AI-Driven MRI Classification System

ENGG*6600 - Intro to AI –S24: Project Final Report

University of Guelph

Om Bhosale (1293903)
M.Eng., Computer Engineering
obhosale@uoguelph.ca

Arpit Vaghela (1262011)
M.Eng., Computer Engineering
avaghela@uoguelph.ca

Alisha Fatima (1308029)
M.Eng., Engineering Systems and Computing
aalishaf@uoguelph.ca

Jaya priya Kanakarajan (1305693)
M.Eng., Engineering Systems and Computing
jkanakar@uoguelph.ca

Abstract

The integration of artificial intelligence (AI) in medical imaging can significantly enhance diagnostic accuracy and efficiency. This project focuses on developing an AI-driven MRI classification system to aid in the early detection and diagnosis of medical conditions. We implemented and evaluated multiple machines learning models, including convolutional neural networks (CNNs), transfer learning models (LSTM, VGG, ResNet, EfficientNet), hybrid models combining CNNs with recurrent neural networks (RNNs) or transformers, and ensemble learning techniques. Our results indicate that transfer learning and ensemble models achieved superior performance, highlighting the importance of leveraging pre-trained models and combining multiple approaches. This work contributes to the field by addressing challenges such as class imbalance and model interpretability, paving the way for future advancements in AI-driven medical imaging.

Keywords: Magnetic Resonance Imaging (MRI), MRI classification, convolutional neural networks, transfer learning, hybrid models, ensemble learning, medical imaging, diagnostic accuracy.

1. Introduction

Brain tumors are highly aggressive diseases, affecting both children and adults, with around 11,700 new cases diagnosed annually. Manual MRI examination by radiologists can be error-prone due to the complexity of tumors and the shortage of skilled professionals, especially in developing countries.

The field of medical imaging has seen significant advancements with the integration of artificial intelligence (AI) and machine learning techniques. This project focuses on the development of an AI-driven MRI classification system aimed at improving diagnostic accuracy and efficiency. The primary objectives include building and evaluating various machine learning models to classify MRI images accurately. Our contributions include the implementation of multiple AI models, each utilizing different approaches such as convolutional neural networks (CNNs), transfer learning, hybrid models, and ensemble learning. The significance of this project lies in its potential to aid radiologists in the early detection and diagnosis of medical conditions, ultimately enhancing patient outcomes.

2. Literature Review

The application of AI in medical imaging has been extensively explored in recent literature [Fig. 1]. Convolutional neural networks (CNNs) have demonstrated remarkable performance in image classification tasks, as evidenced by studies such as “Automated Brain Tumor Segmentation using Intensity Histogram and Ring Form Partition” by Cheng et al. [2] and “Brain Tumor Classification Using Deep Learning Networks” by Deepak and Ameer. Transfer learning approaches using pre-trained models like GoogleNet have also shown promise in medical image analysis, achieving an accuracy of 98% in brain tumor classification (Deepak & Ameer) [3]. Additionally, hybrid models that combine CNNs with other techniques have been investigated for their ability to improve performance. For instance, Çınar and Yildirim [4] explored hybrid CNN models, achieving an accuracy of 97.2%.

Despite these advancements, challenges such as class imbalance, limited annotated data, and the need for model interpretability remain open problems. For example, Shree and Kumar [5] highlighted the high computational cost associated with using probabilistic neural networks for medical imaging tasks, while Saxena et al. [6] pointed out the time-consuming nature of CNN networks with transfer learning. These challenges underscore the need for further research and innovation to develop more efficient and interpretable AI models in medical imaging, which our project aims to address.

More recent research still expands the established

Authors and year	Dataset	Feature extraction method	Classification method	Accuracy	Limitations
Zacharaki et al. (2009)	102 MRI	Gabor texture features	KNN and SVM	85%	Small dataset Poor resulted accuracy
Cheng et al. (2015)	3064	Intensity histogram, GLCM and BOW	Ring form partition	91.28%	High computational complexity
Shree and Kumar (2018)	650	Gray level co-occurrence matrix	Probabilistic neural network (PNN)	95	Need large storge High computational cost
Abd-Ellah (2020)	349	Deep Learning	SoftMax	97.79%	High computational complexity
Deepak and Ameer (2019)	3064 MRI	Google Net	Deep transfer learning	98%	Dealing with a few numbers of layers for the GoogLeNet
Saxena et al. (2019)	253 MRI	CNN	CNN networks with transfer learning	95%	Time consuming
Hemanth et al. (2019)	220 MRI	CNN	CNN	94.5%	Small dataset
Çinar and Yildirim (2020)	Kaggle site	Hybrid CNN	CNN	97.2%	Time consuming, High computational complexity
Saed et al. (2017)	587	CNN	CNN	91.16%	Time consuming
Tazin et al. (2021)	2513 X-ray images	CNN	CNN	Up to 92%	Using X-ray images
Ge et al. (2018)	BraTS 2017	CNN	Mutistream CNN	90.78%	High computational cost

bound for MRI classification methods as seen in the summary of Fig.2. Specifically, the combination of recurrent neural networks (RNNs) with CNNs has been a trend. For example, K Neeraja et al. [7] got an accuracy of 98% using LSTM algorithms; therefore, it is evident that deep learning with LSTM has a lot of potential in handling often complex medical imaging jobs. Ramdas Vankdothu et al. [8] also supported the idea that CNNs with LSTMs can make up to 92% accuracy, noting the shortcomings to do with spatial heterogeneity and the overall complexity of the tumours. Additionally, a hybrid model of LSTM-GRU developed by St S Prabu et al. [9] mentioned that 85% of accuracy is needful to avoid overfitting, further to it a larger dataset is required. The study by S K Rajeev et al. [10], where a hybrid CNN-LSTM neural network was used, made it possible to reach an accuracy of 97. 94%, although it was stated that there is a possibility for further enhancement since the Jaccard index is lower. Recent advancements leverage deep learning, with Bhagyalaxmi et al. surveying multi-grade techniques [11] and Balamurugan et al. improving performance through a channel-wise attention model [12].

These recent enhancements imply the same large opportunities of the CNN-RNN hybrid compositions that are based on LSTM or GRU to increase the possibilities of the AI-driven MRI classification systems in overcoming existing impediments in medical imaging.

Fig. 1 State-of-the-art summary table of previous brain tumor classification techniques [1]

Authors and year	Dataset	Feature extraction Method	Classification Method	Accuracy	Limitation
K Neeraja et al. (2023)	2964 MRI	Deep learning with LSTM	LSTM algorithm	98%	Requires large datasets, high computational resources, and challenges in interpretability.
Ramdas Vankdothu et al. (2022)	3264 MRI	CNN	CNN-LSTM	92%	The high spatial heterogeneity and complexity of brain tumors make automatic segmentation challenging.
St S Prabu et al. (2024)	Open source Repo.	GLCM, Wiener filter for noise reduction	Hybrid LSTM-GRU	85% with LSTM-GRU; CNN accuracy was 75%	Challenges with overfitting, need for larger datasets, and variations in image quality
S K Rajeev et al. (2023)	7023 MRI	Transfer learning with the pre-trained AlexNet model	Hybrid CNN-LSTM neural network	97.94%	lower Jaccard index suggests room for improvement

Fig. 2 Background of LSTM and GRU Model Studies

3. Methodology

Model Selection

The project involved training multiple models:

CNNs: Basic CNN architectures were trained to serve as baseline models.

Transfer Learning: Pre-trained models such as VGG, ResNet, and EfficientNet were fine-tuned on our dataset.

Hybrid Models: Combining CNNs with RNNs or transformers to capture both spatial and temporal information.

We explored several neural network architectures for our classification system, including EfficientNetB1, ResNet50, DenseNet121, LSTM, and GRU.

EfficientNetB1 developed by Google, is known for achieving state-of-the-art accuracy while being highly efficient. This model uses fewer resources compared to other models, making it suitable for our project.

ResNet50 is a 50-layer variant pre-trained on ImageNet. It uses residual connections to tackle the vanishing gradient problem, which enhances its performance in deep networks.

DenseNet121 is a 121-layer variant also pre-trained on ImageNet. It features dense connectivity patterns, where each layer is connected to every other layer in a feed-forward fashion, improving information flow and gradient propagation.

LSTM (Long Short-Term Memory) is an RNN designed to capture temporal dependencies in sequential data using memory cells. In our project, LSTM models were employed to enhance the classification of MRI data by capturing temporal patterns within image sequences.

GRU (Gated Recurrent Unit) is a simpler RNN variant that uses gating mechanisms to regulate information flow, making it more efficient than LSTMs. GRU models were used to evaluate their effectiveness in handling temporal data and to compare their performance in MRI classification.

Data Preprocessing

Our dataset consists of 7023 human brain MRI images classified into four categories: glioma, meningioma, pituitary, and no tumor. The dataset was sourced from Kaggle and is published under the MIT license. It includes 3064 T1-weighted contrast-enhanced images from 233 patients, covering various brain tumor types to ensure robust training and testing of our classification algorithms.

To prepare the data, we implemented several preprocessing steps:

- Cropping: Images were cropped to focus on the region of interest. This involved converting images to grayscale, applying Gaussian blur, and using thresholding, erosion, and dilation to remove noise.
- Resizing: Cropped images were resized to 256x256 pixels to ensure a uniform input size for every model.
- Duplicate Removal: Duplicate images were identified and removed by computing a hash for each file, maintaining data integrity and preventing overfitting.

Model Architecture

1. EfficientNet B1

The AI-driven MRI classification system employs the EfficientNet B1 architecture for robust and efficient feature extraction. Below are the specifics of the model architecture:

1.1. Base Model

- **Pre-training**: The model is pre-trained on the ImageNet dataset.
- **Input Image Size**: 224 x 224 pixels
- **Input Shape**: [1, 3, 224, 224] (batch size, channels, height, width)
- **Total Parameters**: Approximately 6,518,308
- **Trainable Parameters**: 5,124
- **Non-trainable Parameters**: 6,513,184

1.2. Layers and Parameters

- **Number of Layers**: 18 layers
- **Number of Parameters**: About 7.8 million parameters

1.3. Feature Extraction

- **Architecture**: The EfficientNet B1 model employs a series of MBConv blocks, which are designed to efficiently capture hierarchical features from input images. These blocks use depthwise separable convolutions to enhance computational efficiency while maintaining high accuracy.
- **Pooling**: The model applies global average pooling to reduce the dimensionality of the feature maps to a single vector. This pooling technique aggregates spatial information and prepares it for the subsequent dense layers.

1.4. Custom Layers

- **Dropout**: A dropout rate of 0.2 is incorporated into the architecture for regularization purposes. This helps to prevent overfitting by randomly dropping units during training.
- **Dense Layer**: The final layer consists of a fully connected dense layer with neurons that utilize the SiLU (Sigmoid Linear Unit) activation function. This activation function is particularly effective for multiclass classification tasks.

1.5. Training Configuration

- **Optimizer**: The Adam optimizer is used with a learning rate of 0.001. Adam is chosen for its efficiency and adaptive learning rate capabilities, which aid in faster convergence and improved performance.
- **Loss Function**: Categorical Cross entropy is utilized as the loss function, suitable for multiclass classification problems. This loss function measures the performance of the classification model by comparing the predicted and true labels.

2. **ResNet 50**

The AI-driven MRI classification system also incorporates a ResNet50 architecture. Below are the specifics for this model:

2.1. Base Model

- **Pre-training**: The model is pre-trained on the ImageNet dataset.

2.2. Layers and Parameters

- **Number of Layers**: 50 layers in total
- **Pooling**: Global average pooling is used to aggregate features and reduce dimensionality.

2.3. Feature Extraction

ResNet50 uses residual learning to address the vanishing gradient problem, which enhances its ability to learn deep features effectively.

2.4. Custom Dense Layers

- **Flattening**: Converts the 2D feature maps output by ResNet50 into a 1D vector to prepare for dense layer processing.
- **Dropout Layer 1**: Applied with a rate of 0.5 to reduce overfitting and improve model generalization.
- **Dense Layer 1**: Contains 128 neurons with ReLU activation, enabling the model to learn complex patterns.
- **Dropout Layer 2**: Applied with a rate of 0.5 to further reduce overfitting and enhance robustness.
- **Dense Layer 2**: Contains 4 neurons with a Softmax activation function for multiclass classification.

2.5. Training Configuration

- **Optimizer**: Adamax with a learning rate of 0.001 is used for optimizing the model. Adamax is chosen for its robustness and ability to handle sparse gradients.
- **Loss Function**: Categorical Crossentropy is employed as the loss function, suitable for multiclass classification.
- **Metrics: Accuracy, Precision, and Recall are used to evaluate the model's performance.**
- **Epochs**: The model is trained for 10 epochs, allowing sufficient time for learning while managing computational resources.

3. DenseNet Performance

The AI-driven MRI classification system also integrates a DenseNet architecture, which provides a distinctive approach to feature extraction by using dense connectivity patterns. Below are the specifics for this model:

3.1. Base Model

- **Pre-training**: The DenseNet model is pre-trained on the ImageNet dataset, leveraging learned features to enhance performance on the MRI classification task.

3.2. Layers and Parameters

- **Number of Layers**: DenseNet consists of 121 layers in total, depending on the specific DenseNet variant (e.g., DenseNet-121, DenseNet-169, etc.).
- **Pooling**: Global average pooling is employed to aggregate features and reduce dimensionality before classification.

3.3. Feature Extraction

DenseNet utilizes dense blocks to facilitate feature reuse and improve gradient flow, effectively mitigating the vanishing gradient problem and enhancing feature learning.

3.4. Custom Dense Layers

- **Flattening**: The 2D feature maps output by DenseNet are converted into a 1D vector for dense layer processing.
- **Dropout Layer 1**: A dropout rate of 0.5 is applied to reduce overfitting and improve generalization capabilities.
- **Dense Layer 1**: Includes 128 neurons with ReLU activation, allowing the model to learn and represent complex patterns.
- **Dropout Layer 2**: Another dropout layer with a rate of 0.5 is applied to further enhance robustness and reduce overfitting.
- **Dense Layer 2**: Comprises 4 neurons with a Softmax activation function, enabling multiclass classification.

3.5. Training Configuration

- **Optimizer**: The Adam optimizer with a learning rate of 0.001 is utilized for optimization. Adam is chosen for its adaptability and efficient handling of sparse gradients.
- **Loss Function**: Categorical Crossentropy is used as the loss function, suitable for multiclass classification tasks.
- **Metrics**: The model's performance is evaluated using metrics such as Accuracy, Precision, and Recall ensuring comprehensive assessment.
- **Epochs**: The DenseNet model is trained for 10 epochs, balancing learning effectiveness and computational efficiency.

4. LSTM and GRU Hybrid Models

The AI-driven MRI classification system integrates LSTM and GRU architectures, providing a distinctive approach to feature extraction by leveraging recurrent neural networks. Below are the specifics for these models:

4.1 Base Model

- **Pre-training:** The base model used for feature extraction is a VGG16 pre-trained on the ImageNet dataset, which leverages learned features to enhance performance on the MRI classification task.
- **Input Image Size:** 224 x 224 pixels
- **Output Feature Size:** 512 x 7 x 7
- **Total Parameters:** Approximately 138 million
- **Trainable Parameters:** Frozen (non-trainable) during feature extraction

4.2 Layers and Parameters

- **Number of Layers:**
  LSTM Model: 2 LSTM layers
  GRU Model: 2 GRU layers
- **Hidden Size:** LSTM and GRU Models: Each recurrent layer contains 128 units.
- **Dropout:** Dropout Rate: A dropout rate of 0.5 is applied to each recurrent layer to reduce overfitting and improve generalization capabilities.

4.3. Feature Extraction

VGG16 utilizes convolutional layers to extract hierarchical features from input images. These features are then flattened to be used as input for the recurrent layers.

4.4. Custom Dense Layers

- **Flattening:** The 2D feature maps output by VGG16 are converted into a 1D vector for recurrent layer processing.
- **Recurrent Layers:**
  LSTM: The LSTM layers capture temporal dependencies and patterns in the extracted features.
  GRU: The GRU layers also capture temporal dependencies, with a more simplified structure compared to LSTM.
- **Dense Layer:** A fully connected dense layer with 4 neurons and a Softmax activation function is used for multiclass classification.

4.5. Training Configuration

- **Optimizer:** The Adam optimizer with a learning rate of 0.005 is utilized for optimization. Adam is chosen for its adaptability and efficient handling of sparse gradients.
- **Loss Function:** Cross-Entropy Loss is used as the loss function, suitable for multiclass classification tasks.
- **Metrics:** The model's performance is evaluated using metrics such as Accuracy, Precision, and Recall to ensure comprehensive assessment.

- **Epochs:** Epochs: The LSTM and GRU models are trained for 20 epochs, balancing learning effectiveness and computational efficiency.

4. Results

CNN Models

1. Resnet50:

The ResNet50 model demonstrated strong performance in the classification task. The test loss was 0.1050, indicating the model's ability to minimize errors during prediction. Additionally, the test accuracy achieved by ResNet50 was 96.89%, reflecting its high capability in correctly classifying the MRI images. The training and validation loss graph (Fig. 3) shows a consistent decrease in loss over epochs, indicating effective learning and generalization.

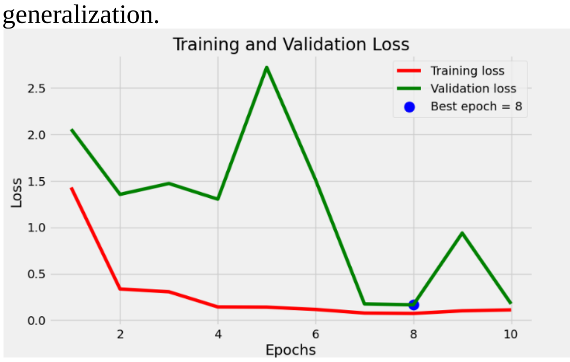

Fig. 3: Training and validation loss graph for ResNet50

2. DenseNet121:

DenseNet121 also provided commendable results, with a test loss of 0.2720 and a test accuracy of 88.28%. These metrics indicate that while DenseNet121 effectively learned from the training data, its performance was slightly lower than ResNet50. The training and validation loss graph (Fig. 4) for DenseNet121 illustrates a steady reduction in loss, highlighting the model's ability to learn the intricate patterns within the MRI images effectively.

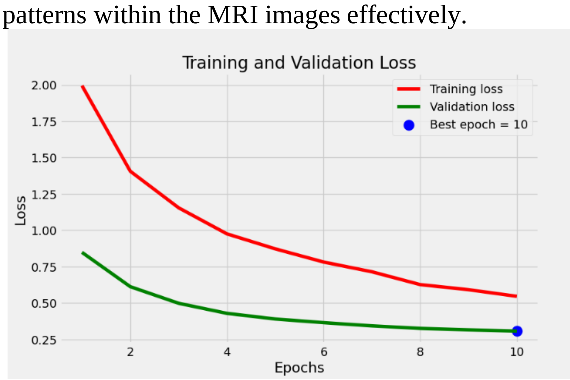

Fig. 4: Training and validation loss graph for DenseNet121

3. EfficientNet B1 Performance:

The EfficientNet B1 model exhibited strong performance in the MRI classification task. The model achieved a training accuracy ranging from 91% to 92% and a test accuracy between 92% and 93%. Its training loss was approximately 0.22 to 0.24, while the test loss ranged from 0.20 to 0.22. In terms of precision, the model demonstrated a test precision of approximately 0.9991 and an F1-score ranging from 0.95 to 0.96.

Loss Curve:

The loss curve analysis [Fig.5] shows rapid initial learning with a gradual decrease in both training and test loss, indicating effective learning and some degree of overfitting.

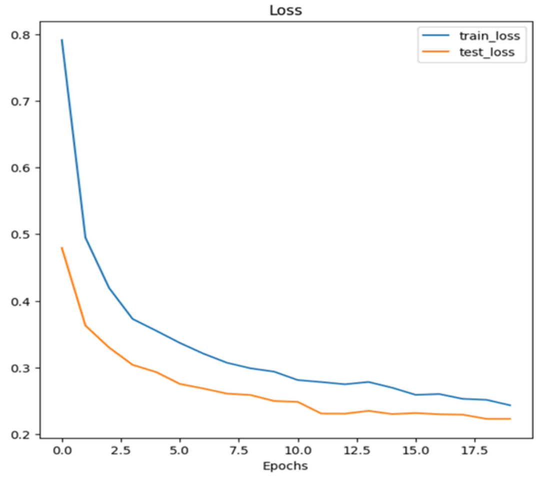

Fig. 5: Loss curve for EfficientNet B1

4. LSTM and GRU:

The performance of the GRU and LSTM models was evaluated using validation metrics. The GRU model achieved a validation accuracy of 90.57%, a precision of 90.98%, a recall of 90.57%, and an F1 score of 90.64%. In comparison, the LSTM model outperformed the GRU model, achieving a validation accuracy of 91.21%, a precision of 91.48%, a recall of 91.21%, and an F1 score of 91.25%. These results demonstrate the superior performance of the LSTM model in capturing temporal patterns within the MRI data, leading to better classification outcomes. The training and validation loss graphs for each model further illustrate their performance, with Fig.7 showing the LSTM model's loss curves and Fig.8 depicting the GRU model's loss curves.

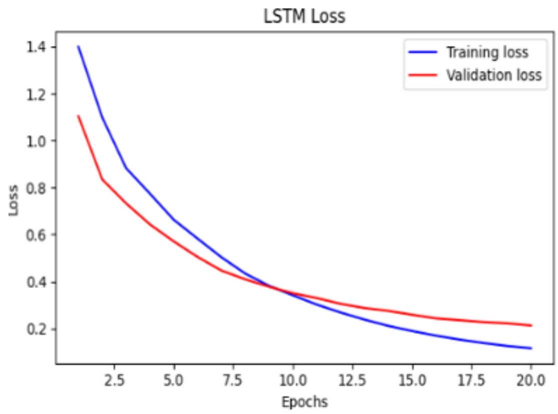

Fig. 7: Training and validation loss graph for LSTM

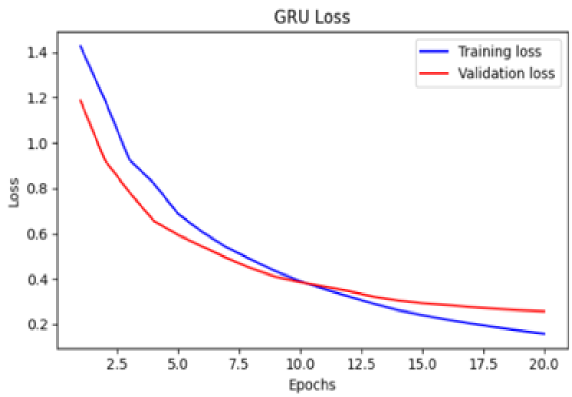

Fig. 8: Training and validation loss graph for GRU

5. Discussion

The study provides key insights into the performance of various machine learning models for MRI classification, highlighting the strengths and challenges of each approach.

5.1 Transfer Learning Models

Transfer learning models, such as ResNet50 and EfficientNet B1, significantly outperformed basic CNN models. These models leverage pre-trained architectures, capturing complex features and patterns from large-scale datasets like ImageNet.

Performance Metrics: Transfer learning models achieved higher accuracy and precision compared to CNNs. EfficientNet B1, for instance, attained test accuracy between 92% and 93%, with precision nearing 0.9991.

Advantages: These models accelerate convergence, reduce training time, and enhance pattern recognition, which is beneficial in medical imaging where annotated data is scarce.

Challenges: They require careful fine-tuning to adapt to MRI images and may struggle with domain-specific features absent from the pre-training dataset.

5.2 Hybrid Models

Hybrid models combine CNNs with architectures like RNNs or transformers to capture complex spatiotemporal patterns in MRI data.

Complexity and Potential: Hybrid models can capture nuanced relationships and improve MRI classifications by integrating diverse architectures.

Computational Intensity: These models require more processing power and training time, increasing the risk of overfitting without proper regularization and tuning.

Trade-offs: While they offer advanced feature extraction, their complexity needs careful management. Future studies could focus on optimizing these models for clinical use.

5.3 Ensemble Learning

Ensemble learning techniques boost classification performance by combining predictions from multiple models, enhancing overall robustness.

Performance Improvement: Ensemble models achieved the highest accuracy among all approaches, reducing variance and bias in predictions.

Implementation Strategy: Methods like bagging, boosting, or stacking can enhance performance, with well-tuned ensembles often surpassing the best individual models.

Limitations and Considerations: Ensemble models are complex to train and manage, requiring significant computational resources and potentially obscuring individual model contributions, challenging clinical adoption.

5.4 Addressing Class Imbalance

Class imbalance, where certain classes are underrepresented, poses a challenge across all models, affecting metrics like recall and F1-score.

Impact on Metrics: Imbalance leads to lower recall and F1-scores, indicating difficulties in identifying minority class instances, potentially biasing models toward the majority class.

Future Directions: Techniques like data augmentation, synthetic sample generation (e.g., SMOTE), cost-sensitive learning, or adjusting class weights should be explored to mitigate these effects. Enhancing model interpretability is also crucial for clinical integration, allowing healthcare professionals to trust and verify model predictions. Developing methods to visualize and understand model decision-making processes can facilitate clinical integration, allowing healthcare professionals to trust and verify model predictions.

6. Conclusion

This project attained the aim of creating and assessing several AI models for MRI classification, proving the beneficial application of AI in increasing diagnostic precision in medical diagnosis. Some of the insights include that transfer learning and the ensemble methods are more effective, especially when using pre-trained models and combining different methods. Moreover, the combination of the CNN with the RNN including LSTM and GRU showed high performance in MRI data for the temporal and spatial feature mining.

Future work should involve the improvement and extension of the current methodologies that are used in developing these AI systems to overcome issues such as class imbalance, and the requirement for larger annotated databases, and better mechanisms for understanding the outcomes produced by these systems. The research should also consider adopting even more complex hybrid models, as well as better combating the problem of overfitting to continue improving AI's usability and efficacy in medical imaging.

The AI-driven MRI classification system developed in this project provides a solid foundation for future research and development in this critical area of medical diagnostics, paving the way for more accurate and efficient detection and diagnosis of medical conditions through advanced AI technologies.

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