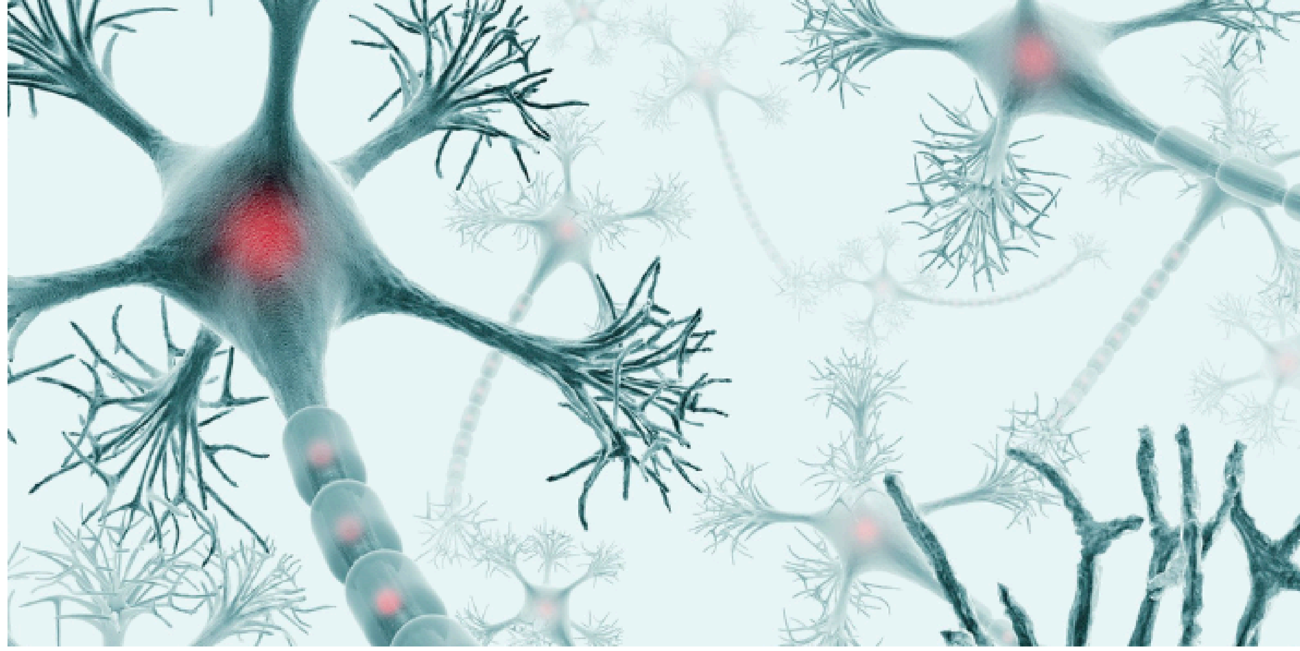
Minor Project

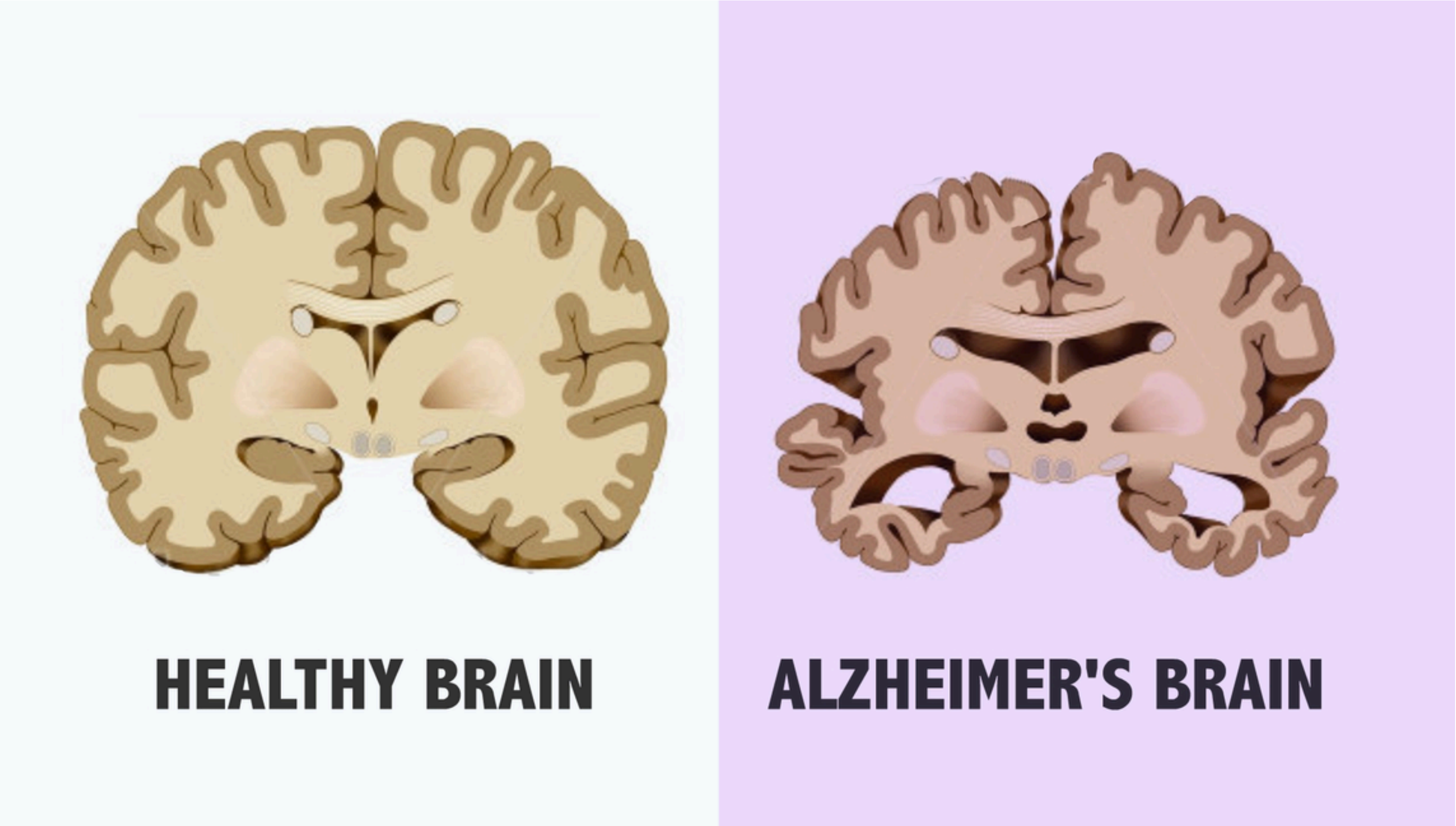
Ensemble Transfer Learning of Alzheimer's Disease (AD) Using MRI Scans

Shiven Aggarwal 2021A1R118
Andleeb Afroz 2021A1R085
Safder Abbas Bhatti 2021A1R152
Sajid Bhat 2021A1R175
Vansh Sharma 2022A1L005

Problem Statement



- Alzheimer's Disease (AD) is a neurodegenerative disorder that progressively impairs cognitive function. Early and accurate diagnosis of AD is crucial for timely intervention and potential disease-modifying therapies. However, traditional diagnostic methods are often time-consuming, subjective, and rely on clinical expertise.



Challenges

- Subjective Diagnosis: Clinical diagnosis can be subjective and prone to errors.
- Time-Consuming: Traditional diagnostic methods, such as neuropsychological tests and brain scans, are often time-consuming.
- Lack of Early Detection: Current methods may not detect AD in its early stages, limiting the window for intervention.

Proposed Solution

We propose a novel transfer learning-based approach to accurately and efficiently diagnose AD using Magnetic Resonance Imaging (MRI) scans. Our solution addresses the limitations of traditional methods and existing AI-based approaches by leveraging the power of transfer learning to extract meaningful features from MRI images.

Components Of TL Based Approach

1. Dataset:

- 113 subjects from the OASIS-3 archive, including 247 MRI scans of cognitively normal patients and 410 MRI scans of mild cognitive impairment patients.
- MRI images in NifTI format with T1-weighted structural sequences processed on the axial plane of brain MRIs.

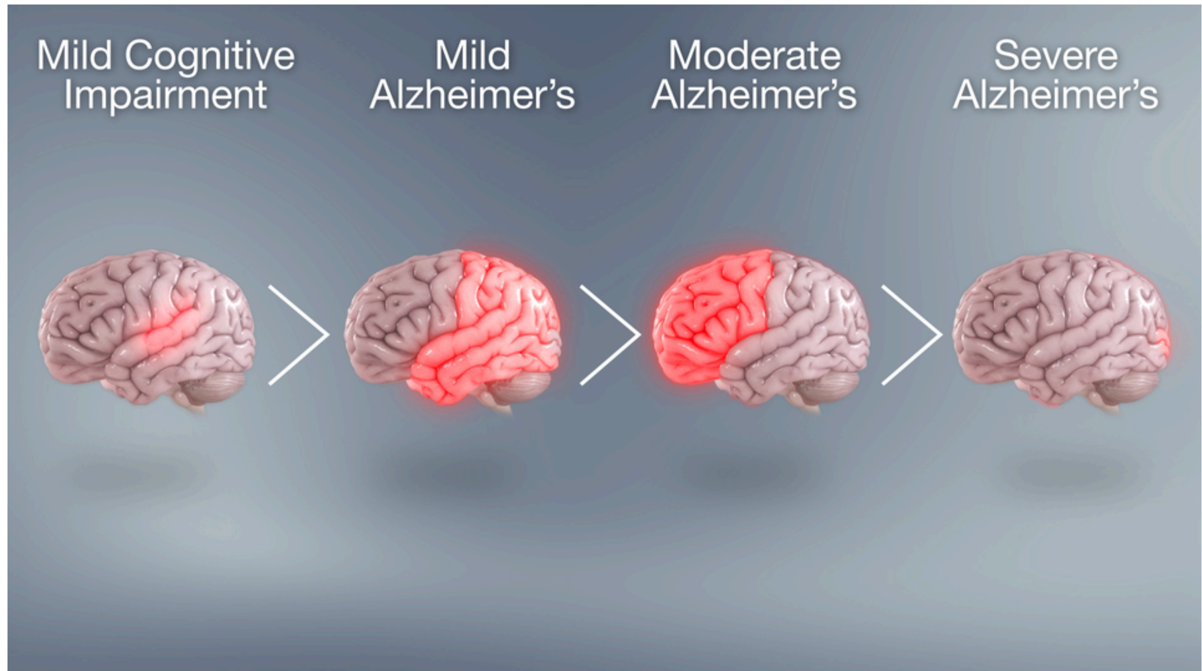
2. Clinical Dementia Rating (CDR) Scale: Used to determine dementia status

   CDR = 0: Cognitively normal.

   0 < CDR < 2: Mild impairment.

3. Preprocessing and Framework:

- Axial plane MRI processing ensures uniformity in structural brain imaging.
- Focused on enabling accurate diagnosis through consistent data preparation and evaluation.



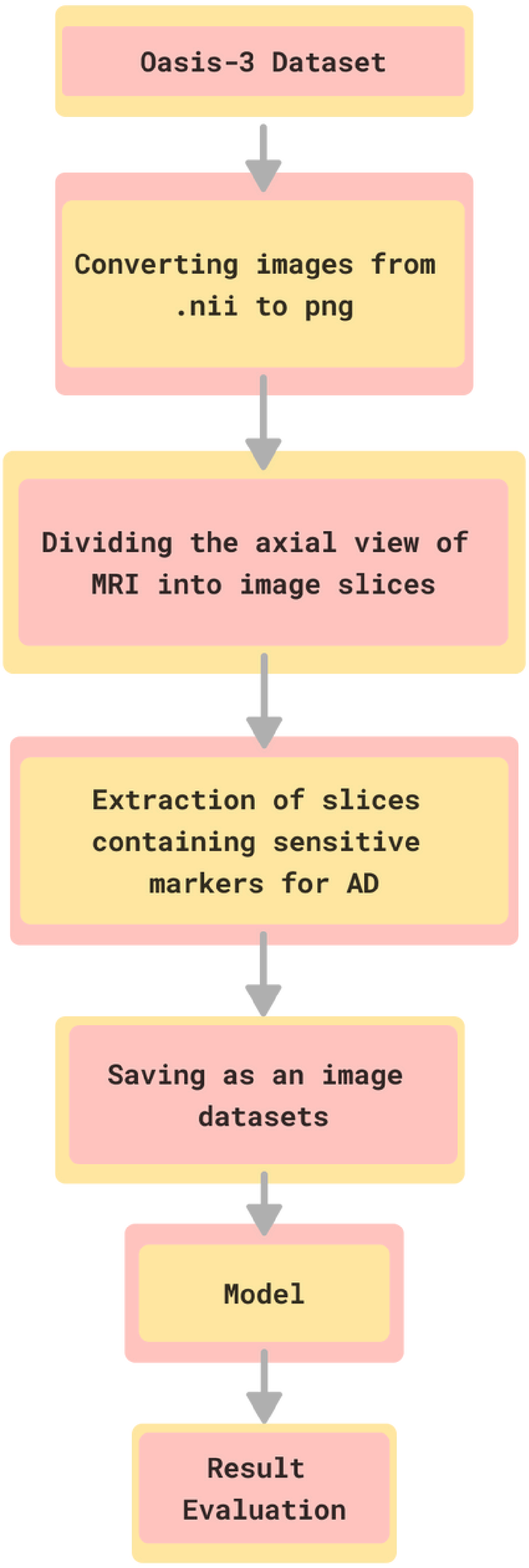
Expected Outcomes

- Achieved higher accuracy compared to state-of-the-art methods for AD diagnosis.
- Presented qualitative evaluation of result variations between cropped and uncropped MRI images across pre-trained models.

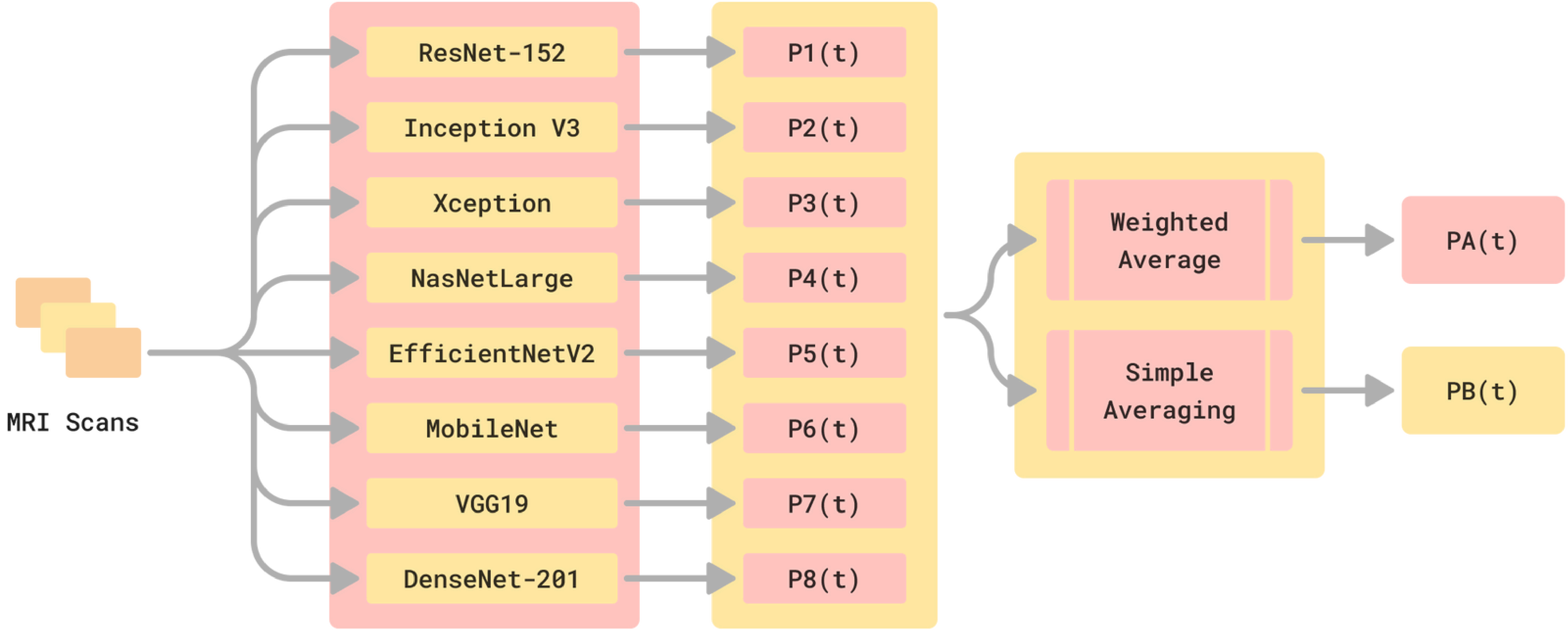
Comparative Analysis of existing AI based techniques

Researcher(s)	Methodology	Accuracy
Castellazzi et al.	Advanced qMRI measurements combined with conventional machine learning techniques	85%
Battineni et al.	Four machine learning algorithms with manual, automatic, and ensemble feature extraction	96.12%
Alickovic et al.	Histogram-based manual feature extraction with Random Forest	85.77%
Ahana et al.	Gradient boosting, voting classifier, and artificial neural networks (ANN)	91.96%
Wang et al.	Ensemble of 3D-DenseNets with probabilistic-based ensemble methods	Improved accuracy (unspecified)
Liu et al.	Monte Carlo ensemble neural network on 2D image slices	90%

Proposed WorkFlow



Ensemble TL Architecture



Comparative Analysis of Models

Model	Accuracy	AUC	Features Analyzed
VGG19	0.982	0.986	Analyzes texture, shapes, and edges of the hippocampus, cerebral artery, and lobes in high detail.
DenseNet201	0.974	0.984	Focuses on feature propagation by analyzing the fine-grained details of brain tissues and hippocampal structure.
EfficientNetV2S	0.975	0.978	Extracts hierarchical features like cerebral cortex edges and spatial relationships within lobes.
ResNet152	0.966	0.972	Captures complex anatomical structures, including cross-sectional brain regions.
InceptionV3	0.952	0.957	Excels in multi-scale feature extraction, identifying patterns in diverse brain regions.
NASNetLarge	0.926	0.911	Focuses on larger features but struggles with subtle hippocampal textures due to lower fine-grained detail.
Xception	0.959	0.965	Analyzes complex spatial relationships and localized structures like the cerebral artery.
MobileNet	0.941	0.920	Extracts essential features like hippocampal edges but lacks depth for intricate patterns.

Table 1: Detailed Performance Comparison of Models with Cropping Technique

Table 2: Effects of Cropping and Feature Maps on Model Performance

Cropping Technique	Key Advantages
Finding Biggest Contour	Isolates the skull area where the hippocampus is located, reducing computation and noise.
Localizing Extreme Points	Identifies brain boundaries, removing irrelevant areas and improving feature extraction.
Thresholding or Canny Edge Detection	Enhances the focus on brain contours, enabling better hippocampal and lobe identification.
Impact on Feature Maps	Initial layers detect edges and simple forms like the hippocampus and cerebral artery.

Table 3: Ensemble Methods Performance

Ensemble Method	Combination	Accuracy	AUC	Remarks
Simple Averaging	M2 (DenseNet201) + M3 (EfficientNetV2S)	0.989	0.985	Best performance due to complementary feature extraction capabilities of DenseNet and EfficientNet.
Weighted Averaging	M1 (VGG19) + M2 + M3	0.941	0.930	Lower performance due to suboptimal weight allocation among models.
Simple Averaging	M1 + M2	0.988	0.986	High AUC as DenseNet201 and VGG19 provide robust ranking probabilities.
Weighted Averaging	M1 + M2	0.945	0.935	Performance hindered by uneven contributions from individual models.

Research and Refrences

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