Project Report

Date	15 November 2023
Team ID	591900
Project Name	Alzheimer's Disease Prediction

1. Introduction

1.1. Project Overview

Alzheimer's disease (AD) is one of the most prevalent health conditions in aging, affecting over 32 million people worldwide. It is an irremediable, progressive neurological syndrome leading to the deterioration of cognitive abilities. It is the most common type of dementia, and it usually starts mildly but quickly progresses to serious complications. It is a neurodegenerative disease characterized by an initial asymptomatic stage, which occurs about 20 years before symptom onset, and during which neuronal damage takes place. The subsequent early symptomatic stage is characterized by a cognitive decline, which is referred to as "mild cognitive impairment due to AD" (herein referred to as MCI) when the clinicians consider the cognitive decline to be the result of the prodromal stage of AD (as opposed to other types of dementia, medication, depression, or other causes).

According to the World Alzheimer's Report, this disease accounts for 70–80% of dementia cases, affecting around 50 million individuals globally. This figure is anticipated to quadruple every 20 years, and by 2050, 131.5 million people worldwide will be afflicted by this preventable disease. The rate at which AD is spreading internationally is worrisome, with one individual succumbing to it every 3 s. Reports reveal that nearly 2 million people in Pakistan are living with AD. In 2015, the entire anticipated cost of addressing the disease worldwide was $818 billion. The cost entered in trillion dollars by 2018 and it will further rise to 2 trillion dollars by 2030 AD mainly affects older people, and it is often considered a normal aging process due to a lack of awareness. According to reports, Alzheimer's disease affects 3% of persons aged 65–74, 17% of those aged 75–84, and 32% of people aged 85 and more.

1.2. Purpose

Artificial intelligence (AI), particularly deep learning, allows algorithms to extract both known and unknown features from images for accurate detection of a condition, without the need for manual identification of specific features. Deep learning methods are widely used to perform multidimensional data analysis, to recognize images and to classify time series. These methods have been commonly applied to detect Alzheimer's disease (AD) from neuroimaging data. The potential genetic biomarkers of AD have also been explored by these deep learning techniques.

We aimed to develop a novel deep learning algorithm for automated detection of Alzheimer's disease-dementia from photographs alone to determine its possible use for Alzheimer's disease screening. To address this, we trained, validated, and tested the deep learning models using photographs from 4 different classes namely Mild Demented, Moderate Demented, Non Demented

and Very Mild Demented. We also tested the ability of our deep learning model to differentiate patients among the given classes.

2. Literature Survey

2.1 Existing Studies

Recent advances in technology, especially in terms of availability and usability, are broadening healthcare to a more ubiquitous paradigm, complementing the traditional hospital-centered approach with the possibility of collecting a great amount of information from the user's daily living or making personalized interventions. Specially related to dementia, sensor-based devices have the advantage of not requiring any interaction effort from the patient and therefore its application at home offers a wide range of possibilities, including assistance in basic daily living activities (as medication reminder systems) or safety monitoring, as the detection of falls [15] or leaving-bed episodes during night time [16].

In this way, wearable sensors have been explored for many different purposes. For instance, approaches based on tri-axial accelerometers have been proved to be useful not only for the detection of the occurrence of falls, which represent a major source of medical complications and disability in patients with dementia, but also for the estimation of risk of falls. In the work conducted by Gietzelt in a nursing home [17], data collected by a tri-axial accelerometer allowed to differentiate between patients with dementia who subsequently suffered falls from those who did not, raising the possibility of making estimations of individual fall risk.

Similar results were found by Van Schooten [18] in a sample of 319 non-demented older people. Another interesting potential use of wearable accelerometers is the monitoring of behavioral disturbances. Several works have shown that actigraphy is able to identify apathy, which constitutes one of the most frequent neuropsychiatric symptoms of AD [19–21].

Additionally, recent work showed the utility of accelerometry to distinguish dementia subtypes, including AD, Dementia with Lewy Bodies and Parkinson's Disease dementia, identifying significant differences in 7 estimated gait features [25].

Changes in gait parameters have also been explored as a risk factor for conversion to dementia in MCI patients. Gillain et al. [26] evaluated MCI patients were evaluated with a tri-axial accelerometer and followed up over time. Parameters such as gait speed, symmetry and regularity showed significantly lower values in those patients who subsequently developed dementia, suggesting that it could be considered as a marker of a worse prognosis. Apart from gait characteristics, changes in daily activity patterns are under actual research as a plausible AD biomarker and, in this sense, wearable devices offer the advantage of continuous and non-invasive monitoring.

One of the first works to show this was the work of Kirste et al. [27], who evaluated everyday motion behavior in 23 AD patients and their cognitively unimpaired partners through the data obtained by ankle-mounted tri-axial accelerometers. Both groups could be differentiated with a classification accuracy of 91%.

Interestingly, the scores in the Mini-Mental State Examination [28], a brief cognitive test frequently used to assess clinical progression in AD patients, were significantly correlated with motion features, which suggest a potential utility of this approach to identify the stage of the disease. Which exact features of daily motion behavior are characteristic of AD have not been elucidated yet, but intra-individual variability of physical activity was found to be significantly different between AD patients with mild-stage dementia and cognitively unimpaired elders in a similar work [29].

Furthermore, recent studies point to possible usefulness of accelerometry for preclinical AD detection. Circadian rhythm disturbances are a frequent finding in AD dementia and have also been evaluated with accelerometry [30], but they are not well known in the early stages of the disease. A recent work analyzed circadian rhythms using actigraphic data from 189 cognitively unimpaired participants who also underwent a study of AD biomarkers (cerebrospinal fluid analysis or amyloid PET), which allow the existence of preclinical AD to be defined [31].

Until now, accelerometry has been investigated as a way to detect the presence of AD, either in clinically affected subjects or in the preclinical state, but rarely to recognize different clinical stages, which would be of capital importance to identify clinical progression. Some previous works describe the classification of AD patients into three functional stages through the use of sensor-based devices [35] [36], but Convolutional Neural Networks have not been applied with Dementia staging purposes until now, having some reference examples that use similar systems to detect different diseases, like in El Maachi et al. [37] that propose a CNN-based method to detect Parkinson's disease analyzing gait data. Improving the results of the work of Nieto-Reyes et al. [35], Bringas et al. [38] gives a first approach to this problem using convolutional neural networks. In addition to introducing a preprocessing system for this data, the paper uses a fixed architecture and optimizes its parameters based solely on the accuracy, obtaining better and more balanced results than the previous methods used.

On this basis, our work will improve the results obtained so far, testing different architectures of several Machine Learning models and making an exhaustive search of hyperparameters. Particular emphasis is placed on 1D-Convolutional Neural Networks, as they gave the best results of all the tested models.

2.2 References

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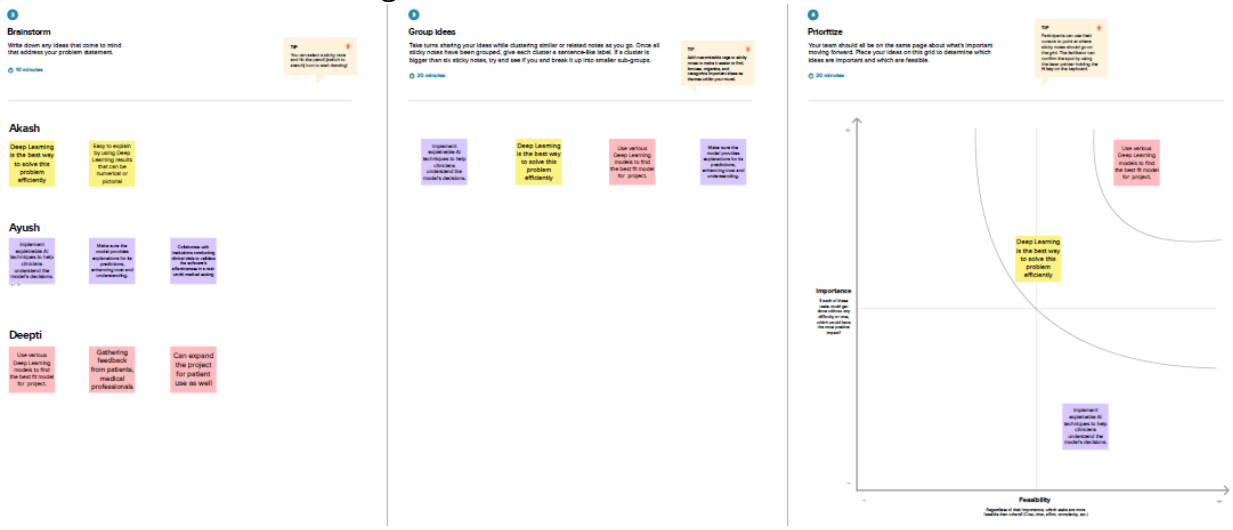
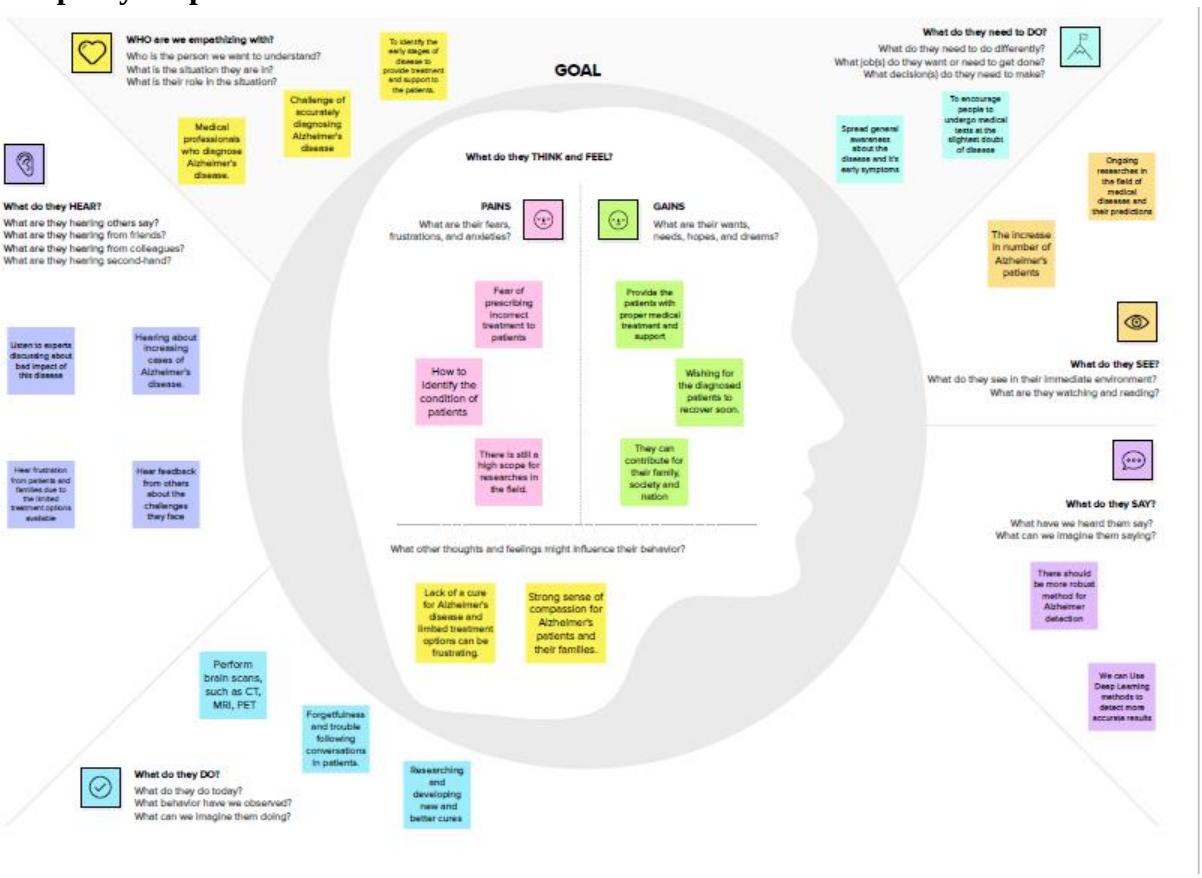
3. Ideation & Proposed Solution

3.1.Ideation & Brainstorming



3.2. Empathy Map Canvas

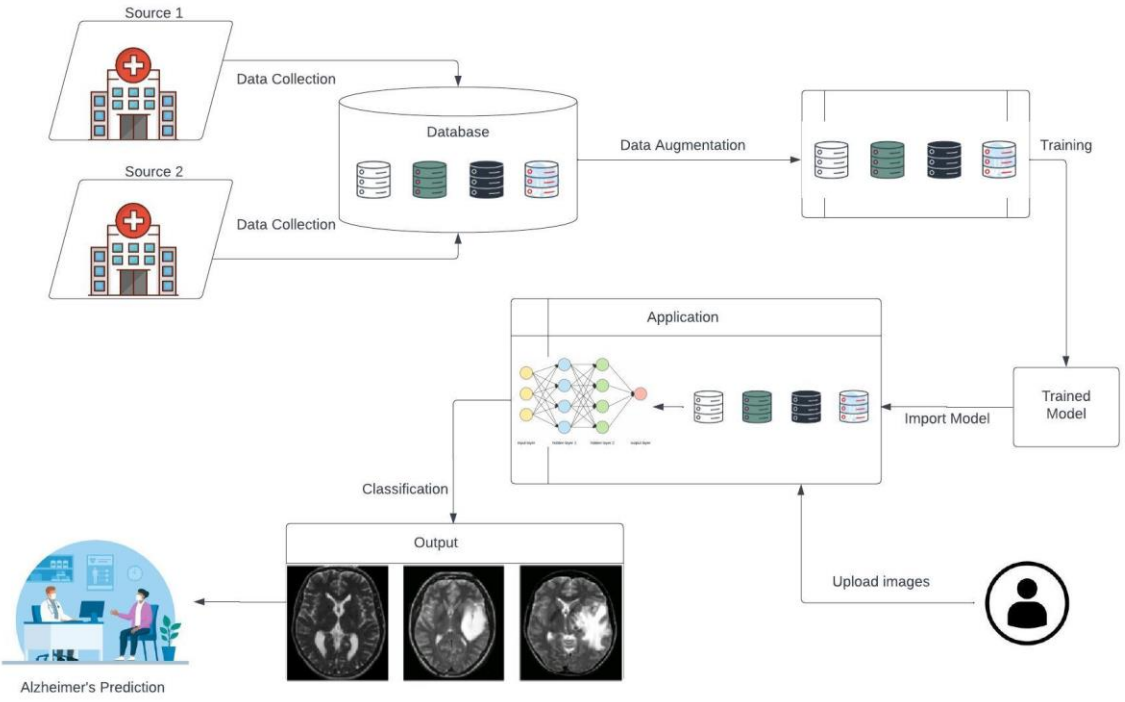


4. Requirement Analysis

OS	**Windows 1O or above**
CPU	**Intel i7**
RAM	**16GB**
GPU	**Provided by Colab**
Editor	**Google Colab**
Programming Language	**Python, HTML, CSS**
Python Libraries Used	**numpy, panda, tensorflow, sklearn**

5. Project Design

5.1. Data Flow Diagram & User Stories



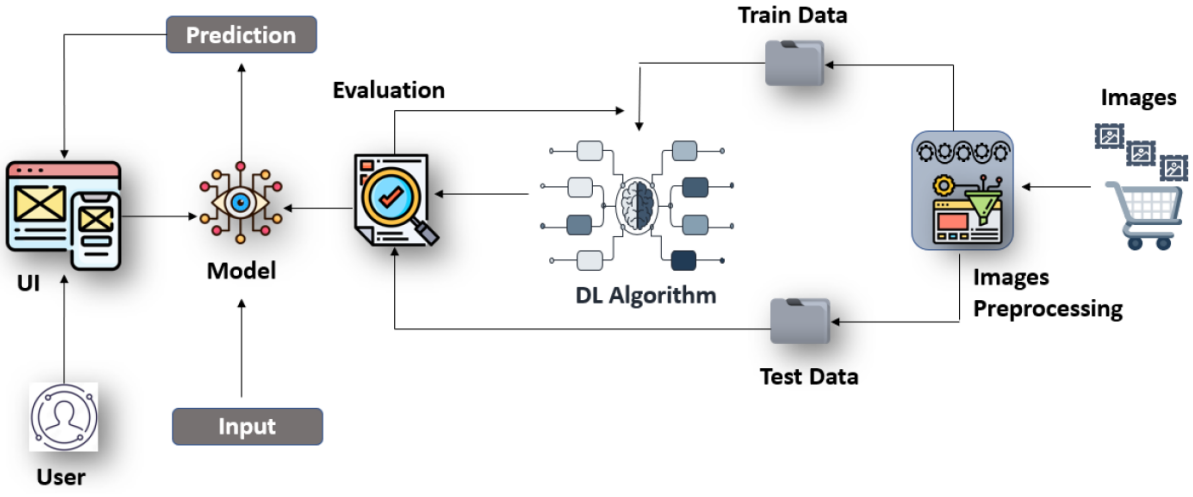
User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Medical Research Centers/ Hospitals	Project Setup & Infrastructure	USN-1	Plan for the real-world need of model. The targeted audience and their needs.	Successfully understood the real-world need of project.	High	Sprint-1
	Development environment	USN-2	Setup the development environment with the required tools and frameworks to start the Alzheimer's	Successfully configured with all necessary	High	Sprint-1

			Disease prediction project.	frameworks and tools		
Patients	Data collection	USN - 3	Gather a diverse dataset of images containing different medical images of brain (MRI, CT) for training the DL model	Gathered a diverse dataset of images	High	Sprint-2
Researchers	Data preprocessing	USN - 4	Preprocess the collected dataset by resizing images, normalizing pixel values, and splitting into training and validation sets.	Processed the collected dataset	High	Sprint-2
Administrator	Model development	USN-5	Explore and evaluate different deep learning architectures to select the most suitable model for Alzheimer's prediction.	We could explore various DL models	High	Sprint-3
Educational institiutes	Training	USN-6	Train the selected DL models using the preprocessed dataset and monitor its performance on validation dataset.	We could do validation	High	Sprint-3
	Testing	USN-7	Implement data augmentation techniques to improve the model's robustness and accuracy	We could do testing	Medium	Sprint-3

	Model deployment and Integration	USN-8	Deploy the trained DL model as an API or web service to make is accessible for Alzheimer's prediction, integrate the model's API into a user-friendly web interface for users to upload images and receive results	We could check the scalability of the model	Medium	Sprint-4
	Testing & quality assurance	USN-9	Conduct thorough testing of the model and web interface to identify and report any bugs or issues, fine-tune the hyperparameters and optimize the performance based on user feedback and testing results.	We could create a web application	Medium	Sprint-5

5.2. Solution Architecture



6. Project Planning & Scheduling

6.1 Technical Architecture

Table-1: Components & Technologies:

S.no	Component	Description	Technology
1.	User Interface	Web Based interface for user Interaction.	HTML, CSS, JavaScript
2.	Application Logic-1	Core Application Logic	Python , Flask ,Django
3.	Application Logic-2	Additional Application Logic	Python , Flask ,Django
4.	Application Logic-3	More Application Logic	Python , Flask ,Django
5.	Database	Store Structured Patient Data	PostGreSQL, MySQL , Other RDBMS
6.	Cloud Database	Cloud hosted Patient Data Service	Amazon RDS , Google Cloud SQL, Azure SQL
7.	File Storage	Repository For Unstructured Data	Amazon S3 , Google Cloud Storage,Azure
8.	External API-1	Integration With External Healthcare APIs	RESTful APIs , GraphQL
9.	External API-2	Integration With External Healthcare APIs	RESTful APIs , GraphQL
10.	Machine Learning Model	Core ML Model For Alzheimer's Prediction	Python, scikit-learn, Tensorflow , PyTorch
11.	Infrastructure (Server / Cloud)	Server/Cloud Hosting For the Application:	AWS , Google Cloud , Azure or other cloud.

Table-2: Application Characteristics:

S.no	Characteristics	Description	Technology
1.	Open-Source Frameworks	Utilizes Open- Source frameworks for development, facilitating collaboration and reducing costs.	Django, Flask, React, Angular
2.	Security Implementations	Implements robust security measures to safeguard patient data and maintain confidentiality	Encryption and access control Authentication.
3.	Scalable Architecture	Adopts a scalable architecture to accommodate a growing	Microservices, containerization and load balancing

		volume of patient data and users.	
4.	Availability	Ensures high availability for Uninterrupted access.	Redundancy, failover mechanisms, cloud provider features
5.	Performance	Optimizes system performance to provide timely results and a seamless user experience.	Caching, efficient, algorithms, hardware acceleration.

6.2 Sprint Planning & Estimation

Sprint	Functional Requirement (Epics)	User Story Number	User Story / Task	Story Point	Priority	Team Member
Sprint-1	Project Setup & Infrastructure	USN-1	Plan for the real-world need of model. The targeted audience and their needs.	1	High	Akash
Sprint-1	Development environment	USN-2	Setup the development environment with the required tools and frameworks to start the Alzheimer's Disease prediction project.	2	High	Ayush
Sprint-2	Data collection	USN - 3	Gather a diverse dataset of images containing different medical images of brain (MRI, CT) for training the DL model	2	High	Deepti
Sprint-2	Data preprocessing	USN - 4	Preprocess the collected dataset by resizing images, normalizing pixel values, and splitting into training and validation sets.	3	High	Akash
Sprint-3	Model development	USN-5	Explore and evaluate different deep learning architectures to	4	High	Deepti

			select the most suitable model for Alzheimer's prediction.			
Sprint-3	Training	USN-6	Train the selected DL models using the preprocessed dataset and monitor its performance on validation dataset.	5	High	Ayush
Sprint-3	Testing	USN-7	Implement data augmentation techniques to improve the model's robustness and accuracy	3	Mediu m	Deepti
Sprint-4	Model deployment and Integration	USN-8	Deploy the trained DL model as an API or web service to make is accessible for Alzheimer's prediction, integrate the model's API into a user-friendly web interface for users to upload images and receive results	1	Mediu m	Akash
Sprint-5	Testing & quality assurance	USN-9	Conduct thorough testing of the model and web interface to identify and report any bugs or issues, fine-tune the hyperparameters and optimize the performance based on user feedback and testing results.	1	Mediu m	Ayush

6.3 Sprint Delivery Schedule

Sprint	**Total Story Points**	**Duration**	**Sprint Start Date**	**Sprint End Date (Planned)**	**Story Points Completed (as on Planned End Date)**	**Sprint Release Date (Actual)**
Sprint-1	3	4 Days	16 Oct 2023	19 Oct 2023	3	19 Oct 2023
Sprint-2	5	6 Days	20 Oct 2023	25 Oct 2023	5	25 Oct 2023
Sprint-3	9	6 Days	26 Oct 2023	31 Oct 2023	12	31 Oct 2023
Sprint-4	1	3 Days	1 Nov 2023	3 Nov 2023	1	3 Nov 2023
Sprint-5	1	2 Days	4 Nov 2023	6 Nov 2023	1	6 Nov 2023

7. Coding & Scheduling

In the Alzheimer's Disease Prediction project, we have employed cutting-edge deep learning techniques, leveraging the powerful Xception model to revolutionize the diagnosis of Alzheimer's disease. The Xception model, an advanced convolutional neural network architecture, excels in capturing intricate patterns and features within medical imaging data, making it particularly well-suited for the nuanced complexities associated with Alzheimer's disease prediction. Our approach involved training the model on a meticulously curated dataset, carefully designed to encompass a diverse array of medical imaging samples relevant to Alzheimer's disease.

```
#Model building
xcept_model = Xception(input_shape=IMAGE_SIZE+[3], weights='imagenet', include_top=False)
```

+ Code + Text

```
with tf.device('/device:GPU:0'):
  for layer in xcept_model.layers:
    layer.trainable=False
```

```
with tf.device('/device:GPU:0'):
  # Creating sequential layers

  custom_inception_model = Sequential([
      xcept_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")
```

Through an iterative training process, the Xception model demonstrated exceptional learning capabilities, achieving an impressive training accuracy of 90.05%. This accuracy signifies the model's proficiency in discerning and learning complex patterns indicative of Alzheimer's disease within the training dataset. Equally significant is the model's ability to generalize its learned features to new, unseen data, attaining a robust validation accuracy of 85.91%. This validation accuracy underscores the model's reliability and effectiveness in making accurate predictions beyond the training set, demonstrating its potential for real-world applications. While predicting unseen images, the model gives a testing accuracy of 82.67%.

```
  train_scores = model.evaluate(train_data, train_labels)
  print("Training Accuracy: %.2f%%"%(train_scores[1] * 100))
```

```
205/205 [==============================] - 29s 88ms/step - loss: 0.2762 - accuracy: 0.9005 - precision: 0.9081 - recall: 0.8923 - auc: 0.9857
Training Accuracy: 90.05%
```

```
with tf.device('/device:GPU:0'):
  test_scores = model.evaluate(test_data, test_labels)
  print("Testing Accuracy: %.2f%%"%(test_scores[1] * 100))
```

```
64/64 [==============================] - 16s 83ms/step - loss: 0.4519 - accuracy: 0.8267 - precision: 0.8429 - recall: 0.8149 - auc: 0.9675
Testing Accuracy: 82.67%
```

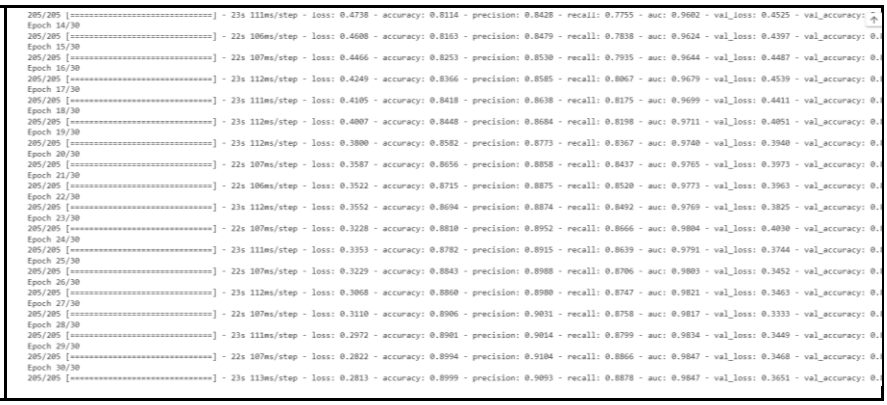
	precision	recall	f1-score	support
NonDemented	0.82	0.88	0.85	505
VeryMildDemented	0.99	0.97	0.98	522
MildDemented	0.73	0.80	0.76	495
ModerateDemented	0.77	0.66	0.71	526
micro avg	0.83	0.83	0.83	2048
macro avg	0.83	0.83	0.83	2048
weighted avg	0.83	0.83	0.83	2048
samples avg	0.83	0.83	0.83	2048

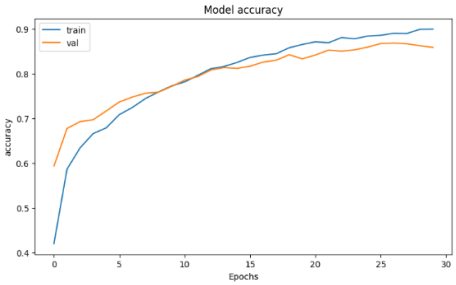
The success of our deep learning approach, as reflected in the high training and validation accuracies, positions the model as a promising tool for early detection of Alzheimer's disease. This achievement not only showcases the prowess of the Xception model but also signifies a significant step forward in the application of deep learning methodologies in clinical settings, where accurate and timely diagnoses can profoundly impact patient outcomes.

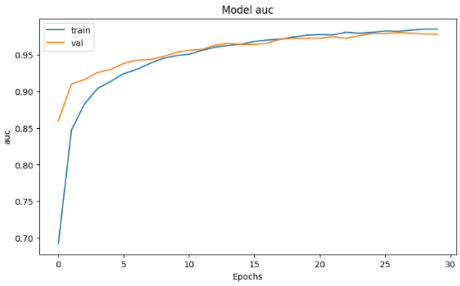
9. Performance Testing

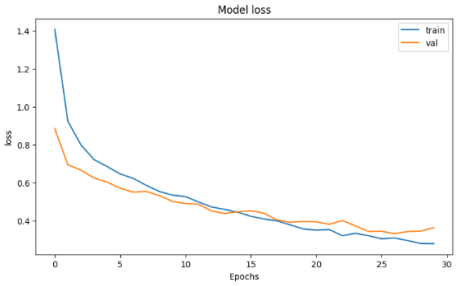
Model Performance Testing:

S.No	Parameter	Values	Screenshot
1.	Model Summary	**Total params: 2,20,95,340** **Trainable params: 12,27,844** **Non-trainable params: 2,08,67,496**	Model: "inception_cnn_model" _____ Layer (type) Output Shape Param # ===== xception (Functional) (None, 6, 6, 2048) 20861480 dropout (Dropout) (None, 6, 6, 2048) 0 global_average_pooling2d (GlobalAveragePooling2D) (None, 2048) 0 flatten (Flatten) (None, 2048) 0 batch_normalization_4 (Bat chNormalization) (None, 2048) 8192 dense (Dense) (None, 512) 1049088 batch_normalization_5 (Bat chNormalization) (None, 512) 2048 dropout_1 (Dropout) (None, 512) 0 dense_1 (Dense) (None, 256) 131328 batch_normalization_6 (Bat chNormalization) (None, 256) 1024 dropout_2 (Dropout) (None, 256) 0 dense_2 (Dense) (None, 128) 32896 batch_normalization_7 (Bat chNormalization) (None, 128) 512 dropout_3 (Dropout) (None, 128) 0 dense_3 (Dense) (None, 64) 8256 dropout_4 (Dropout) (None, 64) 0 batch_normalization_8 (Bat chNormalization) (None, 64) 256 dense_4 (Dense) (None, 4) 260 ===== Total params: 22095340 (84.29 MB) Trainable params: 1227844 (4.68 MB) Non-trainable params: 20867496 (79.60 MB) _____

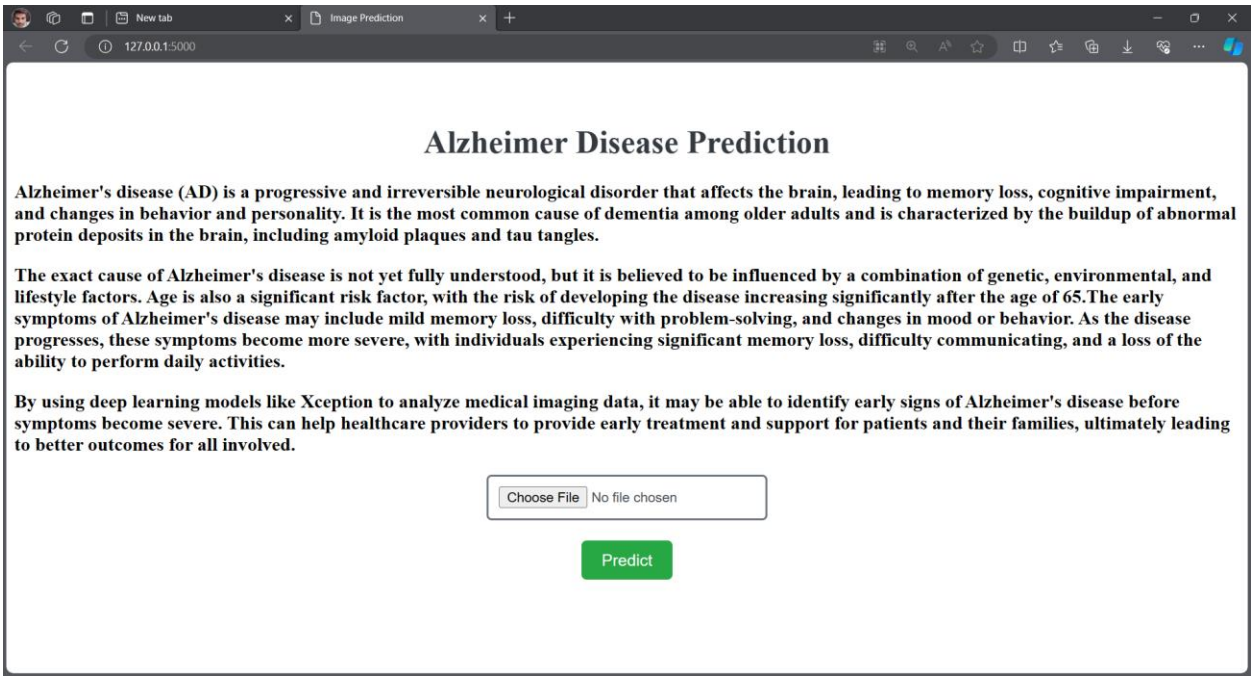
2.	Accuracy	Training Accuracy – 89.99 Validation Accuracy – 85.91	

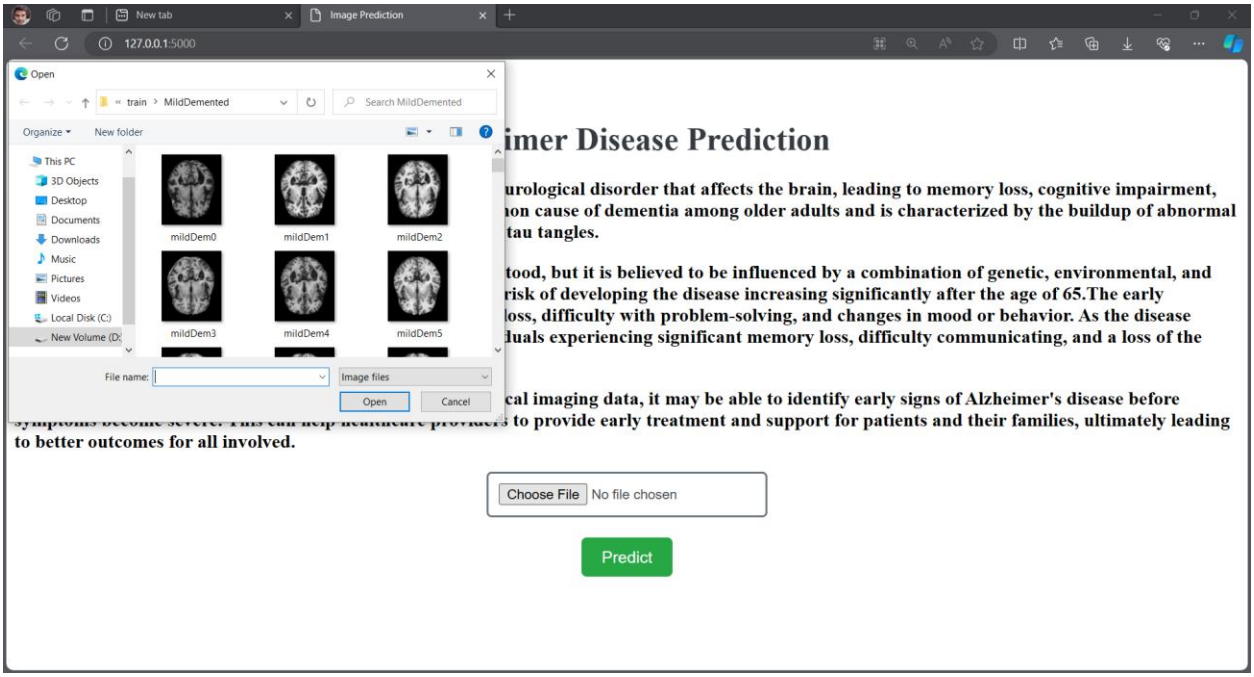


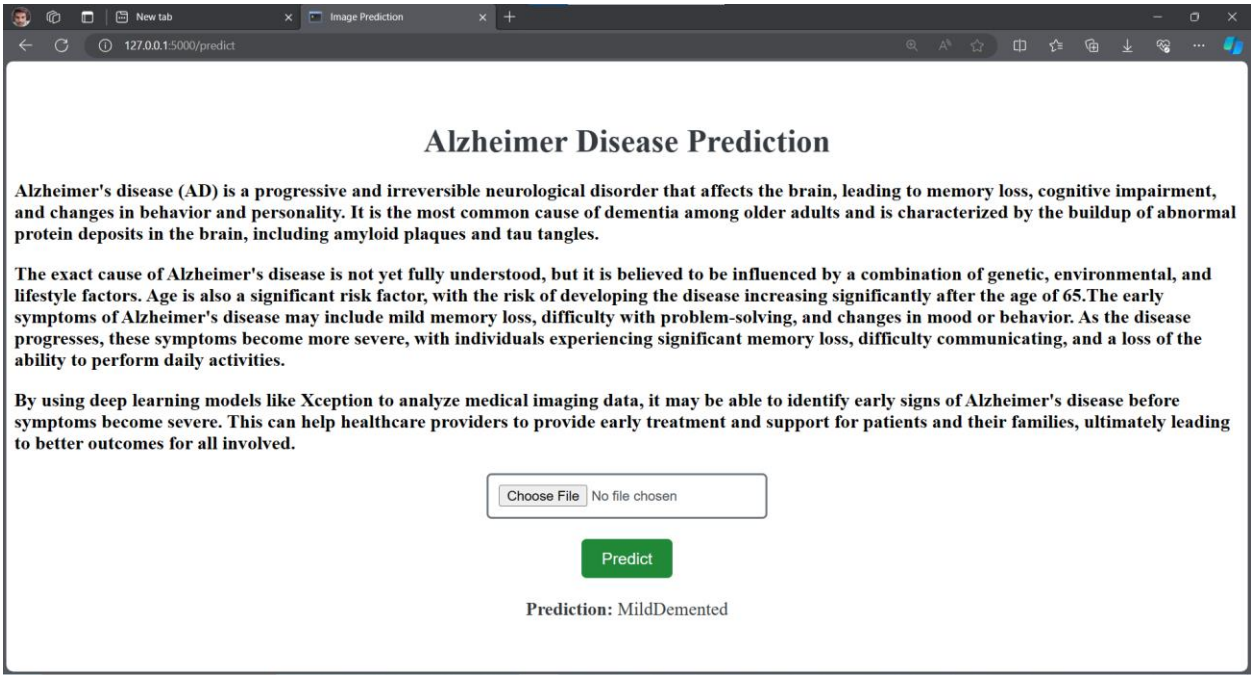




Results







10. Advantages & Disadvantages

Advantages:

1. The project enables early detection of Alzheimer's disease based on medical imaging data, allowing for timely intervention and treatment planning.
2. Early detection and prediction can lead to improved patient outcomes by enabling healthcare professionals to provide targeted care and support.
3. The system assists medical professionals, including neurologists and radiologists, in making more accurate and timely diagnoses, enhancing their decision-making process.

4. Patients and their families gain access to valuable information through detailed reports, fostering better understanding of the disease and empowering them to make informed decisions.
5. The platform supports collaboration among medical professionals, facilitating knowledge sharing and collective efforts in the field of Alzheimer's disease research.

Disadvantages:

1. Machine learning models may produce false positives or false negatives, leading to incorrect predictions and potential emotional distress for patients and their families.
2. The model's performance may be affected by biases in the training data, and the dataset may not be fully representative of diverse populations, potentially impacting the model's generalizability.
3. The system relies on the availability and quality of medical imaging data, and its effectiveness is contingent on the accuracy and relevance of the input data.
4. Training and maintaining machine learning models, especially complex ones like Xception, can be resource-intensive, requiring powerful hardware and computational resources.
5. Deep learning models, including those based on convolutional neural networks (CNNs), are often considered "black-box" models, making it challenging to interpret the rationale behind specific predictions.

11. Conclusion

The Alzheimer's Disease Prediction project represents a pioneering initiative in the realm of healthcare, employing advanced machine learning methodologies to transform the landscape of Alzheimer's disease diagnosis. Central to the project is the utilization of the Xception convolutional neural network model, a robust tool that analyzes medical imaging data to predict the likelihood of Alzheimer's disease in patients. By enabling early detection, the project empowers healthcare professionals to initiate interventions promptly and devise personalized treatment plans, ultimately contributing to improved patient outcomes. Beyond its clinical impact, the project fosters collaboration among medical professionals, providing a platform for knowledge sharing and contributing anonymized datasets for Alzheimer's disease research. Despite challenges inherent in machine learning models, such as interpretability and potential data biases, the project addresses these concerns through ongoing efforts in model transparency and rigorous data curation processes. Ethical considerations remain paramount, with a commitment to user privacy and security, ensuring compliance with healthcare regulations. In essence, the Alzheimer's Disease Prediction project signifies a pivotal stride toward more proactive and personalized healthcare, standing at the forefront of technological advancements in the quest to understand and combat Alzheimer's disease.

12. Future Scope

There are many future amendments that could be applied on the project to enhance the model performance and functioning. One can explore opportunities for refining the machine learning model to achieve even higher accuracy and robustness. This could involve experimenting with different architectures, incorporating additional data modalities, or leveraging advanced

techniques in transfer learning. Continuously enriching the dataset used for training the model to enhance its diversity and representativity. Collaboration with multiple healthcare institutions and the inclusion of longitudinal data could provide a more comprehensive understanding of Alzheimer's disease progression. Integrating the prediction system with electronic health records (EHR) to provide a seamless flow of information between the prediction platform and the broader healthcare ecosystem. This integration can enhance the continuity of patient care and facilitate more holistic assessments.

13. Project Links

Source code – https://colab.research.google.com/drive/1qUjE5RdRA47NH6D6IXeLEsKXC12sdYoT?usp=sharing

Github Link – https://github.com/smartinternz02/SI-GuidedProject-594307-1697559381

Project demo - https://drive.google.com/file/d/18H1_uCrjdMKXv7koY2dAB_WRif0EyKNa/view?usp=sharing