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Together for Tomorrow! Enabling People

Education for Future Generations

Early Detection of Alzheimer’s Disease

“Early Detection Saves Futures.”

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Agenda

- Problem Statement
- Understanding The Data
- Data Preparation
- Data Preprocessing
- Modeling & Performance
- Insights & summary
- Deployment

Problem Statement

Problem Statement

"Alzheimer’s disease is one of the most widespread and devastating disorders worldwide.
It affects millions of individuals every year and places an enormous emotional, social, and financial burden on patients, families, and healthcare systems. As the disease progresses, memory loss, cognitive decline, and functional impairment gradually take away a person’s independence and quality of life"

Understanding The Data

Understanding the Data

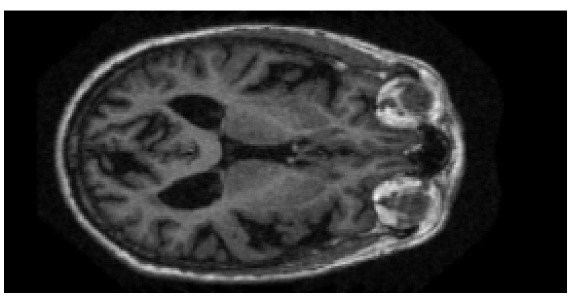
The dataset used in this project contains 85,949 brain MRI images distributed across three categories representing different cognitive conditions:

The class counts are as follows:

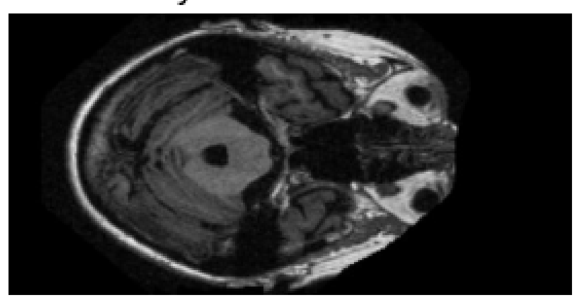
- **Non-Demented**: 67,222 images
- **Very Mild Dementia**: 13,725 images
- **Mild Dementia**: 5,002 images

These images are grayscale medical scans that provide structural information about the brain.

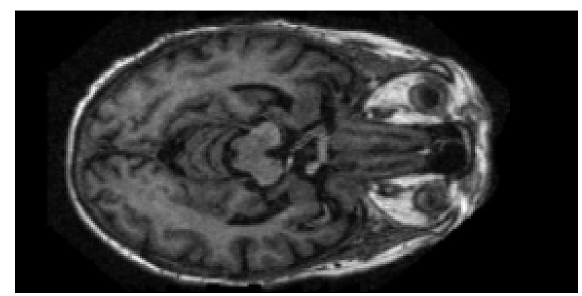
Non Demented



Very mild Dementia

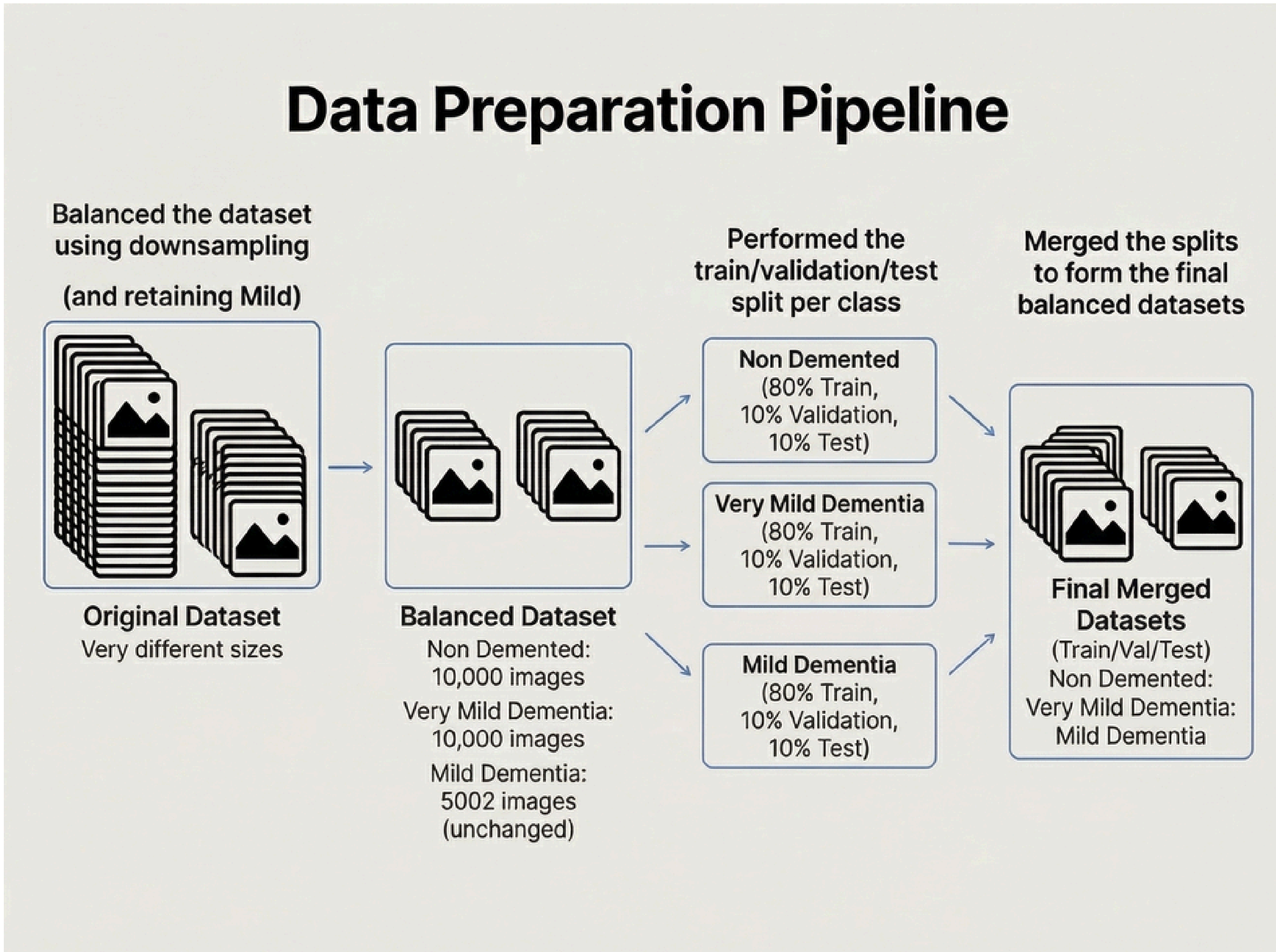


Mild Dementia



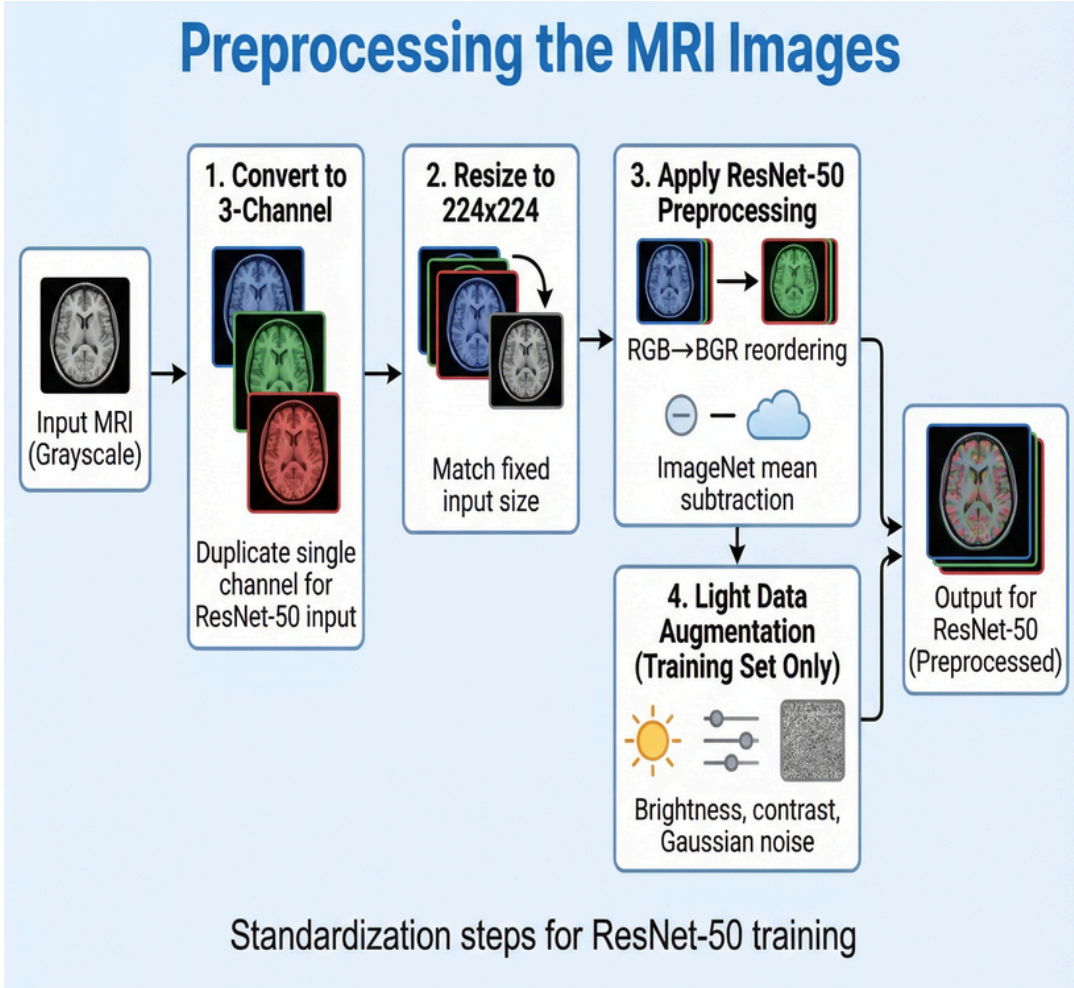
Data Preparation

Data Preparation



Data Preprocessing

Data Preprocessing

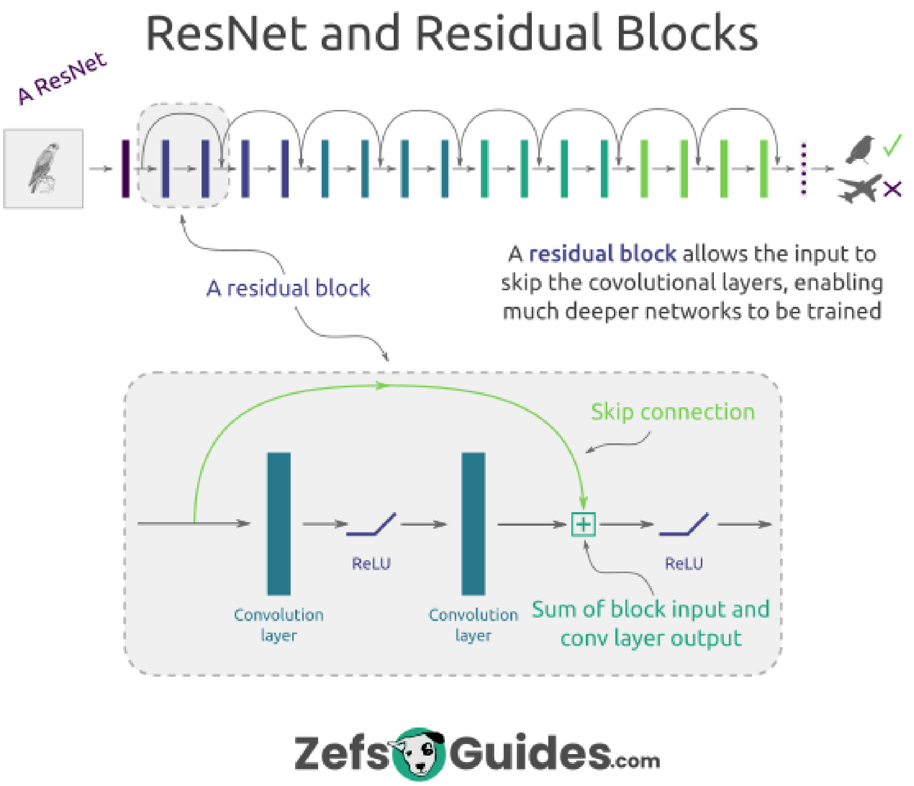


Modeling and Evaluation

Architecture Deep Dive: ResNet (Residual Network)

The Residual Block

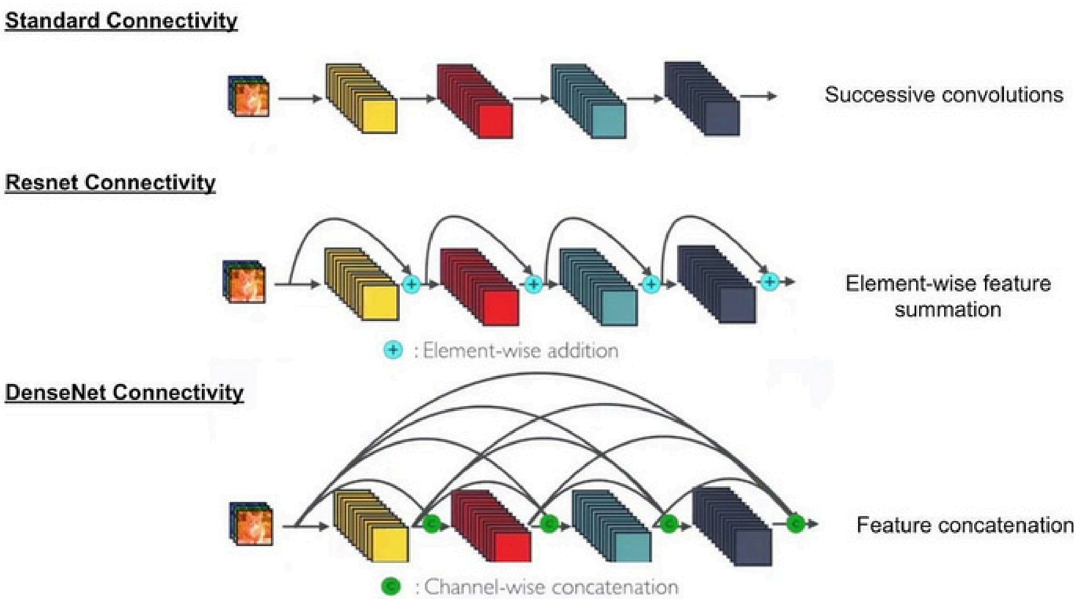
- Skip Connections: ResNet introduces identity mapping paths that bypass one or more layers.
- Solves Degradation: These "shortcuts" allow information from earlier layers to be passed directly to deeper layers, combating the problem of vanishing gradients and enabling training of very deep networks.
- Learning Identity: The block learns a residual function $F(x) = H(x) - x$, meaning the layer only needs to learn the difference, $H(x)$, from the input x.



Architecture Deep Dive: DenseNet (Densely Connected Network)

Feature Reuse and Efficiency

- Dense Connectivity: Each layer in a Dense Block receives feature maps from all preceding layers in that block, and passes its own feature maps to all subsequent layers.
- Maximum Feature Reuse: This deep supervision encourages features to be reused throughout the network, making the network highly parameter-efficient.
- Vanishing Gradient Mitigation: The direct connections provide multiple short paths for the gradient to flow back.



Mitigation Strategy: Weighted Cross-Entropy Loss

Calculating Class Weights

To force the model to prioritize learning the rare class ‘mild’, we calculate inverse class frequencies to generate a loss penalty.

- Purpose: Ensures the loss contribution of a single misclassified Mild Dementia image is equal to or greater than that of many Non-Demented images.

DenseNet: Phase 1 Model Construction (Transfer Learning)

Feature Extractor: Used `DenseNet121` initialized with ImageNet weights.

Head Only Training: This step is crucial it freezes the weights of the entire DenseNet backbone.

New Head: A small custom head (GAP, Dense, Dropout) is stacked on top and is the only part trained in Phase 1.

Low LR: Adam optimizer started with \$10^{-4}\$ learning rate.

DenseNet Training: Advanced Callback Strategy

Custom F1-Score Callback

Given the imbalance, a custom callback was implemented to track the weighted F1-score a more robust metric than accuracy and save the best model based on its performance.

Standard Callbacks Used:

- Checkpoint: Saves best model based on `val_loss`.
- EarlyStopping: Halts training after 5 epochs of no `val_loss` improvement.

Optimization Callbacks Used:

- ReduceLROnPlateau: Decreases LR when `val_loss` plateaus (factor 0.3).

DenseNet Results: Signs of Overfitting and Leakage

Optimized Training Callbacks

For the final ResNet model, we utilized a streamlined set of callbacks with adjusted parameters for higher stability and patience, reflecting a more stable architecture.

Model Fit Call

The ResNet model was trained end-to-end using the same class weights to ensure balanced learning, but with greater patience.

DenseNet: Optimized Training Execution (The Final Model)

The DenseNet model achieved suspicious performance metrics, particularly on the minority class, indicating a failure to generalize robustly.

Class	Precision	Recall	F1-Score	Support
Non Demented	0.99	0.97	0.98	1000
Very mild Dementia	0.99	0.96	0.98	1000
Mild Dementia	0.91	1	0.95	501
Weighted Avg	**0.98**	**0.97**	**0.97**	**2501**

Critical Observation: Achieving 100% Recall on the smallest class (Mild Dementia) is highly unrealistic. This suggests the model has memorized specific features unique to the test data, indicating data leakage or severe overfitting, not robust generalization.

ResNet Results: Robust Generalization

The ResNet model achieved highly reliable metrics, showing good, balanced performance across all classes, indicating true generalization.

Class	Precision	Recall	F1-Score	Support
Non Demented	0.87	0.95	0.91	1000
Very mild Dementia	0.93	0.88	0.9	1000
Mild Dementia	0.97	0.9	0.93	501
Weighted Avg	**0.91**	**0.91**	**0.91**	**2501**

Key Metric: Weighted F1-Score of 0.91 is reliable. Note the strong Recall (Sensitivity) of 0.90 for the critical Mild Dementia class.

Final Model Selection: ResNet-50 vs. DenseNet-121

DenseNet-121 (Rejected)

- **Accuracy:** ~97% (Unrealistically high)
- **Flaw:** **Overfitting & Data Leakage** shown by 100% Recall on the minority class.
- **Outcome:** The model memorized the test set and would fail catastrophically on new, unseen patient data.

ResNet-50 (Selected)

- **Accuracy:** ~91% (Realistic and balanced)
- **Strength:** **Robust Generalization** across all classes.

ResNet: The Future-Proof Solution

The ResNet-50 model is chosen for its superior ability to generalize, which is non-negotiable for a diagnostic tool.

Reliable Accuracy

The 91% accuracy reflects genuine performance, not memorization, ensuring trust in clinical use.

Scalable Improvement

The architecture is sound; performance can be incrementally improved with larger datasets and further fine-tuning.

From Script to Product: Deployment

Deployment framework

- The ML model is wrapped and served via a Streamlit app, instead of a separate API + frontend + container stack.

Streamlit

Demo

Deploy

🧠 Alzheimer's MRI Classification

Upload an MRI slice and click **Classify Image** to detect whether the patient is **Non Demented**, **Very Mild Dementia**, or **Mild Dementia**.

Upload MRI Image

Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

Browse files

Please upload an MRI image to begin.

ssifier

localhost:8501

Upload an MRI slice and click **Classify Image** to detect whether the patient is **Non Demented, Very Mild Dementia**, or **Mild Dementia**.

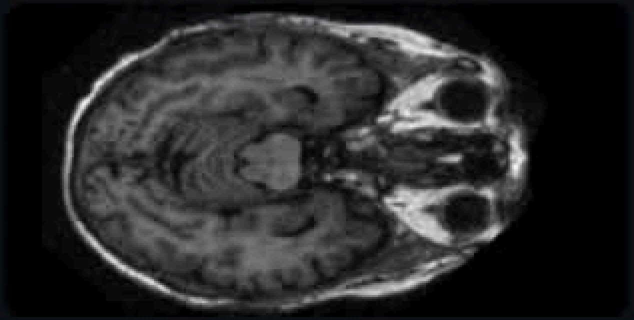
Upload MRI Image

Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

Browse files

Mild.jpg 16.3KB



Uploaded MRI Image

🔍 Classify Image

📃 Prediction: Mild Dementia

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