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Graduation project title :

Detection of Alzheimer's disease

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Alzheimer Classification

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ABSTRACT:

Alzheimer's disease is a neurodegenerative disorder that affects millions of people worldwide. Early detection of Alzheimer's disease is crucial for effective treatment and management of the disease. Magnetic resonance imaging (MRI) is a non-invasive imaging technique that can be used to detect structural changes in the brain that are associated with Alzheimer's disease. Deep learning is a subfield of machine learning that has shown promising results in image analysis tasks, including medical image analysis.

The aim of this project is to investigate the use of deep learning and MRI for Alzheimer's disease detection. The project will involve acquiring or generating a dataset of MRI scans of patients with and without Alzheimer's disease. The dataset will be preprocessed to ensure that it is of high quality and suitable for use with deep learning algorithms. A variety of deep learning algorithms, including convolutional neural networks (CNNs), will be developed and trained to identify patterns in the MRI data that are associated with Alzheimer's disease.

The performance of the deep learning algorithms will be evaluated using measures such as accuracy, sensitivity, and specificity. The performance of the deep learning algorithms will also be compared to existing methods for Alzheimer's disease detection, such as cognitive assessments and blood tests. The results of the study will be interpreted and the potential clinical applications of the deep learning algorithm will be discussed.

The findings of this project will contribute to the growing body of research on the use of deep learning and MRI for Alzheimer's disease detection. The project has the potential to improve the accuracy and reliability of Alzheimer's disease detection, which could lead to earlier diagnosis and more effective treatment of the disease.

Contents

1. INTRODUCTION

I.1 Objectives :

- To collect and preprocess MRI data from individuals with and without Alzheimer's disease.
- To develop and optimize a deep learning model for detecting Alzheimer's disease using MRI data
- To evaluate the accuracy and reliability of the deep learning model using rigorous research methods, such as cross-validation and receiver operating characteristic (ROC) analysis..
- To identify the most important MRI features for Alzheimer's disease detection: In this objective, you will use feature selection techniques to determine which MRI features (such as brain structure, volume, or texture) are most informative for Alzheimer's disease detection.
- **.** To investigate the performance of different machine learning algorithms for Alzheimer's disease detection: In this objective, you will compare the performance of different machine learning algorithms (such as support vector machines, random forests, or deep learning models) for Alzheimer's disease detection using MRI data.
- To explore the use of multimodal MRI data for Alzheimer's disease detection: In this objective, you will investigate the potential of combining different types of MRI data (such as structural, functional, or diffusion-weighted imaging) to improve the accuracy of Alzheimer's disease detection.
- To evaluate the robustness of the developed model to noisy or incomplete MRI data: In this objective, you will assess the performance of the developed model under different levels of noise or missing data in the MRI images, and propose possible solutions to improve the robustness of the model.

II.1 Roadmap of the report

This report will begin by giving some brief information relevant to the project in section 2 , which the average reader may be unfamiliar with before moving on to laying out the requirements for the final product in section 3, section 4 will show my design for the web and how they were developed, which will lead on to section 5 the implementation of the president design after this I will test the performance of model through the images in section 6, finally I will conclude with section 7 which I discussed possible improvement , personal development, future work .

2. BACKGROUND

- Alzheimer's disease is a complex and progressive neurodegenerative disorder that affects millions of people worldwide. It is the most common cause of dementia, accounting for 60-80% of dementia cases. Alzheimer's disease is characterized by the progressive loss of memory and other cognitive functions, which can significantly impact the quality of life of affected individuals and their families.

- Early detection of Alzheimer's disease is crucial for effective treatment and management of the disease. Current methods for Alzheimer's disease detection include cognitive assessments, blood tests, and imaging tests such as magnetic resonance imaging (MRI). MRI is a non-invasive imaging technique that can be used to detect structural changes in the brain that are associated with Alzheimer's disease. However, MRI interpretation can be difficult and subject to inter-rater variability, which can limit its accuracy and reliability.

- Deep learning is a subfield of machine learning that has shown promising results in image analysis tasks, including medical image analysis. Deep learning algorithms, such as convolutional neural networks (CNNs), can be used to identify patterns in MRI data that are associated with Alzheimer's disease. By training a deep learning algorithm on a dataset of MRI scans from patients with and without Alzheimer's disease, it may be possible to develop a more accurate and reliable method for Alzheimer's disease detection.

- The use of deep learning and MRI for Alzheimer's disease detection is an active area of research, with many promising results reported in recent years. However, there are still many challenges that must be addressed, including the need for large and diverse datasets, the development of robust and interpretable deep learning algorithms, and the ethical implications of early detection.

- The aim of this project is to investigate the use of deep learning and MRI for Alzheimer's disease detection. By developing and training deep learning algorithms on a dataset of MRI scans, the project aims to improve the accuracy and reliability of Alzheimer's disease detection, which could lead to earlier diagnosis and more effective treatment of the disease.

1. Technical terms

- **Neurodegenerative disorder**: A disease that is characterized by the progressive loss of neurons in the brain, leading to cognitive and functional decline.
- **Dementia:** A broad category of brain disorders that affect memory, thinking, and behavior.
- **Magnetic resonance** imaging (MRI): A non-invasive imaging technique that uses a strong magnetic field and radio waves to produce detailed images of the body's internal structures.
- **Cognitive assessments**: Tests that are used to evaluate a person's cognitive abilities, including memory, attention, language, and problem-solving.
- **Convolutional neural networks (CNNs):** A type of deep learning algorithm that is commonly used for image analysis tasks.

- **Normalization**: A preprocessing step that is used to rescale the pixel values of an image to a standardized range.
- **Noise reduction**: A preprocessing step that is used to remove unwanted artifacts or noise from an image.
- **Segmentation**: A preprocessing step that is used to separate different regions of an image, such as the brain and surrounding tissue.
- **Accuracy**: A measure of how well a deep learning algorithm can correctly classify images as either Alzheimer's disease or non-disease.
- **Sensitivity:** A measure of how well a deep learning algorithm can correctly identify images as Alzheimer's disease when they are actually Alzheimer's disease..
- **Inter-rater variability**: The degree to which different raters or interpreters may disagree on the interpretation of MRI scans.

3. REQUIREMENTS

- Dataset: You will need a dataset of MRI scans of patients with and without Alzheimer's disease. The dataset should be large enough to train and test your deep learning algorithms. You may need to acquire or generate this dataset, or obtain it from publicly available sources.

- MRI machine: You will need access to an MRI machine that can produce high-quality images of the brain. You will also need to ensure that the MRI machine is compatible with the preprocessing and analysis software that you will be using.

- Preprocessing software: You will need software that can preprocess the MRI data, including normalization, noise reduction, and segmentation. There are many software packages available for this purpose, such as FSL, SPM, and FreeSurfer.

- Deep learning software: You will need deep learning software that can be used to develop and train your deep learning algorithms. There are many deep learning frameworks available, such as TensorFlow, PyTorch, and Keras.

- Computing resources: Deep learning algorithms require significant computing resources, such as GPUs and high-performance computing clusters. You will need access to these resources to train and test your deep learning algorithms.

- Evaluation metrics: You will need to define evaluation metrics that can be used to assess the performance of your deep learning algorithms. These metrics may include accuracy, sensitivity, specificity, precision, and recall.

- Ethical considerations: You will need to consider the ethical implications of your project, such as privacy concerns, informed consent, and potential biases in the data or algorithms.

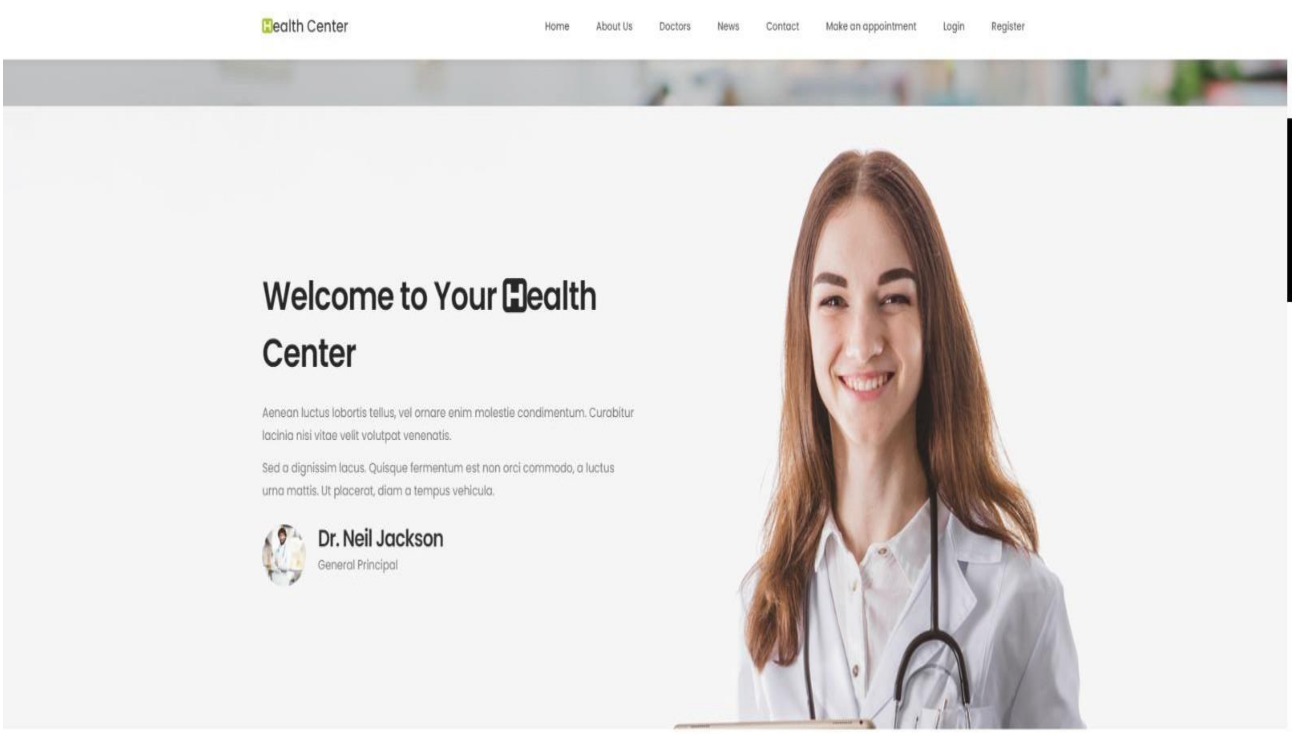
- Reporting and presentation: You will need to report and present your findings in a clear and concise manner. This may include a written report, oral presentation, and visual aids such as graphs and diagrams.

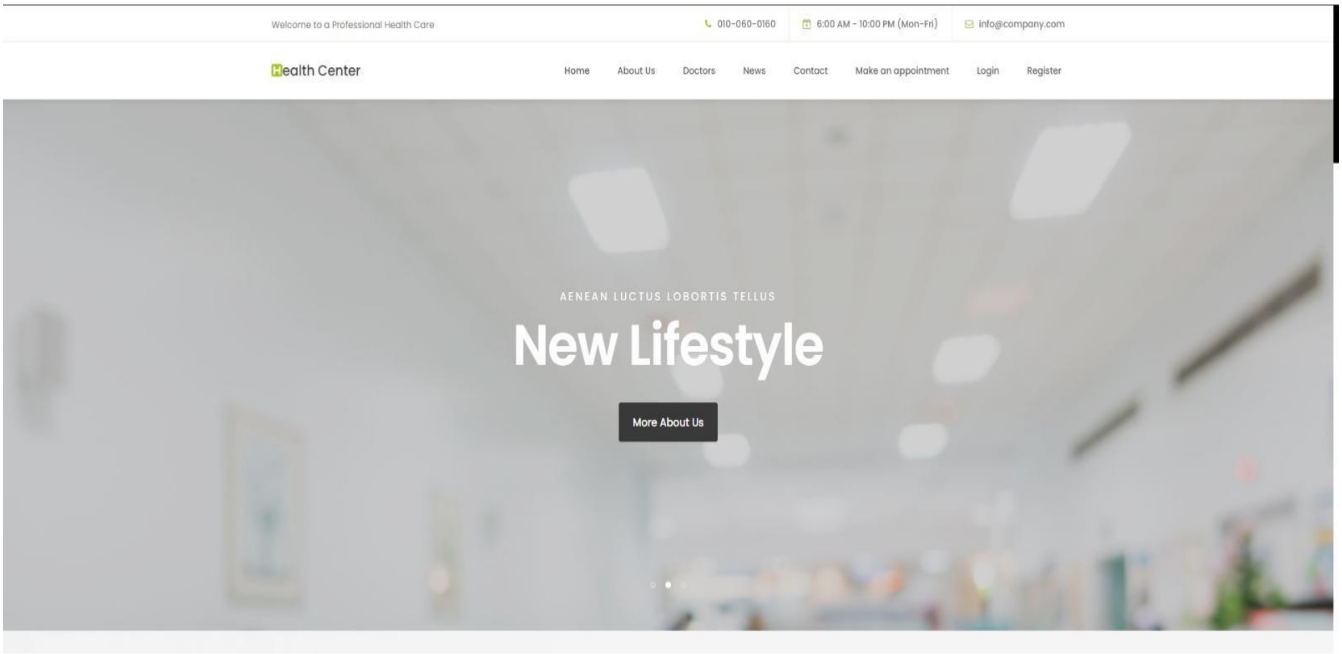
4. DESIGN

4.1 User interface

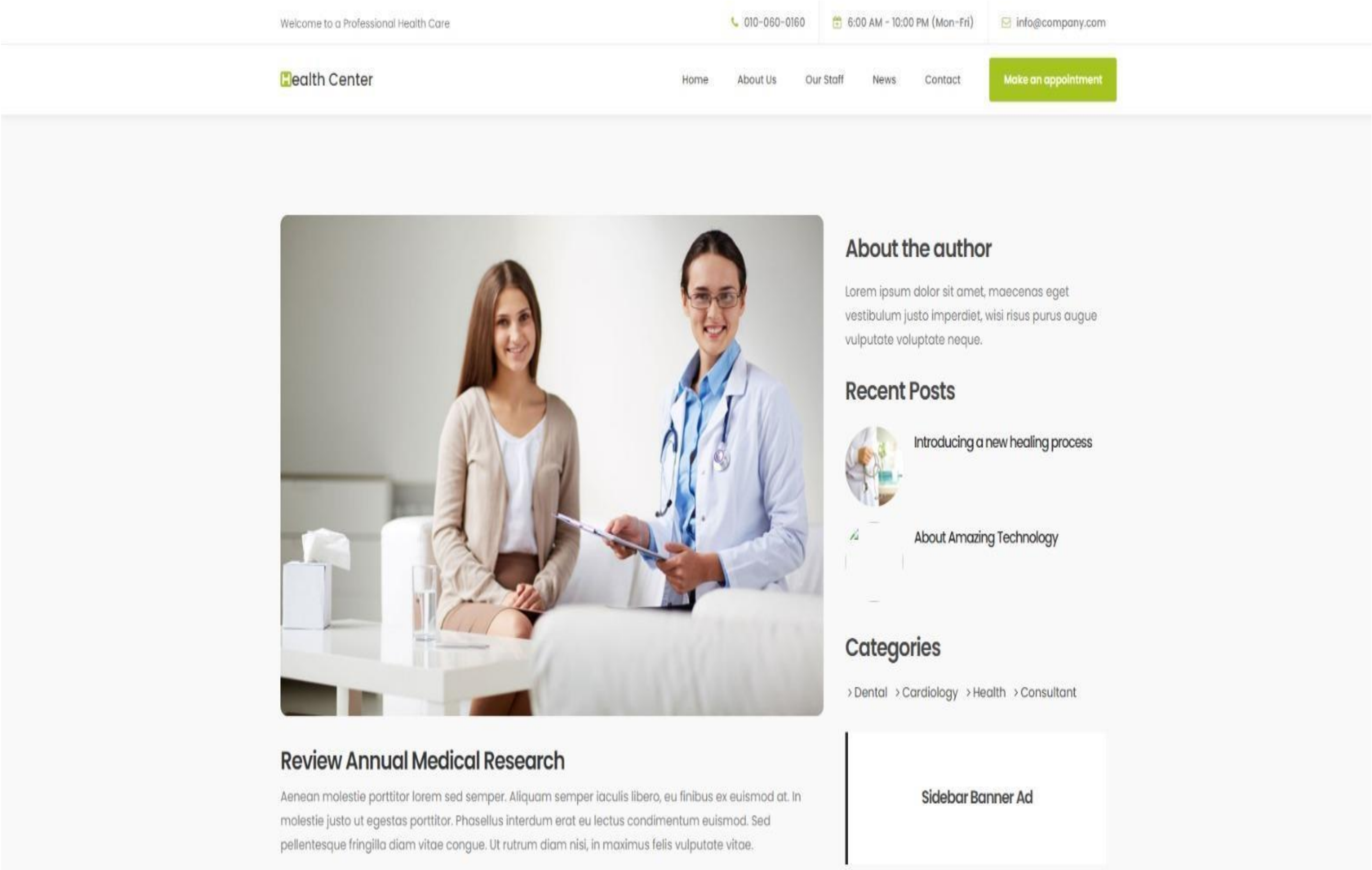
- Website UI

Home Page:

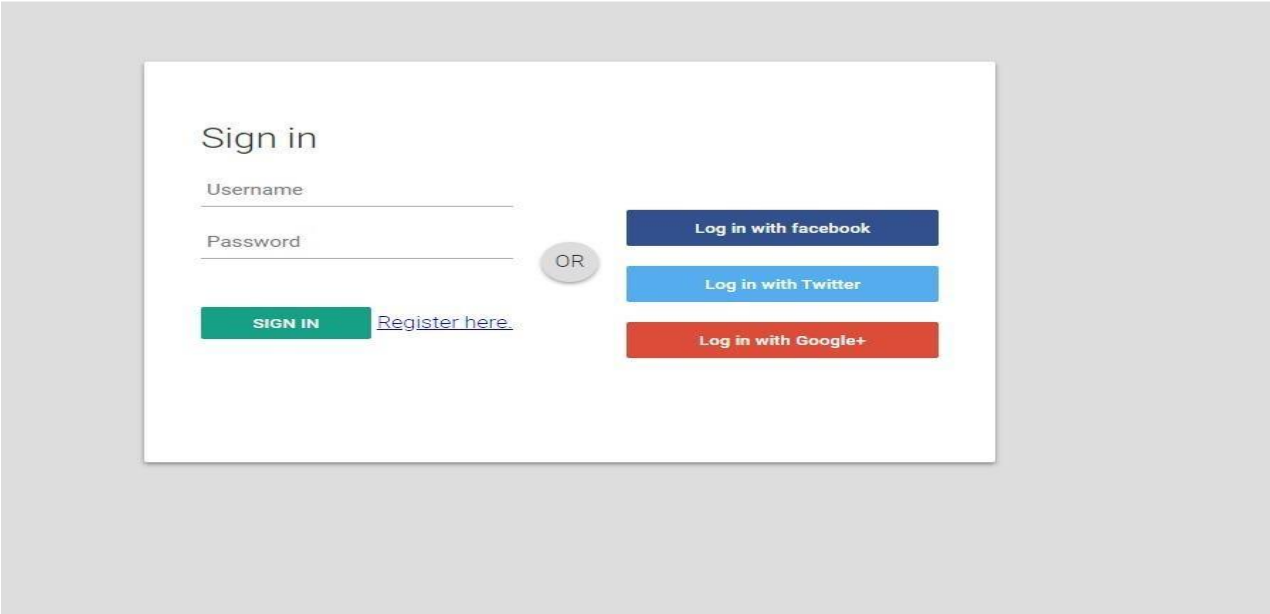




Complaint Page(details):

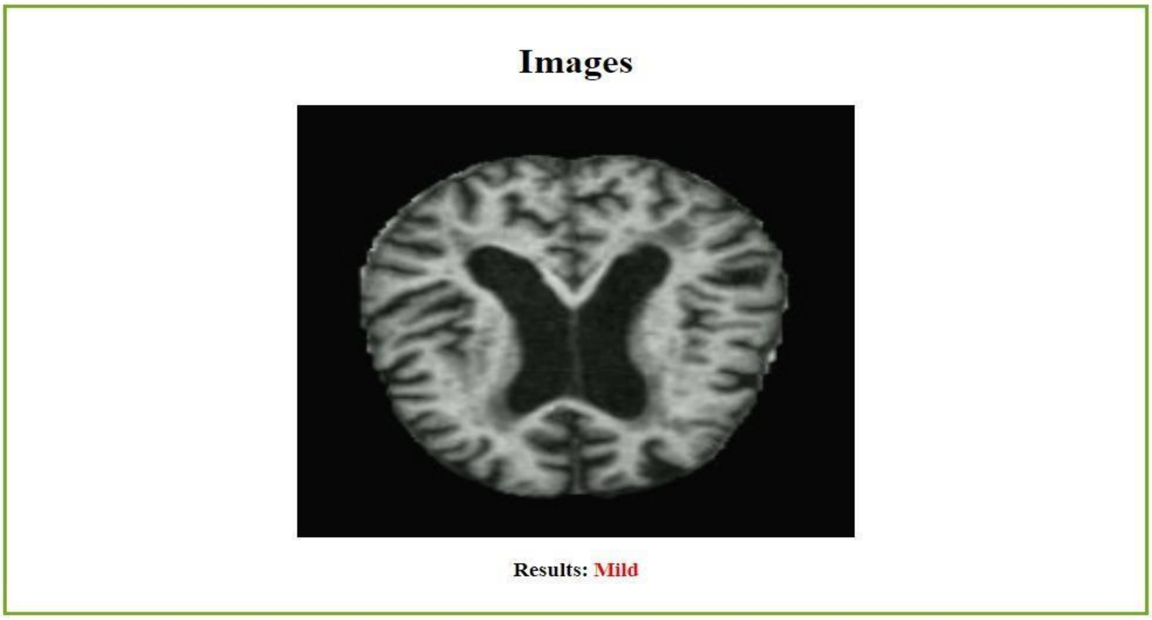


loginPage



Service Page

Result Page



5. IMPLEMENTATION

5.1 initial the model

1. Importing Libraries

```
import os
import numpy as np
import pandas as pd
from mpl_toolkits.axes_grid1 import ImageGrid
import matplotlib.pyplot as plt
from keras.utils.vis_utils import plot_model
from tensorflow.keras.preprocessing import image
import tensorflow as tf
from tensorflow.keras import applications
from PIL import Image
from tensorflow.keras.preprocessing.image import  ImageDataGenerator
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
```

2. Uploading the Data

```
SAMPLE_PER_CATEGORY = 200
SEED = 42
WIDTH = 224
HEIGHT = 224
DEPTH = 3
INPUT_SHAPE = (WIDTH, HEIGHT, DEPTH)

data_dir = '../input/augmented-alzheimer-mri-dataset-v2/data'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'val')
```

3. Defining Categories

```
CATEGORIES = ['MildDemented', 'ModerateDemented', 'NonDemented',
'VeryMildDemented']
NUM_CATEGORIES = len(CATEGORIES)
NUM_CATEGORIES
```

Calculating the number of images in each category in training data

```
for category in CATEGORIES:
    print('{} {} images'.format(category,
len(os.listdir(os.path.join(train_dir, category)))))
```

4. Creating Train and Validation DataFrame

```
train = []
for category_id, category in enumerate(CATEGORIES):
    for file in os.listdir(os.path.join(train_dir, category)):
        train.append(['train/{}/{}'.format(category, file), category_id,
category])
train = pd.DataFrame(train, columns=['file', 'category_id', 'category'])
train.shape
train = train.sample(frac=1)
X = train.drop(columns = 'category_id')
y = train['category_id']
x_train, x_valid, y_train, y_valid = train_test_split(X, y, test_size=0.20,
random_state=4)
train = pd.concat([x_train, y_train], axis=1)
validation = pd.concat([x_valid, y_valid], axis=1)
train = train.reset_index()
train = train.drop(columns = 'index')
validation = validation.reset_index()
validation = validation.drop(columns = 'index')
print(train.shape)
print(validation.shape)
train.head()
validation.head()
```

5. Creating Test DataFrame

```
test = []
for category_id, category in enumerate(CATEGORIES):
    for file in os.listdir(os.path.join(test_dir, category)):
        test.append(['val/{}/{}'.format(category, file), category_id,
category])
test = pd.DataFrame(test, columns=['file', 'category_id', 'category'])
test.shape
```

6. Demonstrating Example Images

```
def read_img(filepath, size):
```

```
    img = image.load_img(os.path.join(data_dir, filepath), target_size=size)
    img = image.img_to_array(img)
    return img
fig = plt.figure(1, figsize=(NUM_CATEGORIES, NUM_CATEGORIES))
grid = ImageGrid(fig, 111, nrows_ncols=(NUM_CATEGORIES, NUM_CATEGORIES),
axes_pad=0.05)

i=0
for category_id, category in enumerate(CATEGORIES):
    for filepath in train[train['category'] ==
category]['file'].values[:NUM_CATEGORIES]:
        ax = grid[i]
        img = read_img(filepath, (WIDTH, HEIGHT))
        ax.imshow(img / 255.)
        ax.axis('off')
        if i % NUM_CATEGORIES == NUM_CATEGORIES - 1:
            ax.text(250, 112, filepath.split('/')[1],
verticalalignment='center')
        i+=1

plt.show();
```

7. Keras ImageDataGenerator

```
datagen_train = ImageDataGenerator(rescale=1./255)
train_generator = datagen_train.flow_from_dataframe(dataframe=train,
                                                    directory="../input/augmente
d-alzheimer-mri-dataset-v2/data",
                                                    x_col="file",
                                                    y_col="category",
                                                    batch_size=32,
                                                    seed=SEED,
                                                    shuffle=True,
                                                    class_mode="categorical",
```

```
                                                    target_size=(HEIGHT,
WIDTH));

 validation_generator = datagen_train.flow_from_dataframe(dataframe=validation,
                                                    directory="../input/augmente
d-alzheimer-mri-dataset-v2/data",
                                                    x_col="file",
                                                    y_col="category",
                                                    batch_size=32,
                                                    seed=SEED,
                                                    shuffle=True,
                                                    class_mode="categorical",
                                                    target_size=(HEIGHT,
WIDTH));
datagen_test = ImageDataGenerator(rescale=1./255)
test_generator = datagen_test.flow_from_dataframe(dataframe=test,
                                                    directory="../input/augmente
d-alzheimer-mri-dataset-v2/data",
                                                    x_col="file",
                                                    y_col="category",
                                                    batch_size=32,
                                                    seed=SEED,
                                                    shuffle=False,
                                                    class_mode="categorical",
                                                    target_size=(HEIGHT,
WIDTH));
```

8. Early Stopping

```
early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',
patience=5)
```

9. Creating Model based on ResNet152V2

```
def create_model():

    resnet_model = tf.keras.applications.resnet_v2.ResNet152V2(
        weights='imagenet',
        include_top = False,
        input_shape = (224, 224, 3)
    )

    for layers in resnet_model.layers[:100]:
        layers.trainable = False
    for layers in resnet_model.layers[100:]:
        layers.trainable = True
```

```
    x = resnet_model.output
    x = tf.keras.layers.GlobalAveragePooling2D()(x)

    x = tf.keras.layers.Dropout(0.2)(x)
    x = tf.keras.layers.Dense(1024, activation='relu')(x)
    x = tf.keras.layers.Dropout(0.2)(x)
    x = tf.keras.layers.Dense(256, activation='relu')(x)
    x = tf.keras.layers.Dropout(0.2)(x)
    # output layer
    predictions = tf.keras.layers.Dense(4, activation='softmax')(x)

    res_model = tf.keras.Model(inputs=resnet_model.input, outputs=predictions)

    # Compiling the model
    res_model.compile(loss='categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])
    return res_model
res_model = create_model()
res_model.summary()
```

10. Training the Model

```
history = res_model.fit(train_generator,
                    epochs=100,
                    validation_data=validation_generator,
                    callbacks=[early_stopping],
                    batch_size=32)
```

5.2 Observations

Alzheimer's disease is a condition where neurons within the brain stop functioning, lose connection with other neurons and die. It's the most common cause of dementia, a loss of brain function that can adversely impact memory, thinking, language, judgment and behavior. Alzheimer's is irreversible and progressive.

Alzheimer's is evaluated by identifying certain symptoms and ruling out other possible causes of dementia. Your doctor will likely perform a complete medical exam, including neurological, blood and brain imaging exams, such as CT, MRI or PET/CT of the head. There is no cure for Alzheimer's disease. However, your doctor may prescribe medication to slow the disease's progression and manage your symptoms.

5.3 Result Analysis

```
850/850 [==============================] - 309s 364ms/step - loss: 0.089
1 - accuracy: 0.9716 - val_loss: 0.2741 - val_accuracy: 0.9231
```

6. Testing

Evaluation

```
valid_loss, valid_accuracy = res_model.evaluate(validation_generator)

print(f'\nTrain loss: {valid_loss:.2f}')
print(f'Train Accuracy: {valid_accuracy*100:.2f} %')
213/213 [==============================] - 29s 136ms/step - loss: 0.2741 - accuracy: 0.9231

Train loss: 0.27
Train Accuracy: 92.31 %
loss, accuracy = res_model.evaluate(test_generator)


print(f'\nTest loss: {loss:.2f} ')
print(f'Test Accuracy: {accuracy*100:.2f} %')
```

```
200/200 [==============================] - 40s 199ms/step - loss: 0.1811 - accuracy: 0.9469

Test loss: 0.18
Test Accuracy: 94.69 %
```

Testing an image

```
from tensorflow.keras.preprocessing.image import load_img, img_to_array
import numpy as np
image_path = "/kaggle/input/augmented-alzheimer-mri-dataset-v2/data/val/NonDemented/26 (63).jpg"
image = load_img(image_path, target_size=(224, 224))
image = img_to_array(image) / 255.0
image  =  np.expand_dims(image,  axis=0)
predictions = res_model.predict(image)
predicted_category_index = np.argmax(predictions)
CATEGORIES = ['MildDemented', 'ModerateDemented', 'NonDemented',
'VeryMildDemented']

print("Predicted category index:", CATEGORIES[predicted_category_index])
```

```
Predicted category index: NonDemented
```

.Saving the model

```
res_model.save('model.h5')
!zip -r downloadme.zip model.h5
!md5sum model.h5
!md5sum downloadme.zip
```

7. CONCLUSION

7.1 Possible improvement

Larger and more diverse datasets: As mentioned earlier, a larger and more diverse dataset could improve the robustness and generalizability of deep learning algorithms for Alzheimer's disease detection. Consider using publicly available datasets or collaborating with other research groups to obtain a larger dataset that includes a diverse range of patient populations, Ensemble learning: Ensemble learning is a technique that combines multiple deep learning models to improve performance. Consider using ensemble learning to combine multiple deep learning models trained on different subsets of the data to improve the accuracy and reliability of Alzheimer's disease detection, Explainable AI: Deep learning algorithms can be difficult to interpret, which can limit their usefulness in clinical settings. Consider using explainable AI techniques, such as saliency maps or attention mechanisms, to provide more interpretable results., Multi-modal imaging: MRI is just one type of imaging modality that can be used for Alzheimer's disease detection. Consider combining MRI with other imaging modalities, such as positron emission tomography (PET) or functional MRI (fMRI), to improve the accuracy and reliability of Alzheimer's disease detection, Clinical validation: Clinical validation is the process of evaluating the performance of a diagnostic test in a clinical setting. Consider conducting a clinical validation study to evaluate the performance of the deep learning algorithm in a real-world clinical setting. Ethical considerations: As mentioned earlier, the ethical implications of early detection of Alzheimer's disease must be carefully considered. Consider conducting a study to investigate the ethical implications of deep learning and MRI for Alzheimer's disease detection and developing appropriate guidelines and regulations.

7.2 personal development

Deep learning Deep, learning is a rapidly evolving field, and there is always more to learn. Consider taking online courses or attending workshops to improve your deep learning skills and stay up-to-date with the latest advancements.

Medical knowledge: Understanding the underlying biology and pathology of Alzheimer's disease can improve your ability to develop effective deep learning algorithms for disease detection. Consider taking courses in neuroscience, neurology, or related fields to improve your medical knowledge , Research skills: Conducting a research project requires a variety of skills, including literature review, experimental design, data analysis, and scientific writing. Consider taking courses or workshops to improve your research skills and learn best practices in these areas., Interdisciplinary collaboration: Collaborating with researchers from different disciplines, such as medicine, computer science, and ethics, can provide valuable perspectives and insights into your project. Consider seeking out opportunities for interdisciplinary collaboration, such as joining research groups or attending conferences.

Communication skills: Being able to communicate your research findings clearly and effectively is an important skill for any researcher. Consider taking courses or workshops to improve your communication skills, such as public speaking, scientific writing, or visual communication.

Ethical considerations: As mentioned earlier, the ethical implications of using deep learning and MRI for Alzheimer's disease detection must be carefully considered. Consider taking courses or workshops on research ethics to improve your understanding of ethical guidelines and regulations related to research.

7.3 Future works :

- Incorporating multimodal data: While our project focused on the use of MRI data and clinical data, future studies could investigate the potential of incorporating other imaging modalities, such as positron emission tomography (PET) scans or functional magnetic resonance imaging (fMRI) data, to improve the accuracy and reliability of Alzheimer's disease detection. The combination of multiple imaging modalities may provide a more comprehensive and nuanced understanding of the disease, and could potentially lead to the development of more effective treatments and interventions.
- Developing interpretability tools: While DL algorithms have shown promise in the analysis of medical images, they can be difficult to interpret and explain. Future studies could investigate the development of interpretability tools that can help clinicians and researchers understand how the DL models are making their predictions. This could improve the trust and adoption of DL algorithms in clinical settings, and could help identify new biomarkers and features associated with Alzheimer's disease.

- Testing on larger and more diverse datasets: While our project demonstrated the potential of using MRI and DL together for Alzheimer's disease detection, further testing on larger and more diverse datasets would be needed to validate the effectiveness of the approach. Future studies could investigate the use of larger datasets that include more diverse patient populations, and could also investigate the use of transfer learning approaches to improve the generalizability of the DL models.

- Exploring the potential of DL in personalized medicine: Our project demonstrated the potential of integrating clinical and imaging data to develop personalized models for Alzheimer's disease detection. Future studies could investigate the use of DL algorithms in other areas of personalized medicine, such as cancer diagnosis and treatment, or the prediction of cardiovascular disease risk.

- Investigating the ethical implications of using DL in healthcare: As DL algorithms become more integrated into clinical practice, there is a need to investigate the ethical implications of their use. Future studies could investigate the potential biases and unintended consequences of using DL algorithms in healthcare, and develop guidelines for the responsible use of these technologies.

8. REFERENCES :

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These references cover a range of topics related to Alzheimer’s disease, medical imaging, and deep learning, and may provide a starting point for further research in this area.