. J. Bus. Quant. Econ. Appl. Manag. Res.*, vol. 7, no. 5, 2022.

[26] R. Tandon, "Face mask detection model based on deep CNN techniques using AWS," *Int. J. Eng. Res. Appl.*, vol. 13, no. 5, pp. 12–19, 2023.

[27] M. A. Mahjoubi, S. Hamida, O. El Gannour, B. Cherradi, A. El Abbassi, and A. Raihani, "Improved Multiclass Brain Tumor Detection using Convolutional Neural Networks and Magnetic Resonance Imaging," *Int. J. Adv. Comput. Sci. Appl.*, 2023, doi: 10.14569/IJACSA.2023.0140346.

[28] Suhag Pandya, "A Machine and Deep Learning Framework for Robust Health Insurance Fraud Detection and Prevention," *Int. J. Adv. Res. Sci. Commun. Technol.*, pp. 1332–1342, Jul. 2023, doi: 10.48175/IJARSCT-14000U.

[29] N. M. Dipu, S. A. Shohan, and K. M. A. Salam, "Deep Learning Based Brain Tumor Detection and Classification," in

2021 International Conference on Intelligent Technologies, CONIT 2021, 2021. doi: 10.1109/CONIT51480.2021.9498384.
[30] N. Cinar, B. Kaya, and M. Kaya, "Comparison of deep learning models for brain tumor classification using MRI images," in *2022 International Conference on Decision Aid Sciences and Applications, DASA 2022*, 2022. doi: 10.1109/DASA54658.2022.9765250.
[31] M. Harahap, A. M. Husein, S. S. Deol, S. Singh, S. D. P. Situmorang, and J. Saputra, "Comparative Analysis of Deep Learning Approach for Detection and Segmentation of Brain Tumor," in *ICOSNIKOM 2022 - 2022 IEEE International Conference of Computer Science and Information Technology: Boundary Free: Preparing Indonesia for Metaverse Society*, 2022. doi: 10.1109/ICOSNIKOM56551.2022.10034876.
[32] M. C. S. Tang and S. S. Teoh, "Brain Tumor Detection from MRI Images Based on ResNet18," in *2023 6th International Conference on Information Systems and Computer Networks, ISCON 2023*, 2023. doi: 10.1109/ISCON57294.2023.10112025.
[33] K. Pikulkaew, "Enhancing Brain Tumor Detection with Gradient-Weighted Class Activation Mapping and Deep Learning Techniques," in *2023 20th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, 2023, pp. 339–344. doi: 10.1109/JCSSE58229.2023.10202020.
[34] N. Abid, "A Climbing Artificial Intelligence for Threat Identification in Critical Infrastructure Cyber Security," *Int. J. Res. Anal. Rev.*, vol. 9, no. 4, 2022.
[35] B. Boddu, "Challenges and Best Practices for Database Administration in Data Science and Machine Learning," *IJIRMPS*, vol. 9, no. 2, p. 7, 2021, doi: https://www.ijirmps.org/research-paper.php?id=231461.
[36] M. A. Gómez-Guzmán *et al.*, "Classifying Brain Tumors on Magnetic Resonance Imaging by Using Convolutional Neural Networks," *Electron.*, 2023, doi: 10.3390/electronics12040955.
[37] H. Sinha, "Advanced Deep Learning Techniques for Image Classification of Plant Leaf Disease," *J. Emerg. Technol. Innov. Res. www.jetir.org*, vol. 11, no. 9, pp. b107–b113, 2024.
[38] M. Gopalsamy, "Artificial Intelligence (AI) Based Internet-of- Things (IoT) -Botnet Attacks Identification Techniques to Enhance Cyber security," *Int. J. Res. Anal. Rev.*, vol. 7, no. 4, pp. 414–419, 2020.
[39] A. S. S. M. Nazmul Arefin, S. M. I. A. K. Ishti, M. M. Akter, and N. Jahan, "Deep learning approach for detecting and localizing brain tumor from magnetic resonance imaging images," *Indones. J. Electr. Eng. Comput. Sci.*, 2023, doi: 10.11591/ijeecs.v29.i3.pp1729-1737.
[40] M. S. Alam *et al.*, "Automatic human brain tumor detection in mri image using template-based k means and improved fuzzy c means clustering algorithm," *Big Data Cogn. Comput.*, vol. 3, no. 2, pp. 1–18, 2019, doi: 10.3390/bdcc3020027.
[41] K. V. V. and S. G. Jubin Thomas , Piyush Patidar, "An analysis of predictive maintenance strategies in supply chain management," *Int. J. Sci. Res. Arch.*, vol. 06, no. 01, pp. 308–317, 2022, doi: DOI: https://doi.org/10.30574/ijsra.2022.6.1.0144.
[42] A. S. Musallam, A. S. Sherif, and M. K. Hussein, "A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images," *IEEE Access*, vol. 10, pp. 2775–2782, 2022, doi: 10.1109/ACCESS.2022.3140289.
[43] G. Raut, A. Raut, J. Bhagade, J. Bhagade, and S. Gavhane, "Deep learning approach for brain tumor detection and segmentation," in *2020 International Conference on Convergence to Digital World - Quo Vadis, ICCDW 2020*, 2020. doi: 10.1109/ICCDW45521.2020.9318681.
[44] A. B. Abdusalomov, M. Mukhiddinov, and T. K. Whangbo, "Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging," *Cancers (Basel).*, 2023, doi: 10.3390/cancers15164172.