<u>**AI Product Service Prototype Development and Business/Financial Modelling**</u>

Developer: Praneet Prabhanjan B

> ***“ Deep Learning - Based Alzheimer's classification from Brain MRI Imaging Patterns: Revolutionizing Neurological Disorders detection .“***

Abstract:

The World Health Organization (WHO) claims that neurological disorders provide one of the biggest risks to public health because they can impact up to 1 billion people worldwide and result in 6.8 million fatalities annually.

By utilizing deep learning techniques, this project seeks to overcome these issues by creating a novel method for the early detection of Alzheimer's from brain imaging patterns.

For this Deep learning project as a part of my internship at FeynnLabs, I have taken a preprocessed dataset from Kaggle (Alzheimer MRI Preprocessed Dataset (128 x 128))

The Data is collected from several websites/hospitals/public repositories. The Dataset consists of Preprocessed MRI (Magnetic Resonance Imaging) Images.
All the images are resized into 128 x 128 pixels. The Dataset has four classes of images.
The Dataset consists of a total of 6400 MRI images.

Class -1: Mild Demented (896 images)
Class - 2: Moderate Demented (64 images)
Class - 3: Non-Demented (3200 images)
Class - 4: Very Mild Demented (2240 images)

The main motive behind this project is to design/develop an accurate framework or architecture for the classification of Alzheimer's Disease.

Deep learning models and feature selection algorithms will be used by the system to extract useful data from challenging imaging datasets. The algorithm will learn to identify specific classifications based on mild demented, very mild demented, non-demented, and moderate demented through intensive training and validation using large-scale datasets that include both healthy individuals and patients with neurological disorders.

Problem statement:

The World Health Organization (WHO) claims that neurological disorders provide one of the biggest risks to public health because they can impact up to 1 billion people worldwide and result in 6.8 million fatalities annually.

As a consequence, many patients' lives can be saved or greatly improved by a quick and precise diagnosis. Clinical evaluations, which can be arbitrary and have a limited ability to spot small changes in the early stages of diseases, are a common component of modern diagnostic techniques.

By utilizing deep learning techniques, this project seeks to overcome these issues by creating a novel method for the classification of Alzheimer’s from brain imaging patterns.

The issue at hand is the creation of a reliable and precise deep-learning model that can assess these intricate datasets and successfully locate patterns that are suggestive of various neurological illnesses.

This initiative seeks to transform the diagnosis and treatment of neurological illnesses by tackling these issues. Clinicians and researchers will be able to recognize at-risk individuals, offer prompt interventions, and personalize treatment plans with the development of a reliable and effective deep learning-based approach for classification.

Market/Customer/Business Need Assessment for Classification:

Market need: An app that uses deep learning to enable the classification of Alzheimer’s from brain imaging patterns in the field of neurological disorders is much needed by the market. Numerous and more people throughout the world are being affected by neurological ailments like Parkinson's disease, multiple sclerosis, and Alzheimer's disease. Classification is essential for better patient outcomes because it enables prompt treatment, individualized treatment plans, and better disease management. There is a need for more sophisticated and accurate diagnostic tools because current diagnostic techniques frequently fail to accurately and sensitively identify early-stage neurological illnesses.

Customer needs: The market demand for an app that can accurately detect and diagnose neurological conditions at an early stage includes patients and healthcare professionals. Early diagnosis is sought by patients and their families in order to initiate effective treatments quickly, acquire quick medical attention, and maybe halt the progression of the condition. The app can meet the demand for a quick and accurate diagnostic tool that enables classification and enhances patient care by utilizing deep learning algorithms, for brain imaging data analysis.

Business need: To begin with, there is a sizable chance to capitalize on the expanding market for medical technologies and diagnostics for neurological disorders. By providing precise and advanced diagnostic methods, the app can stand out from the competition and draw users, healthcare providers, and research organizations.

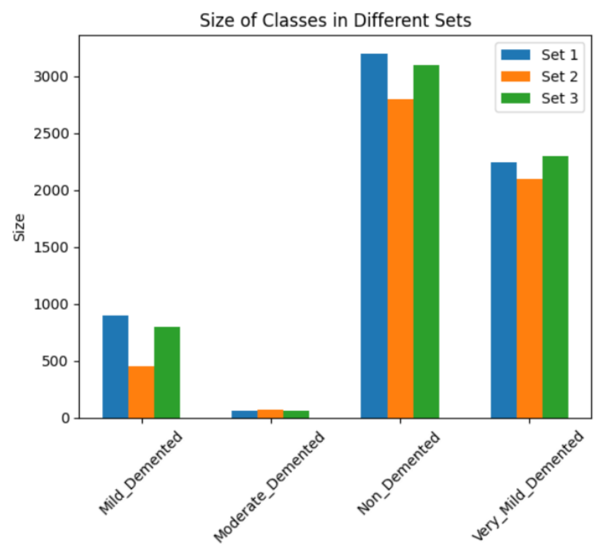
Overall, the app fits the market's need for precise and early diagnosis of neurological disorders, the customer's need for better diagnostic tools, and the company's need for innovation, differentiating itself from the competition, as well as better patient outcomes.

Code Implementation and Data Preprocessing:

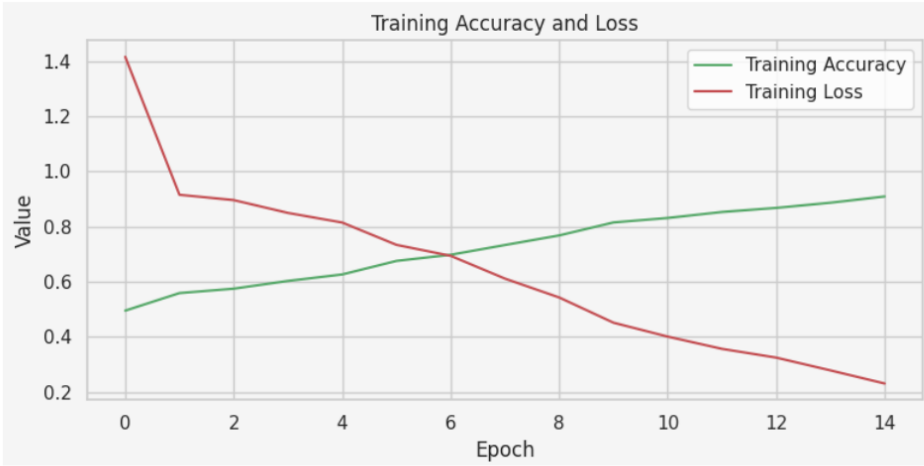
```
# Import necessary libraries for data manipulation and analysis
import pandas as pd            # Data manipulation library
import numpy as np             # Numerical computing library

# Data visualization libraries
import seaborn as sns          # Data visualization library based on Matplotlib
import matplotlib.pyplot as plt # Matplotlib for creating plots
import matplotlib.image as img  # Matplotlib extension for working with images

# Image processing and computer vision library
import cv2                     # OpenCV for image processing
```

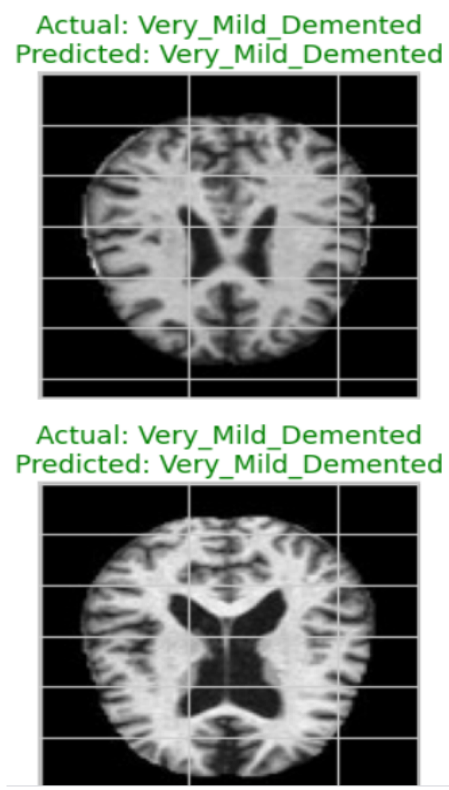
```
# Import machine learning and deep learning libraries
from imblearn.over_sampling import SMOTE          # SMOTE for oversampling
from sklearn.model_selection import train_test_split  # Scikit-learn for splitting data
from sklearn.metrics import matthews_corrcoef as MCC   # MCC metric
from sklearn.metrics import balanced_accuracy_score as BAS # Balanced accuracy score metric
from sklearn.metrics import classification_report, confusion_matrix # Classification metrics

# Deep learning frameworks
from tensorflow import keras
from keras import layers
import tensorflow as tf
import tensorflow_addons as tfa

# Dataset handling
from tensorflow.keras.preprocessing import image_dataset_from_directory
```

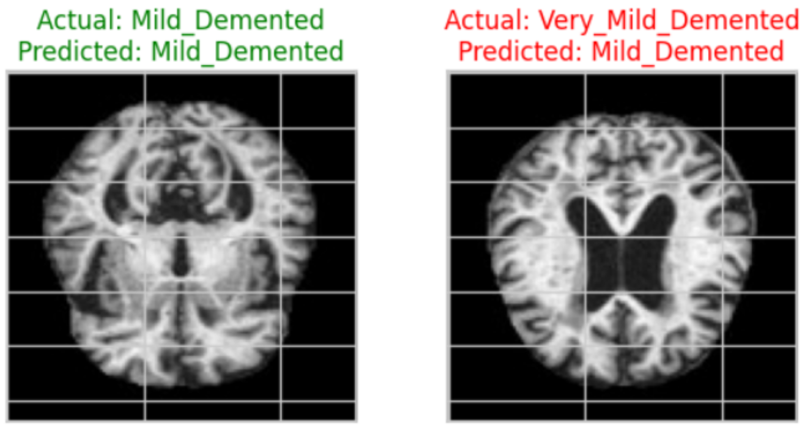
```
# Create a training dataset using images from the "./output/train" directory
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "./output/train",  # Directory containing training images
    seed=123,           # Random seed for shuffling (for reproducibility)
    image_size=(IMG_HEIGHT, IMG_WIDTH),  # Target image size
    batch_size=64       # Batch size for training
)

# Create a test dataset using images from the "./output/test" directory
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "./output/test",    # Directory containing test images
    seed=123,           # Random seed for shuffling (for reproducibility)
    image_size=(IMG_HEIGHT, IMG_WIDTH),  # Target image size
    batch_size=64       # Batch size for testing
)

# Create a validation dataset using images from the "./output/val" directory
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    "./output/val",     # Directory containing validation images
    seed=123,           # Random seed for shuffling (for reproducibility)
    image_size=(IMG_HEIGHT, IMG_WIDTH),  # Target image size
    batch_size=64       # Batch size for validation
)
```

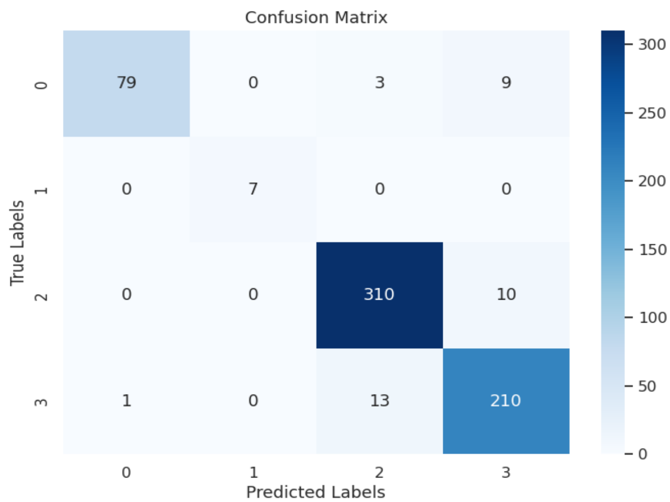



```python
# Compile the model
model.compile(
    loss="sparse_categorical_crossentropy",  # Loss function for multi-class classification
    optimizer="Adam",                         # Optimizer (Adam is a common choice)
    metrics=["accuracy"]                      # Evaluation metric (accuracy in this case)
)
```


Training Accuracy and Loss
Training Accuracy
Training Loss
Value
Epoch
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0
2
4
6
8
10
12
14


Actual: Very_Mild_Demented
Predicted: Very_Mild_Demented
Actual: Very_Mild_Demented
Predicted: Very_Mild_Demented





	0	1	2	3
0	79	0	3	9
1	0	7	0	0
2	0	0	310	10
3	1	0	13	210

Although utilizing basic deep-learning methods this project was completed with an accuracy: of 0.9090 (90%), but the current data provided is very small in size. But provided with time and more data there would have been better implementation and improvement in the overall accuracy of the prediction.

Future scalability:

a . **Feasibility (2-3 years):** This prototype is feasible to develop within the next 2-3 years due to the availability of advanced deep learning techniques, suitable datasets, and the commitment of our team.

b. **Viability (20-30 years):** The prototype holds long-term viability, spanning 20-30 years, as it addresses a critical and persistent healthcare challenge—early Alzheimer's detection. The relevance of such technology is expected to increase as the aging population grows.

c. **Monetization:** The prototype is directly monetizable through potential avenues such as licensing the technology to healthcare institutions, partnering with research organizations, or offering diagnostic services. It aligns with the project's requirement of direct monetization.

d. **Testing and Validation:** Rigorous testing on diverse MRI datasets will ensure the accuracy and reliability of our model. Will report key performance metrics, including accuracy, precision, recall, and F1-score.

e. **Challenges and Solutions:** Expected challenges include data preprocessing complexities and model optimization. Will address these challenges by leveraging transfer learning and advanced data augmentation techniques.

Business/Financial Modeling:

The approach to the business and financial aspects of the prototype involves:

a. **Market Analysis:** In-depth market analysis to understand the demand for Alzheimer's detection technologies and the competitive landscape.

b. **Revenue Model:** The primary monetization strategy involves licensing this technology to healthcare providers, research institutions, and pharmaceutical companies, generating recurring revenue.

c. **Financial Projections:** To create detailed financial projections, including income statements, cash flow forecasts, and ROI estimates, over a defined period.

d. **Investment Requirements:** Initial investments for data acquisition, infrastructure, and development will be estimated, with potential funding sources explored.

e. **Risk Analysis:** To identify and mitigate potential risks related to regulatory approval, data privacy compliance, and market competition.

f. **Business Plan:** A comprehensive business plan will outline value proposition, target customers, and go-to-market strategy.

Financial Modeling with Deep Learning & Data Analysis:

a. **Identify the Market:** To determine the target market, such as healthcare institutions, and specify the scope, like neurological disorders diagnostics.

b. **Collect Data/Statistics:** Gather market data from sources like research reports, government databases, online platforms, and surveys. To ensure data is up-to-date and relevant.

c. **Perform Forecasts/Predictions**: Utilize regression models, time series forecasting, or deep learning techniques to predict market trends, demand, and growth. To evaluate model accuracy with performance metrics.

Scenario Analysis: To consider multiple scenarios to understand the impact of various factors on your financial projections, ensuring robust and adaptable models.

Documentation: Thoroughly document data sources, methodologies, and assumptions to maintain transparency and facilitate ongoing model updates.

This approach empowers data-driven decision-making and enables better financial planning for your product or service launch.

Financial Equation Corresponding to that Market Trend:

In a linearly growing market, the financial equation can be represented as follows:

Total Profit (y) = Pricing of Product (m) × Total Sales/ subscription (x(t)) - Production and Maintenance Costs ©

Beyond the technical aspects, the success of this endeavor hinges on choosing the right business model. Let's explore three viable options:

1. Subscription Business Model:

Description: In this model, customers subscribe to access our Alzheimer's classification service on a recurring basis, such as monthly or annually.

Financial Equation: Total Revenue (R) = Subscription Price (P) × Number of Subscribers (N)
Advantages:

- Provides a predictable stream of recurring revenue.
- Enhances customer retention and engagement through regular updates and improvements.
- Enables scalability as more subscribers join the service.

2. Distributor Business Model:

Description: Under the distributor model, we partner with healthcare institutions, diagnostic centers, or medical equipment suppliers who distribute our Alzheimer's classification tool to end-users.

Financial Equation: Total Revenue (R) = Price per License (P) × Number of Licenses Sold (N)
Advantages:

- Expand our reach through established distribution channels.
- Reduces the need for direct customer acquisition efforts.
- Allows us to leverage existing relationships in the healthcare industry.

3. SaaS (Software as a Service) Business Model:

Description: In the SaaS model, we provide our deep learning-based Alzheimer's classification software as a cloud-based service. Customers access it over the internet on a pay-as-you-go basis.
Financial Equation: Total Revenue (R) = Price per User per Month (P) × Number of Active Users (N)
Advantages:

- Lowers barriers to entry for customers with no need for hardware or software installation.
- Facilitates rapid updates and maintenance.
- Scales effortlessly as more users adopt the service.

Conclusion:

Selecting the right business model for this project is pivotal to its success. The Subscription Business Model ensures steady recurring revenue, the Distributor Business Model leverages established industry networks, and the SaaS Business Model offers accessibility and scalability. Each has its unique advantages, and the choice should align with our market strategy and customer preferences. Ultimately, the aim is not only to revolutionize neurological disorders detection but also to establish a sustainable and profitable venture in the healthcare technology sector.

The development of the Alzheimer’s classification model using deep learning models and the potential application of brain imaging patterns for clinical practice are likely to enhance disease diagnosis, prognosis, predictive modeling, and therapeutic monitoring. I have evaluated the literature on the possible application of deep learning to find patterns for neurological conditions in the current report. Overall, the capacity to employ cutting-edge algorithms to diagnose, enhance the prognosis, and track the progression of the disease classification is the most significant benefit of adding DL for detection.

Github Repo: https://github.com/Praneet-Prabhanjan/Brain_mri_alzheimer_classification