Research paper implementation

ALZHEIMER'S DISEASE CLASSIFICATION USING MULTIMODEL

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AUTHORS

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INTRODUCTION

- Alzheimer's Disease (AD) causes progressive memory loss and cognitive decline.
- Early detection is critical for managing progression and improving outcomes.
- This work proposes a multimodal deep learning model combining MRI scans with clinical/tabular data (age, MMSE, etc.).
- The fusion of imaging and structured data enhances diagnostic performance and interpretability.
- Uses MobileNetV2 for MRI feature extraction and MLP for tabular data; intermediate fusion integrates both.

CHALLENGES

- Limited interpretability of deep learning in clinical settings hinders trust.
- Scarcity of annotated medical data and class imbalance impacts training.
- Fusion techniques often oversimplify modality interaction.
- Real-world deployment faces infrastructure constraints and data privacy issues.

MOTIVATION

- AD diagnosis benefits from both visual imaging (MRI) and clinical attributes.
- Unimodal models miss complementary cues.
- A multimodal approach can leverage rich spatial and demographic information.
- Goal: Improve accuracy, early-stage detection, and explainability.

DATASETS

- Preprocessed structural MRI scans and clinical data (age, MMSE scores, cognitive tests) were used.
- **Source**: Open-source datasets like ADNI enable reproducibility and benchmarking.
- **Use**: Imaging data feeds a CNN, while tabular features are processed by an MLP for multimodal classification.

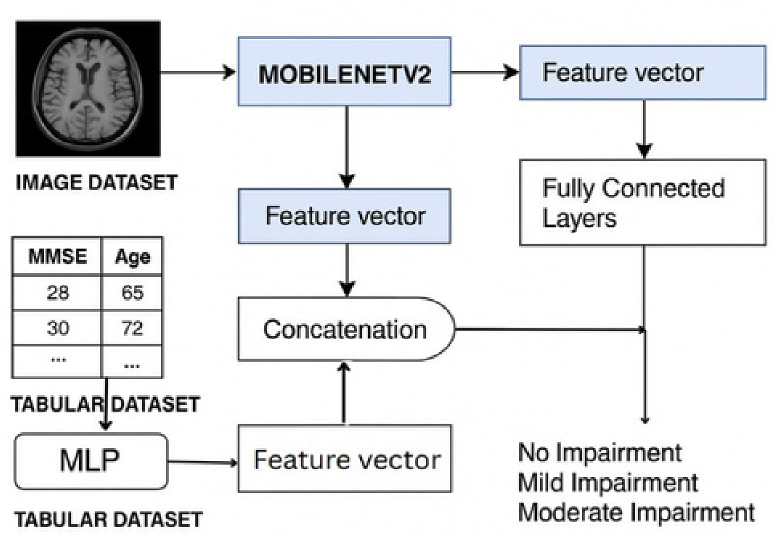
QUALITATIVE ANALYSIS

- Visualizations (e.g., Grad-CAM) highlight relevant brain regions like the hippocampus.
- MLP feature importance identifies cognitive markers like MMSE.
- Multimodal fusion enables holistic, explainable predictions.
- Supports clinical insight by explaining modality contributions.

METHODOLOGY

1. Proposed System Architecture

- Image Feature Extractor (MobileNetV2)
  - Processes MRI brain scans
  - Extracts high-level spatial features
- Tabular Data Feature Extractor (Multilayer Perceptron - MLP)
  - Handles patient-specific structured data (e.g., age, cognitive scores)
  - Learns patterns in clinical data
- Intermediate Fusion Layer
  - Merges image and tabular feature vectors
  - Enables joint representation learning for classification



2. Fusion Strategy

- An intermediate fusion technique is employed:
  - Avoids early fusion of raw data to preserve modality-specific patterns
  - Facilitates effective learning of inter-modality relationships
  - Followed by dense layers and softmax for final binary classification (AD vs. non-AD)

3.Implementation Details

- Image Model: Pretrained MobileNetV2
- Tabular Model: Custom MLP architecture
- Optimization: Binary Cross-Entropy loss, Adam optimizer
- Evaluation Metrics: Accuracy, Precision, Recall, F1-score, AUC

4. Dataset and Training

- An open-source dataset containing MRI scans and clinical variables was used
- The model was trained, validated, and tested to ensure generalization and reliability

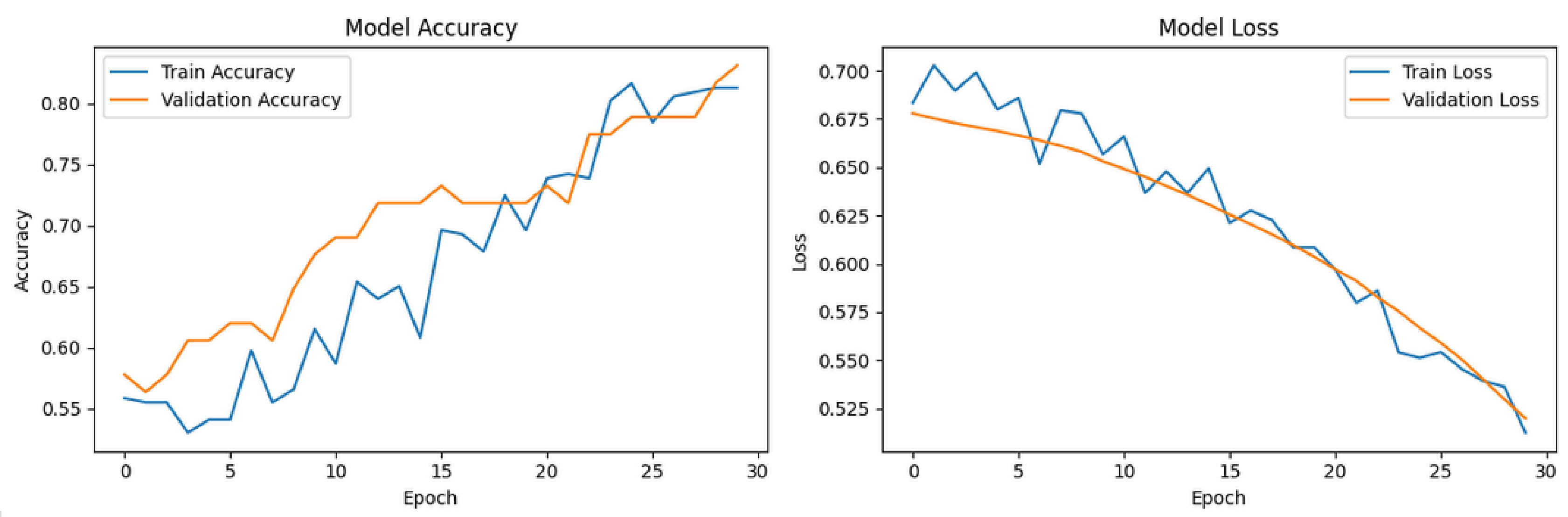
EXPERIMENTAL RESULTS

- Models Tested: ResNet50, VGG16, EfficientNetB0, MobileNetV2.
- Best Model: MobileNetV2 + MLP.
- Accuracy: 86%, with F1-Score: 0.87.
- Metrics: High AUC, precision, recall, low overfitting.
- Fusion helps avoid feature loss, increasing robustness.

Performance Comparison Table

Model	Train Accuracy	Validation Accuracy
ResNet50	55.29%	49.02%
VGG16	72.68%	57.94%
MobileNetV2	81.35%	66.30%
EfficientNetB0	24.31%	35.03%

Model Accuracy and Model Loss



CONCLUSION

We developed a multimodal deep learning model that integrates MRI images and clinical data to improve Alzheimer's Disease classification.

The MobileNetV2 + MLP architecture achieved high accuracy (up to 86%) and enhanced interpretability.

This approach offers a scalable, efficient, and generalizable solution for early diagnosis and clinical decision support.

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