DEEP LEARNING STUDY FOR IMAGE CLASSIFICATION OF ALZHEIMER’S MRI

Simone Castelli

cstsmn.job@gmail.com

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Introduction

- **Project Motivation**: strong interest and background with images and visuals
- **Aim:** classify MRI scans using deep learning
- **Scope:** binary classification: No Alzheimer vs. Early Alzheimer
- **Methodology:** CRISP-DM framework used for structured analysis
- **Approach:** developed, tested, and reported progress in weekly supervisor meetings
- **Software Used:** Google Colab (GPU), Microsoft Word, Microsoft PowerPoint, Microsoft Outlook, Zoom

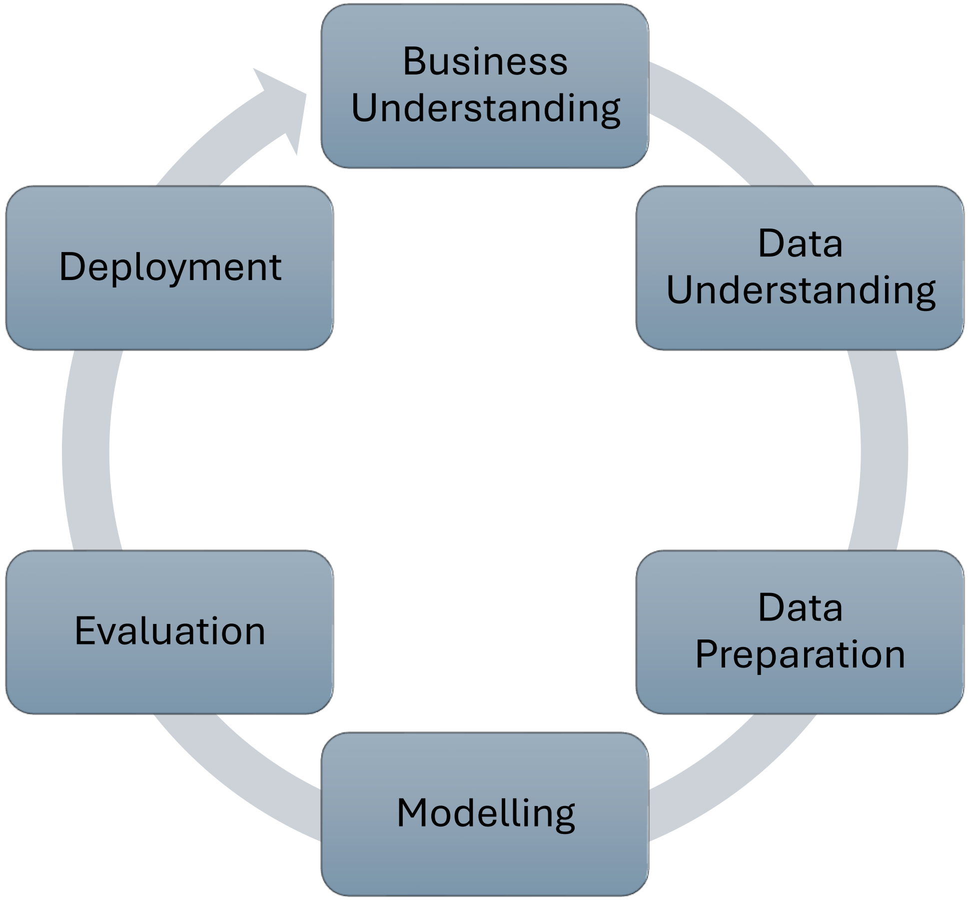

Figure 1: CRISP-DM diagram

Business Understanding

- Alzheimer’s is a progressive neurodegenerative disorder
- Early diagnosis crucial for timely intervention
- MRI scans provide structural and objective insights for detection
- Deep Learning Architectures can automate and improve diagnostic accuracy
- Reduce diagnostic workload and improve accessibility

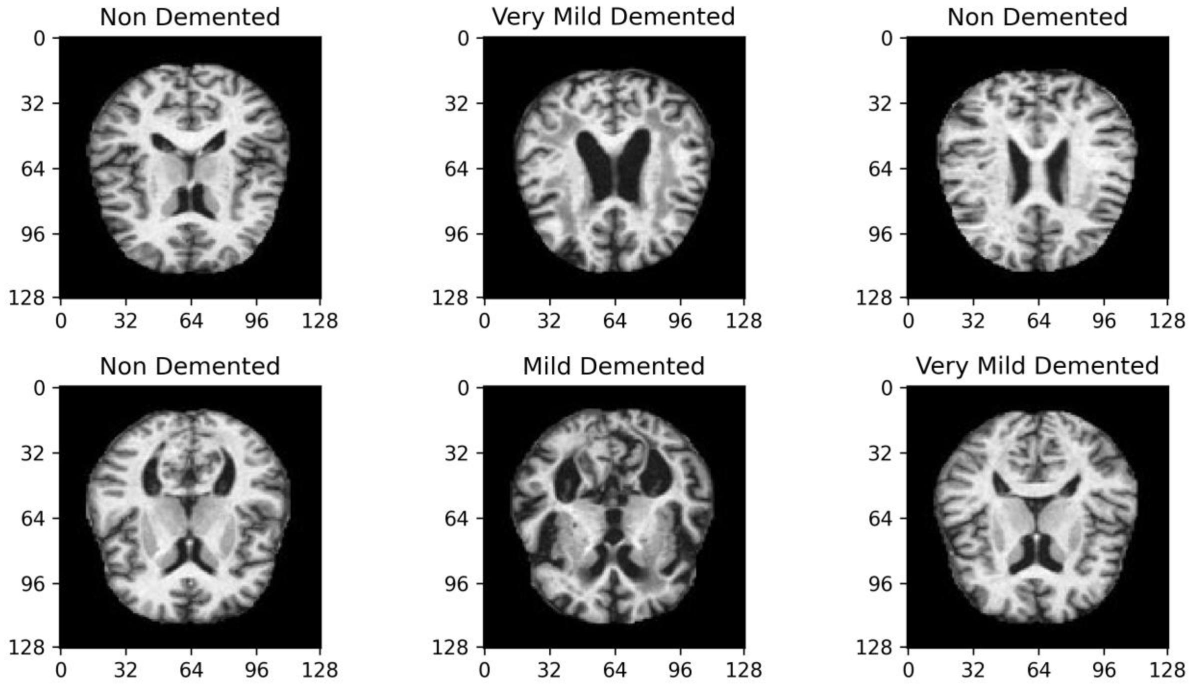

Figure 2: Sample MRI images with labels

Data Understanding

- "Alzheimer MRI Disease Classification Dataset" (BorhaniTrash, 2021) Kaggle
- 5,120 grayscale MRI images (128x128 pixels)
- Four labels: Non-Demented, Very Mild Demented, Mild Demented, Moderate Demented
- Imbalanced dataset: majority (50.1%) Non-Demented, 1% Moderate Demented
- Preprocessing required to handle class imbalance

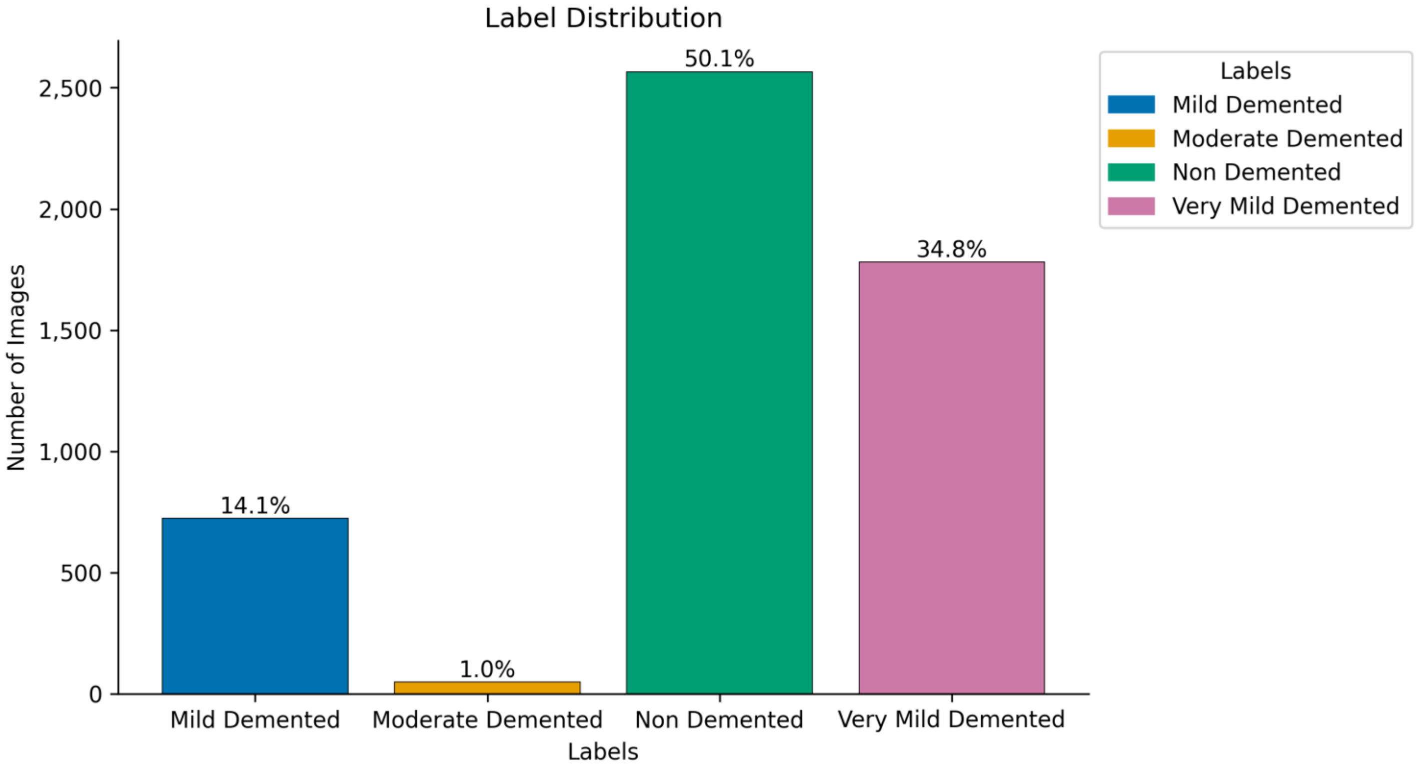

Figure 3: Dataset label distribution

Data Preparation

- Consolidation: four labels merged into two (No Alzheimer & Early Alzheimer)
- Balanced binary classification distribution: 50.1% No Alzheimer, 49.9% Early Alzheimer

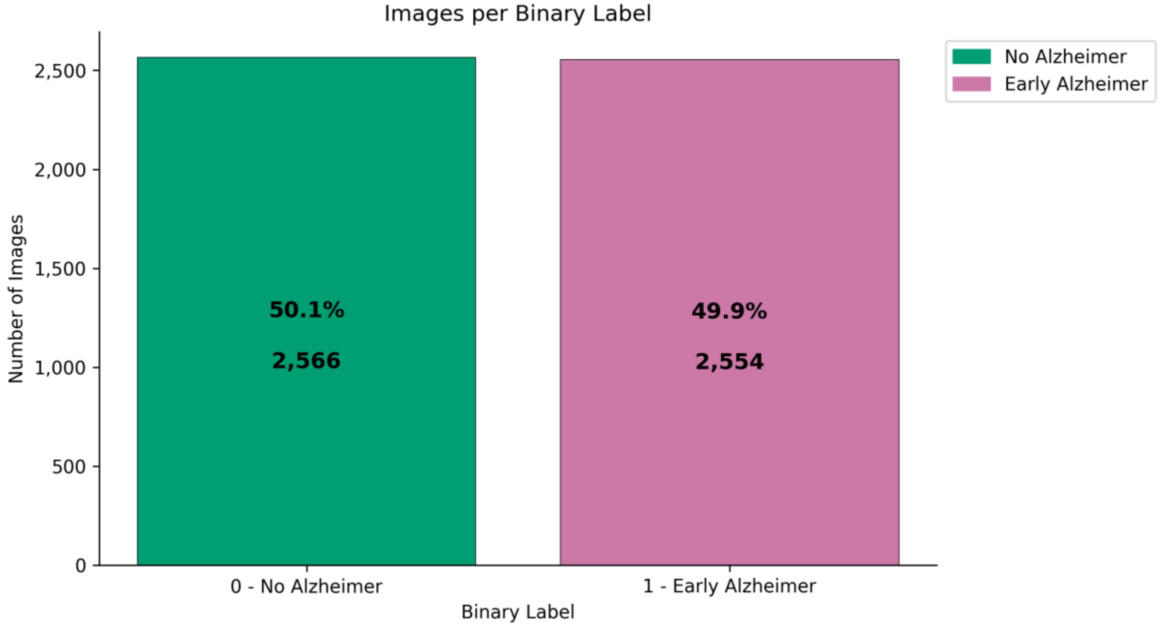

Figure 4: Binary label distribution

- Data split: 60% Training, 20% Validation, 20% Testing
- Oversampling applied to balance training set

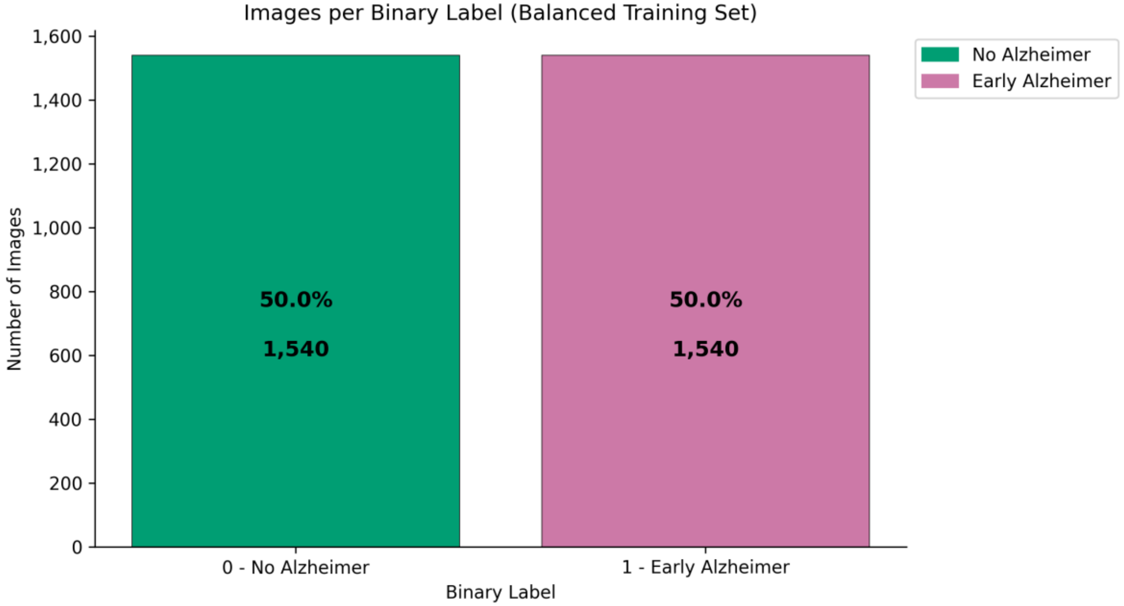

Figure 5: Balanced training set after oversampling

Modelling: Convolutional Neural Networks (CNN)

- **Rationale**: effective for image-based deep learning applications
- **Architecture**: uses convolutional layers to extract patterns and pooling layers to reduce complexity
- **Strength**: excellent at identifying spatial relationships in MRI scans
- **Application**: widely used in medical imaging for automated diagnosis and disease detection

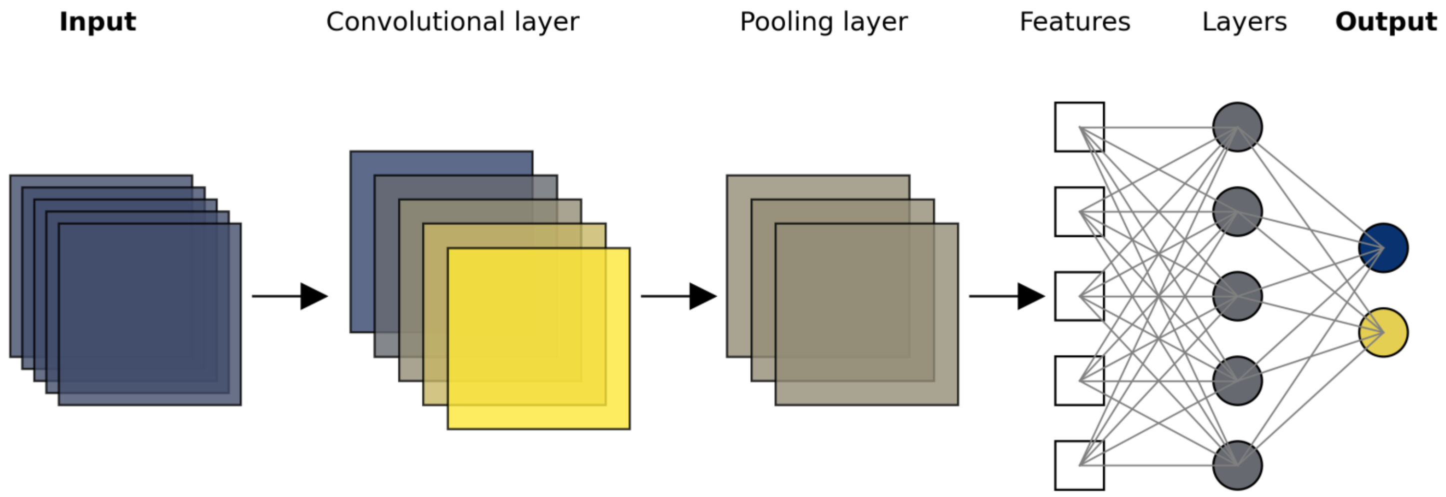

Figure 6: CNN diagram

Modelling: Artificial Neural Networks (ANN)

- **Rationale**: demonstrates core neural principles for classification
- **Architecture**: composes of fully connected layers that process numerical data
- **Strength**: good for structured data with simpler classification tasks
- **Application**: helps understand how neural networks function in medical image analysis

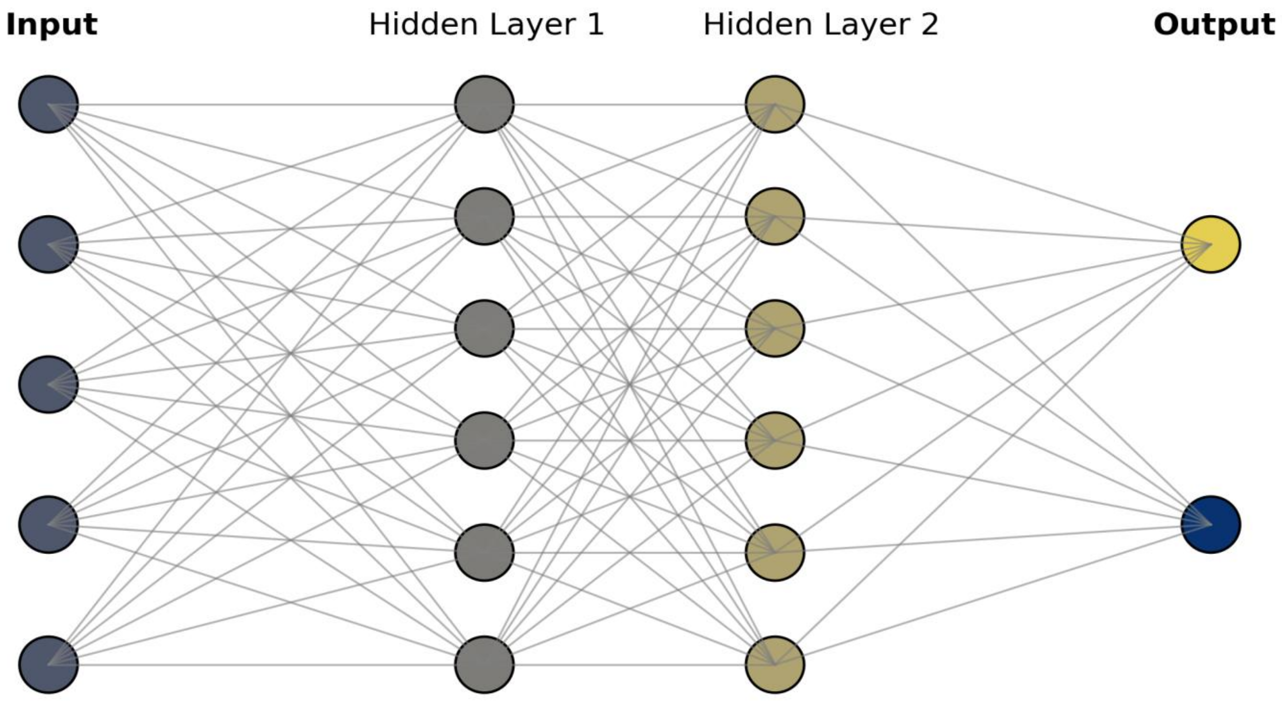

Figure 7: ANN diagram

Modelling: Residual Networks (ResNet50)

- **Rationale**: handles deep networks without losing information
- **Architecture**: includes skip connections to enable better learning across 50 layers
- **Strength**: can detect complex patterns in MRI images without performance degradation
- **Application**: widely used in deep learning tasks requiring efficient learning in very deep networks

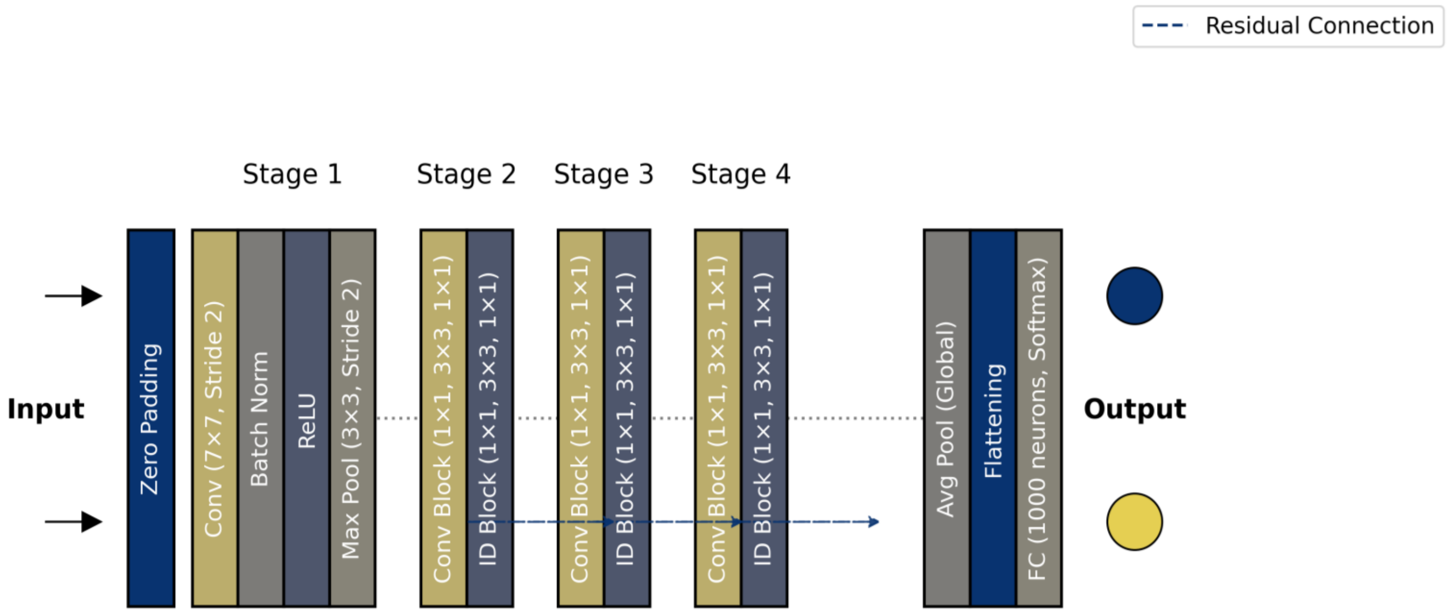

Figure 8: ResNet50 diagram

Modelling: Visual Geometry Group Network (VGGNet16)

- **Rationale**: well-known for strong feature extraction in image classification
- **Architecture**: deep network with 16 layers, using small convolutional filters
- **Strength**: simple yet powerful, making it easy to fine-tune with medical images
- **Application**: commonly applied in transfer learning for enhanced image classification

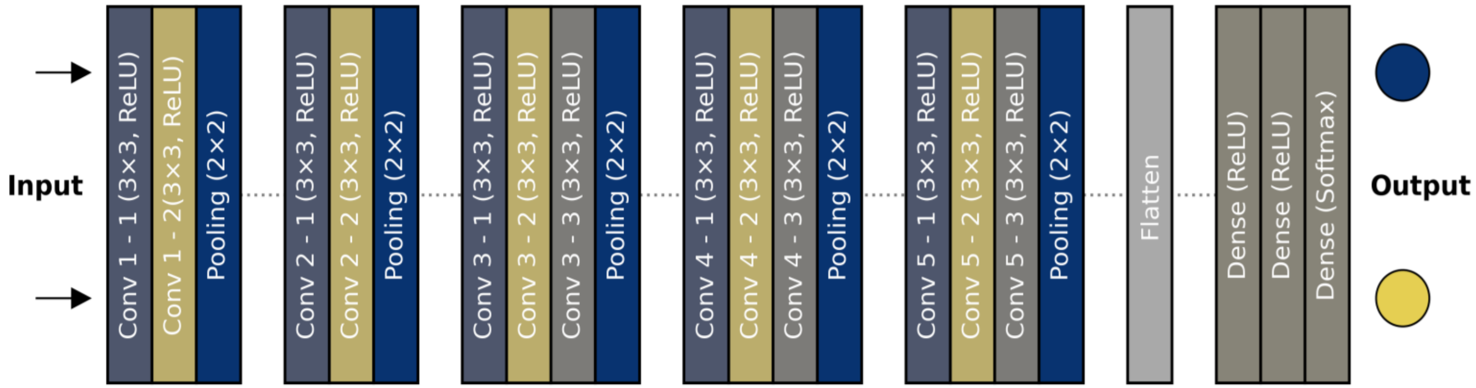

Figure 9: VGG16 diagram

Modelling: Vision Transformers (ViT)

- **Rationale**: uses a novel self-attention mechanism to analyze images without convolutions
- **Architecture**: uses self-attention mechanisms instead of convolutional layers
- **Strength**: captures global relationships, making it useful for detailed analysis
- **Application**: applied in advanced image analysis tasks, leveraging self-attention for high-resolution processing

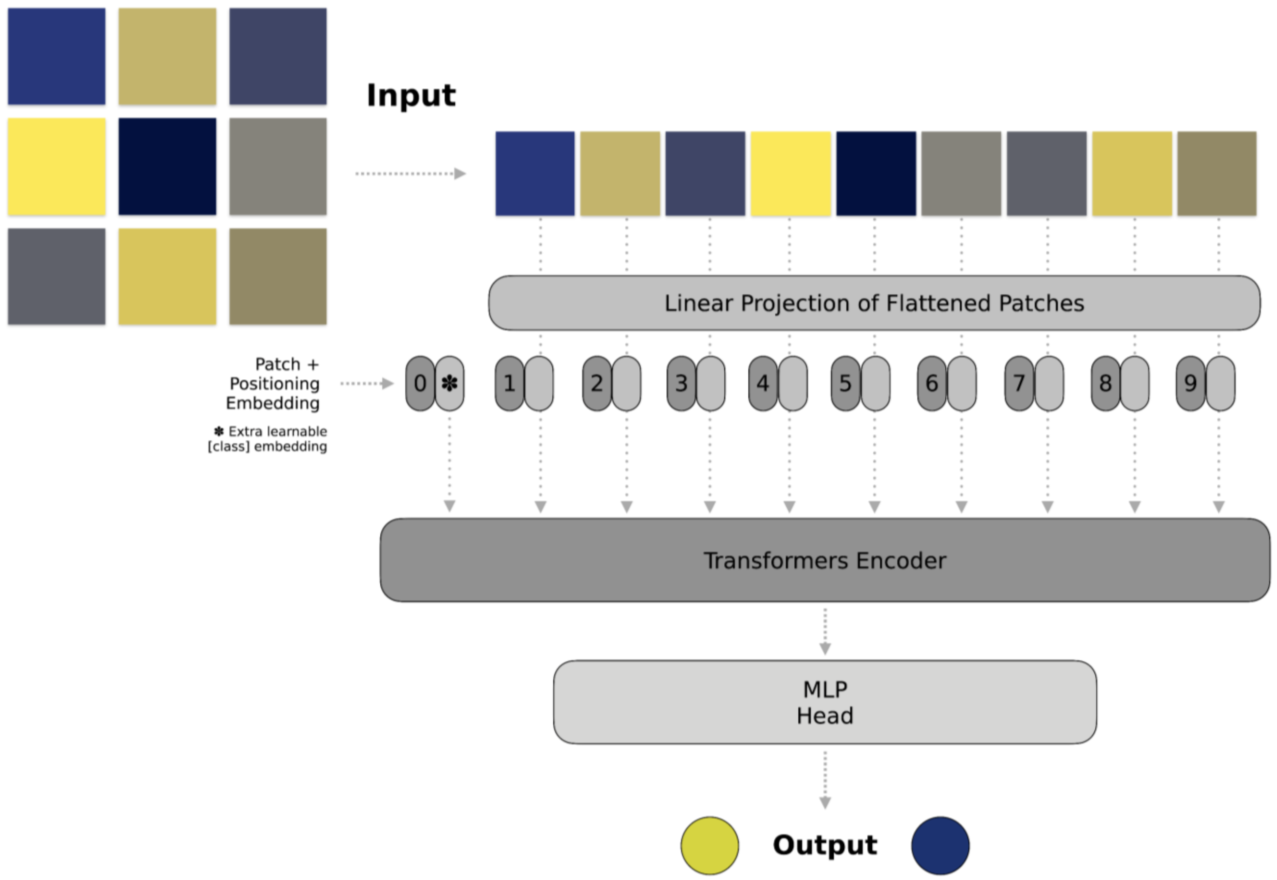

Figure 10: ViT diagram

Evaluation

- **Metrics**: Confusion Matrix, Accuracy, Precision, Recall, F1-score
- **CNN** outperformed other models across all evaluation metrics
- Other models performed well but had more False Positives and False Negatives, reducing overall accuracy
- **Recommendation**: CNN is the most reliable model for deployment

		Predicted condition	
	Total Population = P + N	**Positive (PP)**	**Negative (PN)**
Actual condition	**Positive (P)**	**True Positive (TP)**	**False Negative (FN)**
	Negative (N)	**False Positive (FP)**	**True Negative (TN)**

Figure 11: Confusion Matrix structure

Metric	CNN	ANN	ResNet50	VGGNet16	ViT
Accuracy	0.93	0.90	0.73	0.83	0.86
Precision	0.94	0.90	0.73	0.83	0.86
Recall	0.93	0.90	0.73	0.83	0.86
F1 Score	0.93	0.90	0.73	0.83	0.86
True Positive	467	462	388	407	456
True Negative	490	463	357	442	427
False Positive	23	50	156	71	86
False Negative	44	49	123	104	55

Figure 12: Model performance comparison

Deployment and Future Work

- **Deployment**: cloud-based API with TensorFlow Serving
- **User-friendly interface** for MRI classification
- **Integration** with hospital system for real-time diagnostics
- **Future Work**: improve accuracy by fine-tuning pre-trained models on medical MRI datasets
- **XAI**: enhancing interpretability with Explainable AI techniques

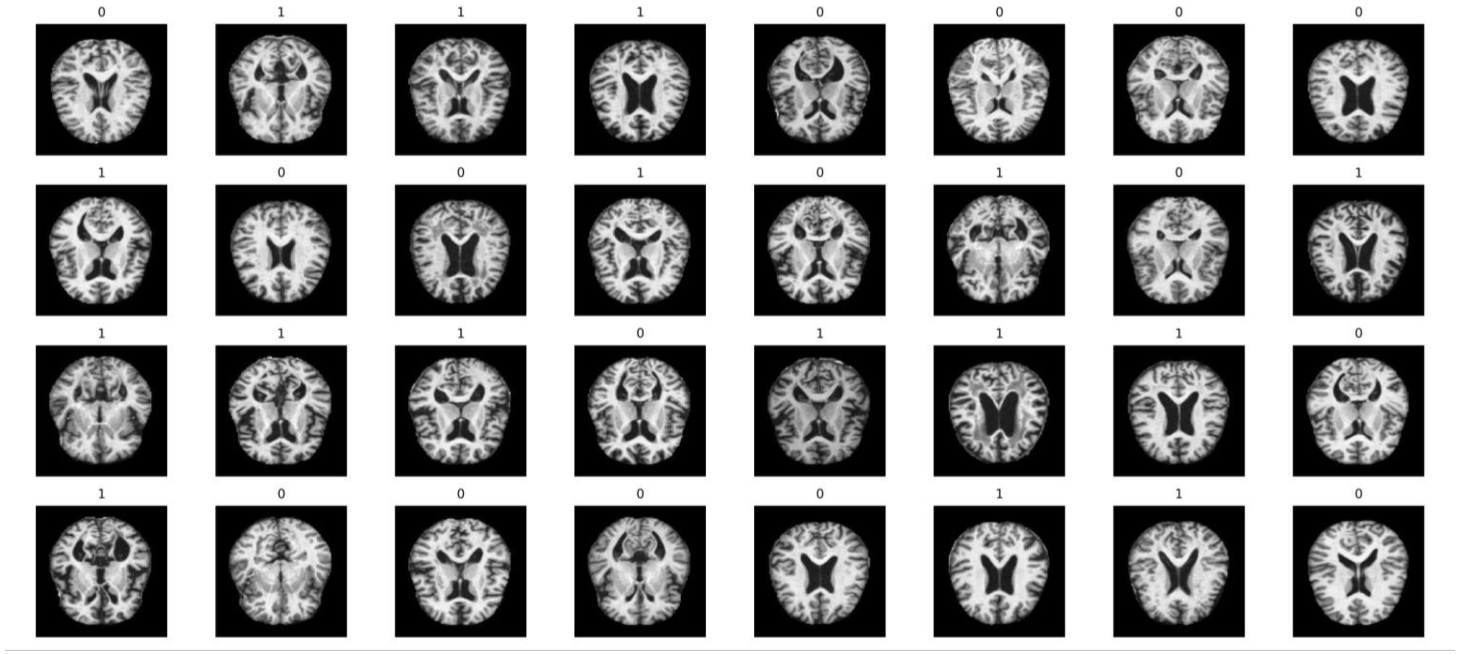

Figure 13: MRI scans