

Data Collection and Preprocessing Phase

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Team ID	SWTID1720426301
Project Title	Cognitive Care: Early Intervention for Alzheimer's Disease
Maximum Marks	6 Marks

Data Exploration and Preprocessing Report

The data exploration and preprocessing approach for Alzheimer's Disease involves a series of steps including resizing, normalizing, augmenting, denoising, contrast adjustment, edge detection, color space conversion, cropping, batch normalization, and data whitening. These methods collectively enhance data quality, facilitate model generalization, and optimize neural network training, essential for achieving accurate and robust Alzheimer's Disease diagnosis through advanced computer vision techniques.

Section	Description
Data Overview	The project utilizes Alzheimer's MRI scans sourced from Kaggle, categorized into four classes.
Resizing	Resizing to 180x180 pixels ensures consistent input dimensions for the Xception model as per the code's preprocessing requirements.
Normalization	Normalization in the code involves scaling pixel values to a range between 0 and 1, ensuring consistent data range across images to facilitate effective model training and convergence.
Data Augmentation	Data augmentation in the code (brightness adjustment, zooming, horizontal flipping) diversifies training data, boosting model robustness in Alzheimer's Disease pattern recognition.
Data Balancing	Data balancing in the code uses SMOTE to address class imbalance by generating synthetic samples, improving model accuracy across all Alzheimer's Disease categories.

[illegible]

<h2>Data Balancing</h2>	<pre>[] train_data, train_labels = train_data_gen.next() # before oversampling print(train_data.shape, train_labels.shape) (5121, 180, 180, 3) (5121, 4)</pre> <pre>from imblearn.over_sampling import SMOTE sm = SMOTE(random_state=42) train_data, train_labels = sm.fit_resample(train_data.reshape(-1, IMG_SIZE * IMG_SIZE * 3), train_labels) train_data = train_data.reshape(-1, IMG_SIZE, IMG_SIZE, 3) print(train_data.shape, train_labels.shape)</pre>
<h2>Transfer Learning</h2>	<pre>xcep_model = Xception(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)</pre> <pre>for layer in xcep_model.layers: layer.trainable = False</pre>
<h2>Batch Normalization</h2>	<pre>from tensorflow.keras.models import Sequential from tensorflow.keras.layers import SeparableConv2D, BatchNormalization, GlobalAveragePooling2D, Dropout custom_inception_model = Sequential([xcep_model, Dropout(0.5), GlobalAveragePooling2D(), Flatten(), BatchNormalization(), Dense(512, activation='relu'), BatchNormalization(), Dropout(0.5), Dense(256, activation='relu'), BatchNormalization(), Dropout(0.5), Dense(128, activation='relu'), BatchNormalization(), Dropout(0.5), Dense(64, activation='relu'), Dropout(0.5), BatchNormalization(), Dense(4, activation='softmax')], name="inception_cnn_model")</pre>