Gazimed: Early Alzheimer's Disease Detection System

Advanced AI-powered early detection of Alzheimer's disease using paired MRI and PET brain imaging

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🧠 Clinical Overview

Gazimed is a state-of-the-art deep learning system designed to assist clinicians in the early detection of Alzheimer's disease. By analyzing paired T1-weighted MRI and ^18F-FDG PET brain scans alongside clinical features, our system provides continuous risk scores (0-1) to support clinical decision-making.

Key Clinical Benefits

- **Early Detection**: Identifies Alzheimer's risk before severe cognitive decline
- **Multimodal Analysis**: Combines structural (MRI) and metabolic (PET) brain imaging
- **Clinical Integration**: Incorporates 118 clinical features for comprehensive assessment
- **Explainable AI**: Provides attention maps highlighting relevant brain regions
- **Validated Approach**: Built on established medical imaging datasets (ADNI, OASIS-3)

🔬 How It Works

```
flowchart TD
    A[MRI T1 Scan] --> D[Preprocessing Pipeline]
    B[PET FDG Scan] --> D
    C[Clinical Features<br/>118 parameters] --> E[Clinical Encoder]

    D --> F[3D Swin-UNETR<br/>Backbone]
    F --> G[Cross-Modal<br/>Attention Fusion]
    E --> G

    G --> H[Multimodal<br/>Feature Integration]
    H --> I[Risk Score<br/>0.0 - 1.0]

    I --> J[Clinical Report<br/>+ Attention Maps]

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    style B fill:#f3e5f5
    style C fill:#e8f5e8
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    style J fill:#fce4ec
```

Technical Architecture

1. **Preprocessing**: N4 bias correction, MNI152 registration, normalization

2. **Feature Extraction**: 3D Swin Transformer with shifted window attention
3. **Multimodal Fusion**: Cross-attention between MRI/PET and clinical data
4. **Risk Assessment**: Continuous score output with confidence intervals
5. **Explainability**: Attention visualization for clinical interpretation

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📊 Target Clinical Performance

We aim to achieve the following performance metrics through our validation studies:

Metric	Target Performance	Clinical Significance
AUC-ROC	0.90+	Excellent discrimination ability
Sensitivity	85%+	High detection of positive cases
Specificity	85%+	Low false positive rate
Correlation	r = 0.80+	Strong agreement with clinical scores

Validation Datasets

- **ADNI**: Alzheimer's Disease Neuroimaging Initiative
- **OASIS-3**: Open Access Series of Imaging Studies
- **AIBL**: Australian Imaging, Biomarker & Lifestyle Study

🏥 Clinical Workflow Integration

```
sequenceDiagram
    participant C as Clinician
    participant G as Gazimed System
    participant P as PACS/Imaging
    participant R as Clinical Report

    C->>P: Order MRI + PET scans
    P->>G: Send DICOM images
    C->>G: Input clinical features
    G->>G: AI analysis
    G->>R: Generate risk assessment
    R->>C: Clinical report + visualizations
    C->>C: Clinical decision making
```

Integration Points

- **PACS Integration**: Direct DICOM import from imaging systems
- **EMR Compatibility**: Clinical feature extraction from electronic records
- **Reporting**: Structured reports with attention visualizations
- **Quality Assurance**: Built-in validation and quality checks

🔍 Explainable AI Features

Attention Visualization

The system provides clinically interpretable attention maps highlighting:

- **Hippocampus**: Memory formation and early AD pathology
- **Entorhinal Cortex**: Gateway to hippocampal formation
- **Posterior Cingulate**: Default mode network alterations
- **Precuneus**: Early metabolic changes in AD

Clinical Validation Tools

- Anatomical region overlap metrics
- Attention consistency across similar cases
- Correlation with known AD biomarkers
- Comparison with radiologist assessments

🚀 Getting Started

System Requirements

Hardware:

- GPU: NVIDIA RTX 3080 or better (12GB+ VRAM recommended)
- RAM: 32GB+ for processing full-resolution volumes
- Storage: 500GB+ for datasets and models

Software:

- Python 3.8+
- CUDA 11.8+
- Docker (optional, for containerized deployment)

Quick Installation

```
# Clone the repository
git clone https://github.com/gazimed/alzheimers-detection.git
cd alzheimers-detection

# Install dependencies
pip install -e .

# Initialize database
gazimed-init --setup-database

# Download pretrained models
gazimed-download --model swin-unetr-pretrained
```

Basic Usage

```python
from gazimed import AlzheimersDetector

# Initialize the detector
detector = AlzheimersDetector.from_pretrained('swin-unetr-v1.0')

# Analyze a case
result = detector.predict(
    mri_path='patient_001_T1.nii.gz',
    pet_path='patient_001_FDG.nii.gz',
    clinical_features=clinical_data
)

print(f"Alzheimer's Risk Score: {result.risk_score:.3f}")
print(f"Confidence Interval: [{result.ci_lower:.3f}, {result.ci_upper:.3f}]")

# Generate clinical report
report = detector.generate_report(result)
report.save('patient_001_report.pdf')
```

Model Performance Details

Target Cross-Validation Results

```
graph LR
    A[5-Fold CV Target] --> B[Fold 1: AUC 0.90+]
    A --> C[Fold 2: AUC 0.90+]
    A --> D[Fold 3: AUC 0.90+]
    A --> E[Fold 4: AUC 0.90+]
    A --> F[Fold 5: AUC 0.90+]

    B --> G[Target Mean: 0.90+]
    C --> G
    D --> G
    E --> G
    F --> G
```

Target Comparison with Baseline Methods

Method	Target AUC	Target Sensitivity	Target Specificity	Notes

Method	Target AUC	Target Sensitivity	Target Specificity	Notes
Gazimed (Goal)	**0.90+**	**85%+**	**85%+**	Multimodal + Clinical
ResNet3D (Baseline)	0.85	82%	83%	MRI only
CNN + PET (Baseline)	0.87	84%	85%	Imaging only
Clinical Features	0.78	75%	79%	Traditional approach
Radiologist	0.83	79%	86%	Human expert

🔧 Technical Architecture Deep Dive

Model Pipeline Overview

```
graph TB
    subgraph "Input Processing"
        A[MRI T1-weighted<br/>Raw DICOM] --> A1[N4 Bias Correction]
        B[PET FDG<br/>Raw DICOM] --> B1[N4 Bias Correction]
        C[Clinical Features<br/>118 parameters] --> C1[Feature Normalization]

        A1 --> A2[MNI152 Registration]
        B1 --> B2[MNI152 Registration]

        A2 --> A3[Resampling to 1mm³]
        B2 --> B3[Resampling to 1mm³]

        A3 --> A4[Z-score Normalization]
        B3 --> B4[Z-score Normalization]
    end

    subgraph "Feature Extraction"
        A4 --> D[3D Swin-UNETR<br/>Encoder]
        B4 --> D
        C1 --> E[Clinical Feature<br/>Encoder]

        D --> F[Spatial Features<br/>2048-dim]
        E --> G[Clinical Features<br/>512-dim]
    end

    subgraph "Multimodal Fusion"
        F --> H[Cross-Modal<br/>Attention Layer]
        G --> H

        H --> I[Feature Fusion<br/>1024-dim]
        I --> J[Classification Head]
    end
```

```
    subgraph "Output"
        J --> K[Risk Score<br/>0.0 - 1.0]
        J --> L[Attention Maps<br/>Explainability]
        J --> M[Confidence Score<br/>Uncertainty]
    end

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    style C fill:#e8f5e8
    style K fill:#fff3e0
    style L fill:#fce4ec
    style M fill:#f1f8e9
```

Data Processing Pipeline

Stage	Input	Process	Output	Purpose
Preprocessing	Raw DICOM	N4 correction, MNI registration	Normalized volumes	Standardization
Feature Extraction	3D volumes	3D Swin-UNETR backbone	Spatial features	Pattern recognition
Clinical Encoding	118 features	Multi-layer perceptron	Clinical embeddings	Risk factor encoding
Multimodal Fusion	All features	Cross-attention mechanism	Fused representation	Information integration
Classification	Fused features	Regression head	Risk score + uncertainty	Final prediction

Model Components Breakdown

3D Swin-UNETR Architecture

```
Input: [B, 2, 91, 109, 91] (MRI + PET)
├── Patch Embedding: 4×4×4 patches → 768-dim
├── Swin Transformer Blocks (4 stages)
│   ├── Stage 1: 96-dim, 2×2×2 patches
│   ├── Stage 2: 192-dim, 4×4×4 patches
│   ├── Stage 3: 384-dim, 8×8×8 patches
│   └── Stage 4: 768-dim, 16×16×16 patches
├── Skip Connections for U-Net structure
└── Output: [B, 2048] feature vector
```

Clinical Feature Encoder

```
Input: [B, 118] clinical features
├── Layer 1: 118 → 512 (ReLU + Dropout)
├── Layer 2: 512 → 256 (ReLU + Dropout)
├── Layer 3: 256 → 128 (ReLU + Dropout)
└── Output: [B, 512] clinical embeddings
```

📊 Training & Validation Process

Training Configuration

Parameter	Value	Description
Optimizer	AdamW	Weight decay: 0.01
Learning Rate	1e-4	Cosine annealing schedule
Batch Size	2-8	Flexible based on GPU memory
Mixed Precision	FP16	Memory optimization
Gradient Accumulation	8 steps	Effective larger batch size
Data Augmentation	3D transforms	Rotation, scaling, noise
Cross-Validation	5-fold	Stratified by diagnosis

Performance Metrics

```
graph LR
    subgraph "Regression Metrics"
        A[Mean Squared Error<br/>MSE]
        B[Mean Absolute Error<br/>MAE]
        C[R² Score<br/>Coefficient of Determination]
        D[Pearson Correlation<br/>Linear Relationship]
    end

    subgraph "Classification Metrics"
        E[AUC-ROC<br/>Discrimination]
        F[Precision/Recall<br/>Class Balance]
        G[F1-Score<br/>Harmonic Mean]
        H[Specificity<br/>True Negative Rate]
    end

    subgraph "Clinical Metrics"
        I[Sensitivity<br/>Early Detection]
        J[NPV/PPV<br/>Predictive Values]
        K[Calibration<br/>Probability Accuracy]
        L[Fairness<br/>Demographic Parity]
    end
```

```
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    style I fill:#e3f2fd
```

🚀 Getting Started

Model Checkpoints

Model Version	Performance	Download	Size
v1.0-base	AUC: 0	WILL BE UPLOADED	245 MB
v1.1-enhanced	AUC: 0	WILL BE UPLOADED	267 MB
v2.0-multimodal	AUC: 0	WILL BE UPLOADED	312 MB

📄 License

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Gazimed - Advancing early Alzheimer's detection through AI innovation 🧠✨