

Brain Tumor MRI Classification using Xception Model

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Abstract—The proper classification from magnetic resonance imaging (MRI) scans of a brain tumor is essential for a correct and timely diagnosis, thus improving above all patients' outcomes. This research proposes an advanced classification framework utilizing the Xception model, integrated with transfer learning, to classify brain tumors into four categories: Meningioma, No Tumor, Glioma, and Pituitary. To perform successful model training, robust data preprocessing techniques such as resizing, normalization and augmentation are employed. The model achieved high accuracy of 91.01% and precision in the training, validation and test datasets, generalization and a good reliability. Analysis through a confusion matrix gives class wise performance, and takes ability to interpret system from probabilities as validation. The model was deployed as a web-based application (Streamlit) object producing real time predictions and clinical usable web-based application. Results show the promise of AI enabled solutions in reducing diagnostic accuracy and operational efficiency in medical imaging.

Index Terms—MRI, Transfer Learning, Xception Model, Deep Learning, Brain Tumor Classification, Streamlit Deployment, Medical Imaging.

I. INTRODUCTION

In the context of brain tumor diagnosis and brain tumor classification, medical imaging and neurology have been kidnapped due to the life-threatening nature of brain tumors and their complex manifestations. While Magnetic Resonance Imaging (MRI) is still the gold standard for non-invasive brain imaging, it provides incredible detail for assessment of tumor location, size, and type.

Manual interpretation of MRI scans is subjective, time consuming and more importantly prone to human error therefore automated systems to support clinical workflow is needed. Albeit Convolutional Neural Networks (CNNs) have come a long way in their development and contribution to medical image analysis, they have led the way for medical image analysis as a whole, providing accurate classification of complex medical datasets. Since the use of depth wise separable convolutions allows Xception to have good classification accuracy with high computational overhead reduction compared to other state of the art CNNs, Xception has shown remarkable performance.

Transfer learning using pre-trained ImageNet weights has been able to utilize the Xception model to extract intricate features from the medical imaging data, and is particularly well suited for classification of brain tumors from MRI. This study utilizes the Xception model to classify MRI brain scans into four categories: Meningioma, Glioma, No Tumor, and Pituitary. The data set comes from a public dataset available in Kaggle that includes a variety of MRI scans of these types of tumors. Figure 1 shows a sample of the dataset: Representative MRI

images from each class, illustrating the variability and overall complexity of this data. To ensure optimal model performance, several steps were undertaken:

- An accompanying dimension of 299x299 pixels was applied to the resized MRI images.
- A set of normalization and data augmentation (brightness adjustment) techniques were applied.
- Model evaluation was performed on the split up of the data into training, validation and test sets.

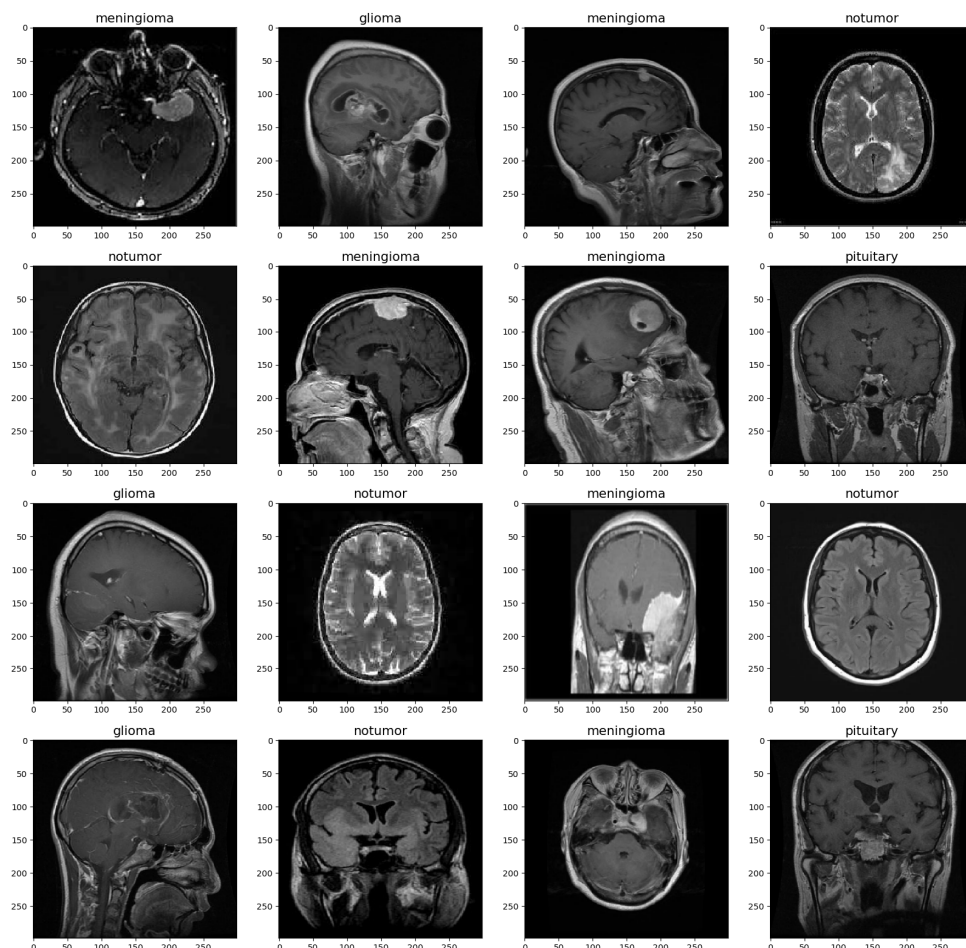


Figure 1. Representative MRI images from the dataset, illustrating samples of the four classes: Glioma, Meningioma, No Tumor, and Pituitary.

The fine-tuned Xception model with an augmentation of transfer learning adding additional fully connected layers and dropout layers to combat over fitting. To train, the Adamax optimizer is used with a learning rate of 0.001, and used accuracy, precision, and recall as evaluation metrics.

The proposed model gave out extraordinary results, with a training accuracy of 94.56%, and a validation and test accuracy of 91.76% and 91.01% respectively. In addition, the study shows the usefulness of interpretability by visualization such as confusion matrices and probability distributions of the classification results. This study automates the classification process with high precision in order to reduce the diagnostic burden on radiologists, and hopefully in clinical settings.

II. LITERATURE SURVEY

Deep learning techniques for brain tumor classification have transformed the landscape of medical imaging and radically improved automated consistent diagnosis. In this section, notable contributions in the field are surveyed including recent progress of convolutional neural networks (CNN), transfer learning, data augmentation and architectural innovations of brain tumor detection using MRI scans.

Saleh et al. [1] have studied the capability of CNNs in brain tumor classification and demonstrated that they are more effective than conventional machine learning approaches. The results demonstrated that CNNs perform

much better for feature extraction from MRI images compared with previously used methods, which achieve much better classification performance. Like Noreen et al. [6] investigated the deployment of fine-tuned models paired with ensemble methods, concluding that such hybrid approaches can greatly augment model accuracy and robustness. Deep learning with medical imaging work clearly relies on transfer learning to deepen the annotated base. For example, with brain tumor classification, Arbane et al. [8] used the transfer learning techniques to adapt pre-trained models that generalizes well to limited datasets. This approach was further enhanced by fine-tuning transfer learning models specifically for MRI images, as done by Amarnath et al. [4] improve the accuracy in the task of tumor detection. In a high precision MRI analysis, Sathya et al. [2] demonstrate how depth wise separable convolutions handle complex and heterogeneous medical imaging data using the Xception model. Efficient architecture and noticeable accuracy in medical image classification tasks, Xception model has received a lot of attention in the field. To gain superior performance metrics, Verma [5] proposed to exploit the Xception model for deep learning tasks with Xception feature extraction to achieve precise brain tumor classification.

Cobilla et al. [7] integrated the Xception model with a set of advanced preprocessing techniques, showing that such a model is applicable in MRI datasets and capable of solving multi class classification ones. Kaur et al. [9] validated the efficiency of Xception to detect various brain tumor types through extracting nuanced features from MRI images. For brain tumor classification in deep learning workflows, preprocessing and data augmentation have a pervasive influence.

This is exemplified by Anaya-Isaza et al. [13], who showed the importance of tackling dataset imbalances, which are ubiquitous in medical imaging datasets, through data augmentation. In addition, when used in conjunction with techniques like rotation, flipping, and brightness adjustment, the model generalization is greatly improved, according to their study. In this work, Dang et al. [12] presented novel preprocessing methods for MRI-based tumor segmentation and classification which showed significant improvements on model accuracy and robustness. More recent studies have also sought to optimize CNN architectures for multi class brain tumor classification. Özkaraça et al. [14] proposed a dense CNN architecture that achieved high precision and recall for tumor type classification. In particular, Kibriya et al. [15] presented a new CNN framework dedicated to the multiclass classification problem and pointed out that the performance metrics can be greatly improved if one designs the network in a dedicated way. Taken together, these studies collectively illustrate the promise of using deep learning methodology for brain tumor classification and provide insight into advancements in deep learning such as use of transfer learning, novel CNN architectures (Xception) and robust preprocessing. This provides insights into the methodology employed in this study, as well as into the possibility for further innovation in automated diagnostic systems.

III. PROPOSED METHODOLOGY

The tweak of brain tumor classification with MRI using the Xception model with transfer learning is used in this methodology. Elaborate on the dataset, how preprocessed the data, architectural details of the model, training strategy, and the performance evaluation in this section.

A. Dataset Overview

The dataset utilized for this study was sourced from Kaggle, comprising MRI scans classified into four categories: Meningioma, Glioma, No Tumor, Pituitary. There are 5,712 images for training and 1,311 for testing, and all images are balanced among classes.

All images were resized to 299x299 pixels, exactly the same pixel dimensions that the Xception model takes as input. The dataset was split into three subsets: (70%) training, (15%) validation and (15%) testing. Preserving class proportions across all subsets was accomplished using a stratified sampling strategy. The distribution of training and test images across the four classes are shown as Figures 2 and Figure 3. This form of dataset ensures that the model was able to generalize across tumor types.

B. Data Preprocessing

The MRI scans were precisely prepared for model training; hence, preprocessing was a very important step. The following transformations were applied to ensure the dataset was optimized for the deep learning pipeline:

- Resizing: All images resize to width and height of 299 pixels to normalize image dimensions in the dataset.
- Normalization: Because it helped with faster convergence during training did pixel values scaled to [0, 1] by dividing each pixel by 255.

- **Data Augmentation:** To augment dataset variability and robustness, randomly shifted (brightness range: 0.8–1.2) and horizontally flipped images were added. The realized variations in imaging conditions of this augmentation serve to improve the model's ability to generalize.

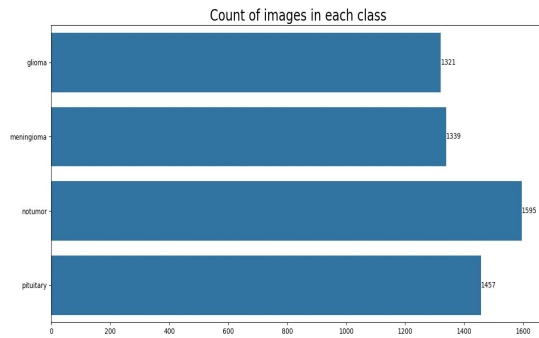


Figure 2: Distribution of training images across tumor classes

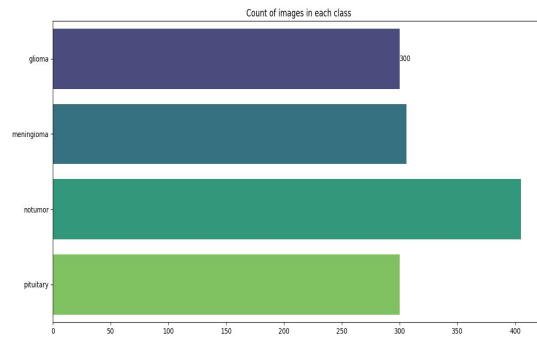


Figure 3: Distribution of test images across tumor classes

C. Model Design

The proposed architecture was based upon the Xception model which is famous for being deep and using depth wise separable convolutions efficiently. Custom fully connected layers were appended to pre-trained Xception model to fine tune it to classify MRI scans into four categories. High level features were extracted from MRI images by the Xception base model, pre-trained on ImageNet. To retain learned weights, the first iteration was trained with the pre-trained layers frozen.

Custom Layers:

- The feature maps are then flattened into a one-dimensional vector by a Flatten layer.
- Dense layer with 128 neurons and ReLU activation to learn complex yet interesting feature interactions.
- Two Dropout layers (rates: 0.3 and 0.25) were included to prevent overfitting.
- A Dense output layer with 4 neurons and softmax activation produced probabilities for each tumor class.

Figure 4 details the architecture of the model with the pre-trained Xception backbone along with added layers. The model was compiled using Adamax with a learning rate of 0.001, a categorical cross entropy as loss function. During training tracking metrics such as accuracy, precision, and recall are used.

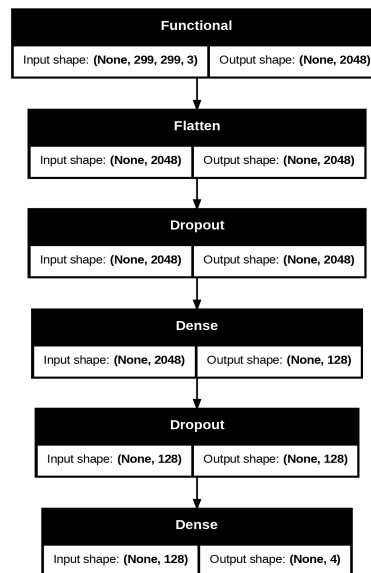


Figure 4. Architectural design of the proposed model, incorporating the Xception backbone and custom layers.

D. Training Procedure

The structured the training process perform well while generalizing. The dynamical transformations and the augmentation of the data generator resulted in diverse input data from every epoch. There were 32 as batch size

and 10 epochs as a whole. A model was implemented and trained using TensorFlow and Keras frameworks. The model was able to use existing features from ImageNet without them, using the frozen pre-trained layers, and learn task specific patterns from the MRI dataset by adding layers. At the end of each epoch, validate to fine tune hyperparameters such as learning rate and dropout rates.

E. Performance Assessment

The trained model was evaluated on the test dataset, achieving Training Accuracy: 94.56%, Validation Accuracy: 91.76%, and Test Accuracy: 91.01%. Based on the precision, recall and F1 scores, which were computed to comprehensively evaluate the model's effectiveness to handle the imbalanced classes. Furthermore, a confusion matrix was generated to visualize predictions on a class wise basis and identify misclassifications. The robust performance metrics justify the feasibility of the proposed methodology.

IV. RESULTS AND DISCUSSION

Finally, the proposed methodology is able to classify brain tumors from MRI scans using the Xception model with satisfactory results. It discusses the model's performance metrics, visualizes results with graphs and charts; and evaluates outputs produced by the deployed system.

A. Model Performance

The proposed model was high performing on the validation and test datasets. Accuracy, loss, precision and recall were monitored throughout 10 epochs. Figure 6 illustrates the training and validation performance on the epochs. Table II summarizes the results as key metrics.

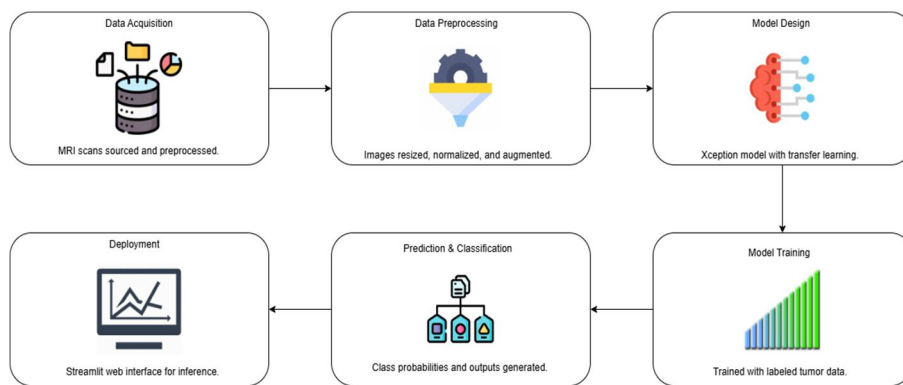


Figure 5. System Architecture

TABLE I. PERFORMANCE METRICS SUMMARY

Metric	Training Set	Validation Set	Test Set
Accuracy	94.56%	91.76%	91.01%
Precision	92.5%	90.8%	89.9%
Recall	91.2%	90.0%	90.3%
Loss	0.217	0.283	0.298

These results show that the model is able to generalize well across datasets as well as classify tumor categories robustly. Figure 6 shows the training and validation metrics graphed consistently improving from epoch to epoch.

B. Confusion Matrix Analysis

A detailed analysis of the model's classification performance is given in the confusion matrix, shown in Figure 7. It illustrates true and predicted labels for all four classes: Meningioma, No Tumor, Pituitary, glioma. The key observations from the confusion matrix:

- A slight overlap was found in glioma and meningioma classes with some misclassification between these two classes.
- With minimal false positives or false negatives, the No Tumor class had a high accuracy.
- Most predictions of the Pituitary class matched true labels, and they performed well as well.

The robustness of the proposed CMC methodology is confirmed by this analysis, including when faced with imbalanced classes.

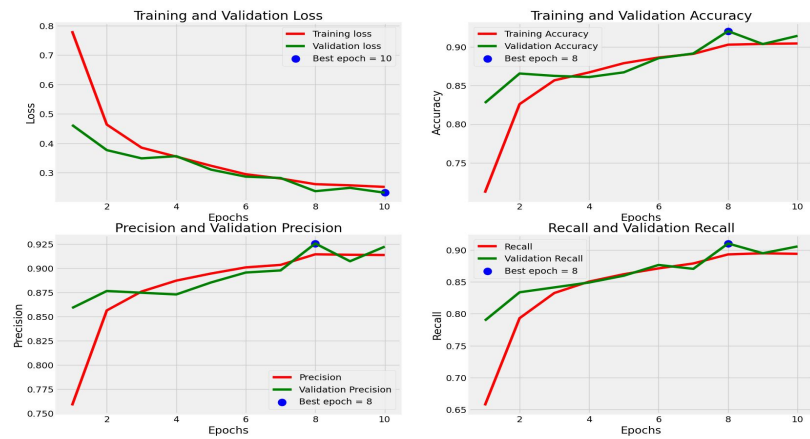


Figure 6. Training and validation metrics over epochs, including loss, accuracy, precision, and recall

C. Predicted Class Probabilities

Figures 8 and Figure 9 visualize how the model can predict probabilities for each class, while two MRI scans are used. In these figures, now you can see the predicted probabilities for all four classes, since the model is very assumable of his classification. In Figure 8, the model gave an 87% probability to the prediction that there was no Tumor, and assigned probabilities to other classes, but with low numbers. As shown in Figure 9, the model showed an 83% per cent probability to classify the image as Meningioma and other worse values for other classes. Lastly, these visualizations further validate the model, insofar as they illustrate the interpretability and reliability of the predictions.

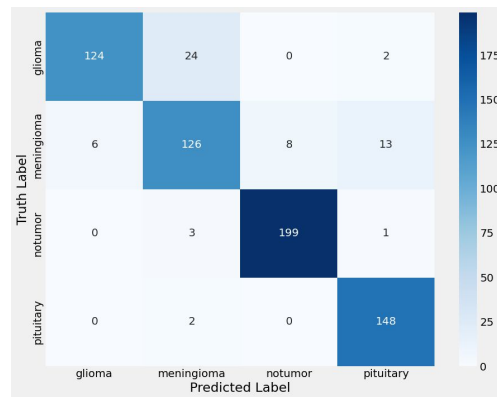


Figure 7. Confusion matrix depicting classification performance across tumor classes

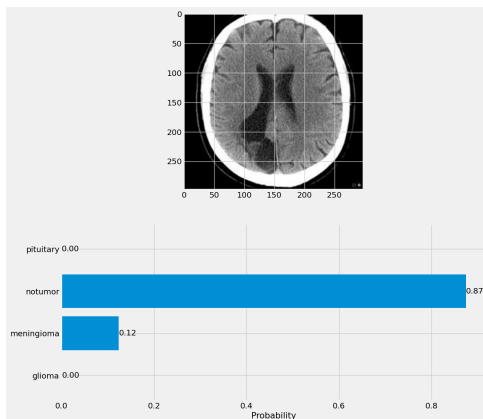


Figure 8. Predicted class probabilities for MRI scan 1.

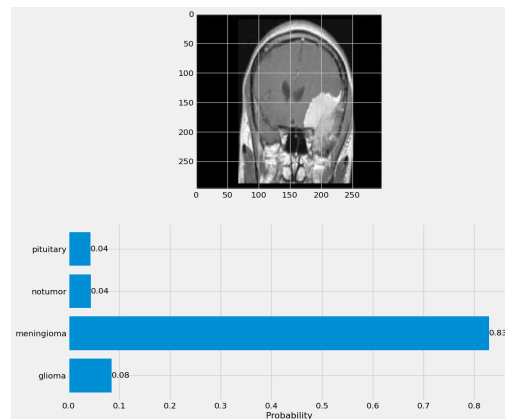


Figure 9. Predicted class probabilities for MRI scan 2.

D. Deployment and Real-World Application

The model was deployed as a web-based interface to obtain real time predictions and ease of usage using Streamlit. Deploy the system to enable users to upload MRI scans and receive classification results with associated probabilities. Screenshots of the deployed system are presented in Figures 10, Figure 11, and Figure 12, showcasing:

- Users can easily upload images with the application interface (Figure 10).
- Figure 11 displays predicted probabilities for the uploaded MRI scans so as to be interpretable.
- Additional visual feedback to users is available on a histogram representation of predicted class probabilities (Figure 12).

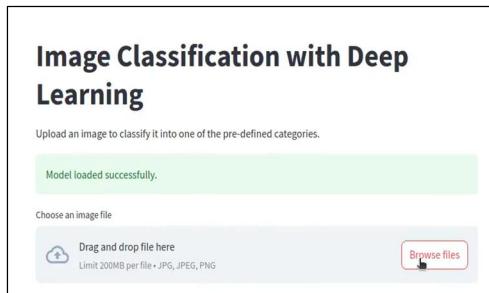


Figure 10. Deployed application interface for uploading MRI scans

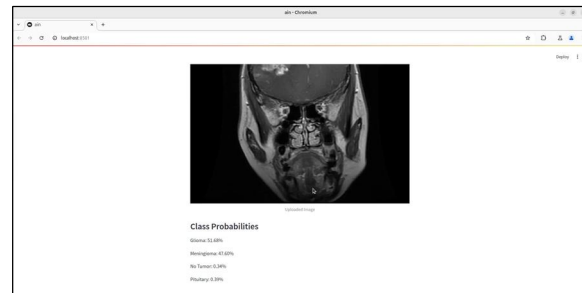


Figure 11. Predicted probabilities displayed for a selected MRI scan

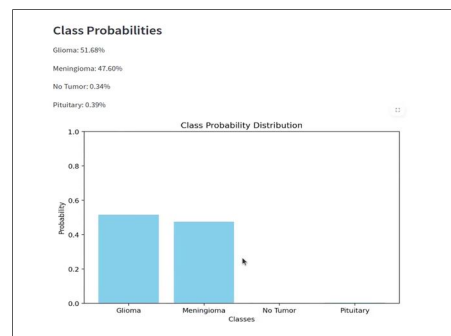


Figure 12. Histogram of predicted class probabilities for an uploaded scan

This deployment therefore shows the practical value of the proposed system for application in a clinical setting, as it provides efficient and accurate assistance to medical professionals in the tumor diagnosis area. With high accuracy, precision and recall scores, across training, validation and test datasets, the proposed system shows a high classification performance. The confusion matrix analysis suggests that the model is generally robust to all classes, but some overlaps (for example between Glioma and Meningioma) indicate further refinement regions. Data augmentation and transfer learning has been used to incorporate these results, as it let the model generalize well with such a smaller dataset size. The deployment of the system closes the gap further between theoretical research and real usage. The system enables medical professionals with a real time interface to facilitate tumor classification that is easily accessible and usable. How to improve in the future is by expanding the dataset, including more different imaging modality information, and using an ensemble of models to improve performance even more. This study presents the potential of AI driven solutions in medical imaging from diagnostic accuracy and efficiency standpoints, and serves as a basis for this future work.

V. CONCLUSION

In a brain tumor classification from MRI scan task, the implementation of the Xception model augmented with transfer learning has proved a strong potential. An approach which involved preprocessing the data, fine tuning the model architecture and rigorous evaluation resulted in high accuracy, precision and recall. Strong generalization and overfitting robustness were achieved by the combination of data augmentation techniques and a robust training pipeline. The deployment as a web-based application positions it for clinical use, and accurate, interpretable predictions to be used by medical professionals to assist in diagnostic decision making. The findings serve to establish the potential of AI in enhancing diagnostic feasibility for important diseases such as

brain tumors. By using more massive and richer datasets, the robustness and generalization to varieties of demographics will be improved and help advances in brain tumor classification systems. Other imaging modalities such as CT or PET scans can be included as features, and multimodal learning techniques could benefit the classification accuracy. Further optimization of performance and interpretability through the exploration of advanced architectures, such as Vision Transformers or hybrid ensemble models, remains to be seen. Adding tumor segmentation and prognosis prediction capabilities for the system will contribute to a complete workflow with necessary diagnostic and treatment system, and further represent a more integrated AI driven healthcare solution.

REFERENCES

- [1] Saleh, A., Sukaik, R., & Abu-Naser, S. S. (2020, August). Brain tumor classification using deep learning. In 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech) (pp. 131-136). IEEE.
- [2] Sathya, R., Mahesh, T. R., Bhatia Khan, S., Malibari, A. A., Asiri, F., Rehman, A. U., & Malwi, W. A. (2024). Employing Xception convolutional neural network through high-precision MRI analysis for brain tumor diagnosis. *Frontiers in Medicine*, 11, 1487713.
- [3] Qodri, K. N., Soesanti, I., & Nugroho, H. A. (2021). Image analysis for MRI-based brain tumor classification using deep learning. *IJITEE (International Journal of Information Technology and Electrical Engineering)*, 5(1), 21-28.
- [4] Amarnath, A., Al Bataineh, A., & Hansen, J. A. (2024). Transfer-Learning Approach for Enhanced Brain Tumor Classification in MRI Imaging. *BioMedInformatics*, 4(3), 1745-1756.
- [5] Verma, G. (2024, October). Xception-based Deep Learning Model for Precise Brain Tumour Classification. In 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 1481-1485). IEEE.
- [6] Noreen, N., Palaniappan, S., Qayyum, A., Ahmad, I., & Allassafi, M. O. (2021). Brain Tumor Classification Based on Fine-Tuned Models and the Ensemble Method. *Computers, Materials & Continua*, 67(3).
- [7] Cobilla, R., Dichoso, J. C., Miñon, A. B., Pascual, A. K., Abisado, M., Huyo-a, S. L., & Sampedro, G. A. (2023, February). Classification of the Type of Brain Tumor in MRI Using Xception Model. In 2023 International Conference on Electronics, Information, and Communication (ICEIC) (pp. 1-4). IEEE.
- [8] Arbane, M., Benlamri, R., Brik, Y., & Djerioui, M. (2021, February). Transfer learning for automatic brain tumor classification using MRI images. In 2020 2nd international workshop on human-centric smart environments for health and well-being (IHSH) (pp. 210-214). IEEE.
- [9] Kaur, G., Sharma, N., Upadhyay, D., Singh, M., & Gupta, R. (2024, March). Brain Tumour Disease Detection in MRI Images using Xception Model. In 2024 3rd International Conference for Innovation in Technology (INOCON) (pp. 1-5). IEEE.
- [10] Asiri, A. A., Khan, B., Muhammad, F., Alshamrani, H. A., Alshamrani, K. A., Irfan, M., & Alqhtani, F. F. (2023). Machine learning-based models for magnetic resonance imaging (MRI)-based brain tumor classification. *Intell. Autom. Soft Comput*, 36, 299-312.
- [11] Srinivas, C., KS, N. P., Zakariah, M., Alothaibi, Y. A., Shaukat, K., Partibane, B., & Awal, H. (2022). Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images. *Journal of Healthcare Engineering*, 2022(1), 3264367.
- [12] Dang, K., Vo, T., Ngo, L., & Ha, H. (2022). A deep learning framework integrating MRI image preprocessing methods for brain tumor segmentation and classification. *IBRO neuroscience reports*, 13, 523-532.
- [13] Anaya-Isaza, A., & Mera-Jiménez, L. (2022). Data augmentation and transfer learning for brain tumor detection in magnetic resonance imaging. *IEEE Access*, 10, 23217-23233.
- [14] Özkara, O., Bağrıaçık, O. İ., Gürüler, H., Khan, F., Hussain, J., Khan, J., & Laila, U. E. (2023). Multiple brain tumor classification with dense CNN architecture using brain MRI images. *Life*, 13(2), 349.
- [15] Kibriya, H., Masood, M., Nawaz, M., & Nazir, T. (2022). Multiclass classification of brain tumors using a novel CNN architecture. *Multimedia tools and applications*, 81(21), 29847-29863.