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DeepCNN-AD: Leveraging U-Net for Enhanced Alzheimer’s Disease Detection

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Abstract—Alzheimer’s disease (AD) is a long-term neurologicalillness that causes brain cell degeneration and irreversible cogni- tive impairment, as well as dementia. Deep learning and artificialintelligence developments have opened the door to creative usesin healthcare, such as the early identification and detection of brain disorders. The primary purpose of such a system is toenable early and accurate diagnosis, a critical factor in improvingpatient outcomes and quality of life. This technology providesthe possibility of precision medicine by utilizing deep learning algorithms to customize therapies for specific patients based on their distinct brain scans and medical histories. Additionally, automation and efficiency enhancements can reduce the burden on healthcare professionals, leading to faster and more effective diagnoses. However, ethical considerations related to patient privacy, data security, and algorithmic bias must be addressedas these systems become more prevalent. Interdisciplinary col- laboration between data scientists, neurologists, radiologists, and other healthcare professionals will remain pivotal in advancing these systems. In conclusion, Alzheimer’s detection system using deep learning offers a promising future for early diagnosis, precision medicine, and research in the field of neurology. Its potential impact on patient care and treatment outcomes is significant, making it a crucial area of development in healthcaretechnology.

Keywords—Alzheimer’s disease, Deep Learning, Convolu- tional Neural Networks (CNN).

I. INTRODUCTION

With the ageing population continuing to rise, Alzheimer’s disease—a degenerative and crippling brain disorder—presentsan increasing global health concern. Since there is currentlyno known cure, prompt and precise detection is essential forefficient management and intervention. Artificial intelligence(AI), and deep learning in particular, has become a potenttool in the field of medical diagnostics in recent years. Thisstudy investigates the creation of a novel deep learning-basedAlzheimer’s disease detection system with the goal of offeringa non-invasive, effective, and dependable early diagnosis tool. Cognitive decline, memory loss, and a variety of behavioural and psychiatric symptoms are hallmarks of Alzheimer’s dis-ease. Early detection is crucial because it enables prompt interventions that can halt the disease’s progression and en-hance the lives of those who are impacted. Neuroimaging methods including MRIs and PET scans, clinical evaluations,and cognitive tests have historically been used to diagnoseAlzheimer’s disease. These techniques, however, can be costly, time-consuming, and not always available in settings withlimited resources. Furthermore, a healthcare provider’s levelof competence frequently determines how accurate a diagnosisis made.

Artificial intelligence’s deep learning subfield has demon- strated great potential in pattern recognition and medical picture analysis. MRI and PET scans have been used to successfully diagnose and classify Alzheimer's disease, amongother medical imaging tasks that have been successfully tack- led by Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These deep learning models have the ability to lower human error, automate the diagnosingprocess, and provide an affordable early detection solution.

The design, development, and assessment of a novel deep learning-based Alzheimer's disease detection system are thor- oughly examined in this study report. In order to improve the precision and dependability of early diagnosis, the research makes use of a wide range of datasets that include brain imaging and related clinical data. The U-Net deep learning architecture, a specialised neural network model well-known for its efficacy in picture segmentation tasks, has been selectedfor this project.

This research aims to give medical practitioners a potent tool to help in the early diagnosis of Alzheimer's disease by utilising deep learning skills. The general public may be im- pacted by this work since prompt diagnosis can help afflicted people and their families make decisions and get the right medical attention and support systems. A glimmer of hope in the fight to enhance the quality of life for individuals impacted by this terrible illness is provided by the incorporation of deep learning into diagnostic procedures, as the globe struggles with the increasing prevalence of Alzheimer's disease.

II. Literature Survey

Alzheimer's disease, predominantly lethal in its later stages,poses a growing threat to the aging population. This survey explores the pivotal role of MRI scans in diagnosis, leverag- ing sophisticated classification algorithms like deep learning and machine learning. These advancements hold promise in enhancing our understanding of Alzheimer's progression, facilitating timely intervention and personalized treatment strategies.

Table I: Literature Survey

Sr. No.	Paper Name	Model	Accuracy	Advantages	Disadvantages	Year
1	Diagnosis and Detection of Alzheimer's Disease Using Learning Algorithm	CNN model	97.57%	High Accuracy, Scalibility, Transfer Learning, Automation	Data Requirements, Overfitting, False Positives and Negatives	2020
2	DeepCurvMRI: Deep Convolutional Curvelet Transform-Based MRI Approach for Early Detection of Alzheimer's Disease	CNN (Curvelet Transform)	98.62%	Enhanced Interpretability, Improved Robustness, Potential for Reduced Data Requirements	Complex Preprocessing, Model Complexity, Hyperparameter Tuning, Limited to Imaging Data, Poor Scalability	2023
3	Automatic Early Diagnosis of Alzheimer's Disease Using 3D Deep Ensemble Approach	CNN (3D CNN + DenseNet201)	70.33%	Enhanced Generalization, Improved Accuracy, Robustness, Interpretable	High Complexity, Increased Computational Resources, Hyperparameter Tuning, Deployment Complexity, Risk of Overfitting	2022
4	Computational Modeling of Dementia Prediction Using Deep Neural Network	Capsule Networks	92.39%	Hierarchical Feature Learning, Reduced Routing Overhead, Improved Generalization, Dynamic Routing, Interpretable Routing Weights	Limited Availability of Pretrained Models, Computationally Intensive, Complex Architectures, Lack of Standardization, Risk of Overfitting	2021
5	Resting State fMRI and Improved Deep Learning Algorithm for Earlier Detection of Alzheimer's Disease	Auto-encoder network	94.6%	Dimensionality Reduction, Anomaly Detection, Unsupervised Learning, InterpretableFeatures	Data Dependence, Overfitting, Limited to Data Representation, Sensitivity to Hyperparameters	2020

6	Alzheimer’s Disease Diagnosis using Deep Learning Approach	CNN (LeNet-5)	98.66%	Simplicity, Early Success, High Efficiency	Architectural Limitations, Overfitting, Inadequatefor Modern Datasets, Lack of Pretrained Models	2023
7	Deep Learning Framework for Alzheimer’s Disease Diagnosis via 3D-CNN and FSBi-LSTM	3D-CNN and FSBi-LSTM	94.83%	Utilizes spatial information effectively, Automatically extracts relevant features, Transfer learning can be applied	Computational complexity, Data Requirements, Overfitting, Interpretability, More Training Time	2019
8	Volumetric Feature-Based Alzheimer’s Disease Diagnosis From sMRI Data Using a Convolutional Neural Network and a Deep Neural Network	Hough-CNN	94.82%	Feature Extraction, Robustness, Interpretable Features	Limited to Geometric features, Manual tuning, Limited generalization, Computational cost, Data variability	2021
9	TriAD: A Deep Ensemble Networkfor Alzheimer Classification and Localization	CNN (TriAD)	95.18%	Improved Sensitivity and Specificity, Robustness, Early Detection , Clinical Relevance	Data availability, High Complexity, High Computational Resources, Interpretability, Overfitting, ValidationChallenges	2023
10	DEMNET: A Deep Learning Modelfor Early Diagnosis of Alzheimer Diseases and Dementia From MR Images	CNN (DEMNET)	95.23%	High Accuracy, Early Detection, High Efficiency, High Scalability	Data Requirements, Computational Resources, Overfitting, High Complexity, False Positives/Negatives Cost	2021

A convolutional neural network (CNN) based on curvelet transform (CT) called DeepCurvMRI was introduced to im- prove the accuracy of early AD detection using magnetic resonance imaging (MRI) pictures. After pre-processing the MRI data with CT, a CNN model was trained with the updated picture representation. The Alzheimer’s MRI image dataset, which was hosted on the Kaggle platform, was usedin this study to train DeepCurvMRI for binary and multiple classification tasks.

Five deep neural networks (DNNs) were investigated byYoon et al. Because U-Net demonstrated the most dependablesegmentation performance, the researchers chose it. Using thetest dataset, the framework showed an accuracy of 91.21% and83.% of the Dice coefficient score for atlas segmentation[17].Gamal et al. examined the performance of various catego- rization architectures before applying an ensemble learningtechnique to the best-performing models. By distinguishingbetween the three stages of the illness, the researchers also targeted the multiclass task [6].

Guo et al. distinguished between the evolution of a con- dition and normal ageing using a specialised network of autoencoders in an earlier diagnosis. This method combines efficiently biassed neural network functioning and enables a trustworthy identification of Alzheimer’s disease. With respectto traditional classifiers that rely on time series R-fMRI data, the suggested deep learning technique has shown notable advancements. The forecast model is more dependable and effective than traditional approaches, as evidenced by the team’s 94.6% accuracy [16].

Using the benefits of fully stacked bidirectional long short- term memory (FSBi-LSTM) and 3D-CNN architecture, Feng et al. created a novel deep learning framework. MRI images are used by the 3D-CNN architecture to extract deep feature representation. To further enhance its performance, FSBi- LSTM is used to the hidden spatial information from deep feature maps. With an accuracy of 94.82%, our techniqueis verified using the AD neuroimaging initiative (ADNI) dataset [14].

A system utilising CNN’s deep learning architecture(LeNet) was created by Pershiya et al. The MNIST dataset, which consisted of 28x28 MRI pictures, was utilised for testingand training. The network is known as Lenet-5 because it con-tains five layers of learnable parameters. It has been verified and tested, and its classification accuracy is 98.664% [2].

Basher et al. devised a technique for Alzheimer's dis- ease diagnosis that focuses on individual image slices using volumetric characteristics extracted from the left and righthippocampi in structural magnetic resonance imaging (sMRI) data. The suggested technique has shown mean weighted classification accuracies of 94.82% and 94.02%, respectively, based on recovered volumetric characteristics associated to theleft and right hippocampi [5].

Mercaldo et al. presented a method utilising a neural net- work they had constructed, named "TriAD", for the automaticdetection and localization of Alzheimer's disease. This neural network's ability to analyse three input MRI brain pictures simultaneously along the three reference planes—axial, coro-nal, and sagittal—is one of its noteworthy features. Combiningthese three evaluations produced exceptional quantitative re-sults: precise heatmaps for locating the region of interest insidethe photos, as well as accuracy, precision, and recall of 95%.The ADNI dataset [8] served as the training and testing dataset.Murugan et al. suggested the DEMNET method, which uses CNN to diagnose dementia and AD in their early stages usingMRI pictures. AD was categorised by the system into fourstages: non-demented (ND), very mildly demented (VMD),moderately demented (MOD), and mildly demented (MID).

The dataset from the Kaggle platform was used by the systemto obtain an accuracy of 95.23%[14].

To identify individuals with dementia, Lu et al. suggesteda novel multimodal deep neural network using a multistagemethod. This approach predicts mild cognitive impairment(MCI) with 82.4% accuracy, and in three years, it identifiespatients who will eventually develop Alzheimer's disease. Forthe class of people without Alzheimer's disease, the modelobtains an accuracy of 86.33% and a sensitivity of 94.23%[18].Using data from the ADNI and National Research Centrefor Dementia (NRCD) datasets, Gupta et al. brought forward adiagnostic technique for classifying Alzheimer's Disease (AD)by combining characteristics retrieved from MRI images in thecortical, subcortical, and hippocampus areas. The accuracy ofthis strategy in differentiating between the AD and Healthy Control (HC) groups is enhanced to 96.42% [19].

III. METHODOLOGY

A. Data Acquisition

The Alzheimer's disease dataset, which includes around6400 magnetic resonance imaging (MR) images classified into four categories—Mildly Demented (MID), ModeratelyDemented (MOD), Non-Demented (ND), and Very Mildly Demented (VMD), was collected from the open-access Kaggleplatform. The training data includes roughly 5000 MR images,while the testing data has approximately 1400 images. The original size of these images were 176 × 208. Below are the samples of the 4 data classes' images:

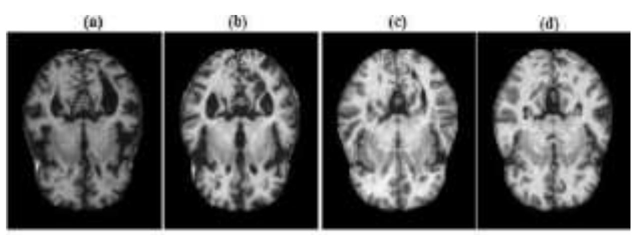

Fig. 1: (a)MID (b)MOD (c)ND (d)VMD

B. Image Preprocessing

When using deep learning to diagnose Alzheimer's disease,preprocessing MRI images is an essential step. The objectives are to improve image quality and extract pertinent features. The following are typical preprocessing activities:

- Image Resampling: MRI images may have varying reso- lutions. Resampling ensures consistent voxel sizes, mak- ing it easier for deep learning models to process them.

- Intensity Normalization: MRI intensities can vary be- tween scans. Normalization techniques such as z-score standardization can make the intensities comparable.

- Noise Reduction: Applying filters (e.g., Gaussian, me- dian) can reduce noise in the images.

- Contrast Enhancement: Adjusting the image contrast can highlight subtle features.

- Segmentation: Segmentation techniques can be used to identify and separate brain regions like gray matter, whitematter, and cerebrospinal fluid.

- Feature Extraction: Extract relevant features (e.g., texture,shape) from the preprocessed images to feed into the deep learning model.

It's essential to experiment and fine-tune these steps to op- timize the performance of your Alzheimer's disease detection model.

C. Deep Learning

Deep learning, a subdivision of artificial intelligence and machine learning, is characterized by its utilization of arti- ficial neural networks with multiple layers, allowing for the automatic extraction of intricate features from data. Deep learning models are typically trained through supervised learn-ing, where they learn to make predictions that closely alignwith labeled target data. This technology has found extensive application in various domains, ranging from computer vision (with convolutional neural networks) and natural languageprocessing (using recurrent neural networks) to speech recog- nition and autonomous vehicles. Notably, deep learning has produced groundbreaking results in tasks like image classifica-tion, object detection, machine translation, and even defeating human champions in complex games like Go. However, its success is contingent on access to sizable labeled datasets, significant computational resources, and the need for careful tuning and regularization techniques to mitigate issues like overfitting. Despite these challenges, deep learning remains at the forefront of modern artificial intelligence, driving innova- tions and solutions for complex real-world problems.

D. Convolutional Neural Network

An artificial neural network type that works especially well for computer vision and image recognition applications is called a convolutional neural network, or CNN or ConvNet. CNNs have also been used with other kinds of data, like sequences in tasks involving natural language processing. Theyare made to take in input data and automatically and adaptivelylearn the spatial hierarchies of characteristics. Here are some key concepts and components of CNNs:

1) Convolutional Layer: The convolutional layer is the fundamental component of a CNN. Convolutional op-erations involve sliding a small filter (also known as a kernel) over the input data, element-wise multiplying thevalues in the filter with the corresponding values in the input, and then summing up the results. This operationis used to detect patterns and features within the data.

2) Pooling Layer: Pooling layers are often used to reduce the spatial dimensions of the feature maps produced by convolutional layers. Popular pooling methods include max pooling, average pooling, and global pooling. Pool-ing helps in reducing the computational load and makingthe network more robust to variations in input.

3) Activation Function: After each convolutional and pool-ing operation, an activation function (typically ReLU - Rectified Linear Unit or sigmoid, tanh, Leaky RelU, etc)is applied to introduce non-linearity into the model. Thisnon-linearity allows CNNs to learn complex patternsand features and thus helps in improveing the overall accuracy.

4) Fully Connected Layer: ConvNets usually end with one or more fully connected layers. These layers perform traditional neural network operations and are responsiblefor making final predictions.

5) Convolutional Filters: Filters in convolutional layers arelearned during the training process. They capture various features in the input data, such as edges, textures, and more complex patterns, depending on their depth in the network.

6) Stride: Stride is a parameter that determines how the convolutional filter moves across the input data. A larger

stride reduces the spatial dimensions of the output, whilea smaller stride increases the output size.

7) Padding: Padding is often added to the input data beforeapplying convolution to ensure that the output dimensions match the input dimensions. Common paddingtypes include" valid" (no padding) and "same" (zero- padding to keep the output size the same as the input).

8) Weight Sharing: In CNNs, the same set of weights (filters) is used across different regions of the input data. This weight sharing allows the network to learn and recognize features irrespective of their location in the input.
In a wide range of computer vision applications, such as object identification, image segmentation, and image classification, CNNs have demonstrated remarkable success. They have greatly influenced the creation of artificial intelligence applications and are an essential part of cutting-edge modelsin these domains the feature maps' representations while decreasing their spatialresolution. Consequently, the capture of progressively abstractcharacteristics is achieved, which is similar to the functionof feedforward layers in traditional convolutional neural net- works. Conversely, the primary goal of the expansive path isto find the characteristics precisely and decode the encoded information while maintaining the spatial resolution of theinput. This path's decoder layers carry out extra convolutionaloperations in addition to upsampling the feature maps. In order to help the decoder layers achieve more precise feature localization, the skip connections from the contracting pathare essential in preserving spatial information lost during the contraction process.

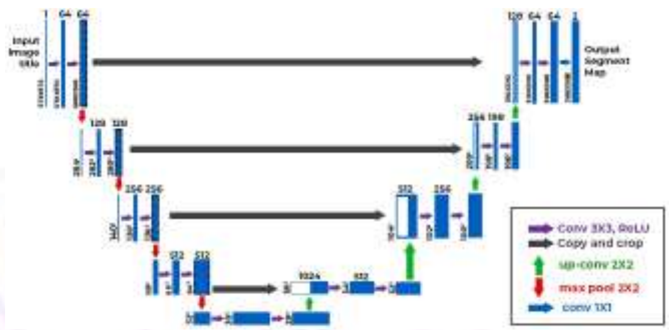

Fig. 3: UNet Architecture

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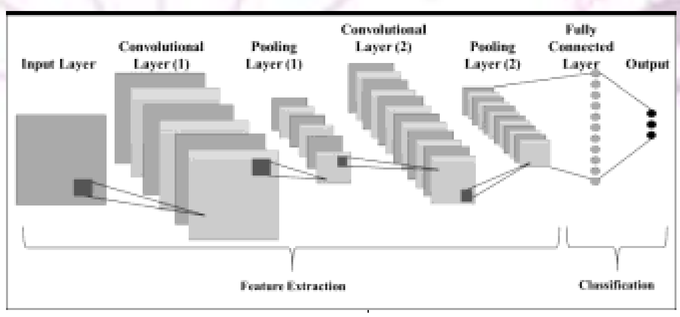

Fig. 2: Convolutional Neural Network

E. UNet Architecture

Originating from the traditional convolutional neural net- work, UNet was first created and utilised in 2015 for thepurpose of analysing images related to medicine. Olaf Ron- neberger, Philipp Fischer, and Thomas Brox presented it in their paper "U-Net: Convolutional Networks for Biomedical Image Segmentation" from 2015. In biomedical circumstances,determining the existence of a disease is not enough. Theyalso need the aberration to be precisely located. UNet is designed expressly to tackle this problem. Because it performspixel-wise classification, which ensures that the input and output remain the same dimensions, it is able to recogniseand pinpoint borders.

Because of its unique design, which combines an expandingpath and a contracting path, the U-Net architecture distin-guishes out. The encoder layers that make up the contracting path are in charge of gathering contextual data and reducing the input's spatial resolution. The expanding path, on the otherhand, has decoder layers that are responsible for decodingthe encoded data. These decoder layers build a segmentation map by using skip connections to access data from the contracted path. During the U-Net's contraction phase, the focus is on identifying relevant elements in the input picture. Convolutional techniques are used to do this, strengthening

F. *Output Classification*

The model classifies the brain MRI images into any ofthe 4 classes viz. Mild Demented, Moderate Demented, Very Mild Demented, Non-Demented based on the degenerationof various regions in the brain including Hippocampus and Amygdala.

IV. System Architecture And Workflow

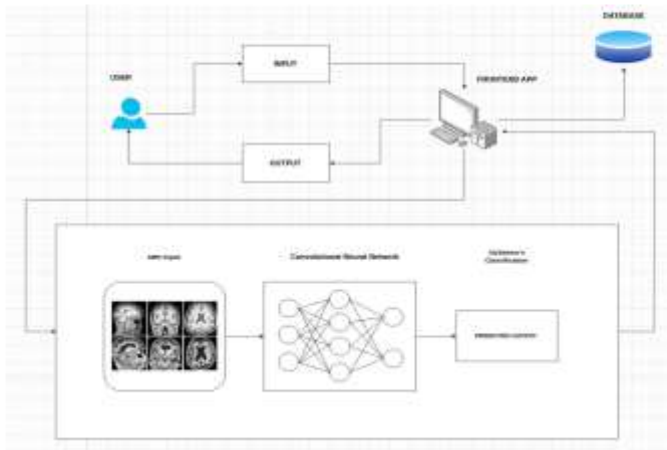

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Fig. 4: System Architecture

A. Frontend React WebApp

To obtain the results, the user would be able to upload an MRI image of their brain using the react web application.After that, the input image would be transferred to the backendserver and stored there as well. There, the CNN model would perform the detection and classification, returning the resultsto the frontend application for the user to view.

B. Backend

The CNN model (based on the U-Net architecture) on the backend processes the input image from the user and classifiesit accordingly into any of the 4 classes viz. MID, MOD, VMDand ND. It then sends the output to the frontend app for the user to see the results.

I. IMPLEMENTATION

A. Data Preprocessing

- **Rescaling the images**: MRI scans can have varying pixel intensity ranges. To ensure consistency and improve model training, we rescaled all images to a common range. We used normalization method(normalization be- tween 0 and 1) to achieve this. We successfully rescaled the images to the size 224x224.

- **Data Augmentation**: Since our dataset was unbalanced, we artificially expanded it using data augmentation tech- niques. This helped the model learn from a wider variety of image variations potentially encountered in real-world scenarios. We applied various augmentation techniques such as random flipping (horizontal/vertical), random rotations, random zooming.

- **Deep Learning Model**: Technologies: TensorFlow, Keras(Unet model) Description: We implemented a Unet model using TensorFlow and Keras. Unet is a well-suited archi- tecture for medical image segmentation tasks like ours. We configured the U-net model with 19 convolutional layers and used ReLU activation function. During train- ing, we experimented with different hyperparameters likelearning rate and optimizer (e.g., Adam) to achieve the best possible accuracy.

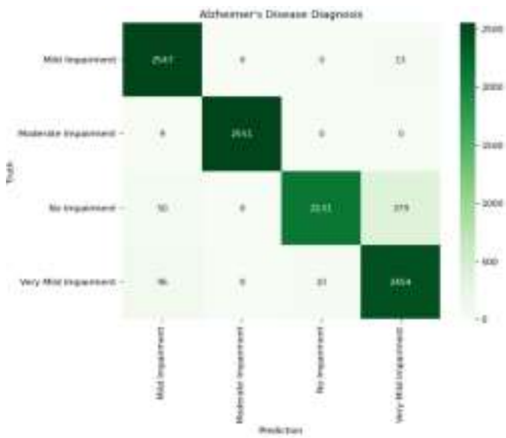

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Fig. 6: Heat map

V. Results

– 1. **Model Performance**: - Evaluation Metrics: Wechose different metrics to evaluate our model's per- formance. These included accuracy, precision, recall,and F1 score. - Quantitative Results: We got an accuracy of 0.5, precision of 0.4, recall of 0.5 and f1-score of 0.4.

– 2. **Impact of Experimentation**: Data Augmentation: Data augmentation caused a slight increase in model accuracy. It did not have a significant impact ongeneralization and robustness of the model.

– 3. **Limitations and Future Work**: Limitations: A ma- jor factor was the limited dataset size, challenges with class imbalance, or the inherent difficulty of medical diagnosis using a single modality (MRI scans). Future Work: Aim to improve accuracy by optimizing the model for future development. This might involve: Collecting a larger and more diverse dataset. Exploring other deep learning architectures or incorporating additional modalities for a more comprehensive diagnosis. Refining the user interfacefor better usability and interpretability of results.

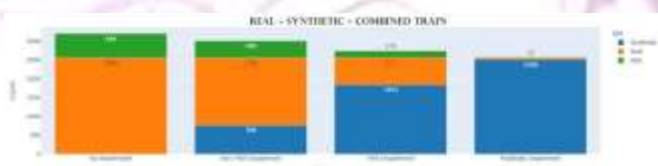

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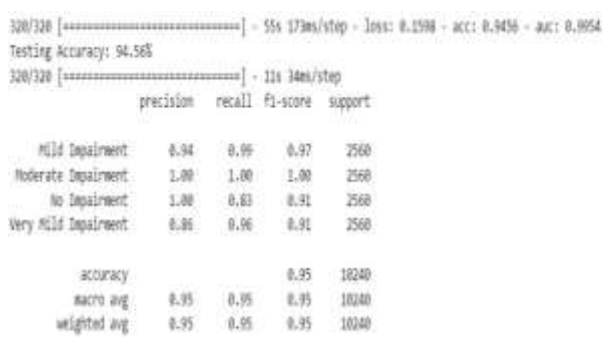
Fig. 5: Dataset Distribution

• Heat maps play a crucial role in the context ofAlzheimer's disease detection using the U-Net archi- tecture and deep learning techniques. It helps in the visualization of model attention, Interpretability, explain-ability, and diagnostic support. Heat map enabled themodel for the identification of disease progression, modelvalidation, and debugging.



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320/320 [==============================] - 55s 173ms/step - loss: 0.1598 - acc: 0.9456 - auc: 0.9954
Testing Accuracy: 94.56%
320/320 [==============================] - 11s 34ms/step
                      precision    recall  f1-score   support

     Mild Impairment       0.94      0.99      0.97      2560
 Moderate Impairment       1.00      1.00      1.00      2560
       No Impairment       1.00      0.83      0.91      2560
Very Mild Impairment       0.86      0.96      0.91      2560

            accuracy                           0.95     10240
           macro avg       0.95      0.95      0.95     10240
        weighted avg       0.95      0.95      0.95     10240
```

Fig. 7: Model Results

VI. Future Scope

– Model Enhancement: Incorporating advanced tech- niques like attention mechanisms and transformersto improve accuracy and robustness.

– Clinical Integration: Implementing the model intoclinical workflows for real-time diagnosis support.

– Multi-Modal Data: Integrating MRI, PET scans, and clinical data for a comprehensive assessment.

– Longitudinal Studies: Adapting the model for ana- lyzing disease progression over time for early inter- vention.

– Collaborative Research: Encouraging data sharingand collaboration to foster innovation.

– Regulatory Approval: Addressing ethical and regula-tory considerations for AI deployment in healthcare.

VII. Conclusion

In conclusion, considering the rising global burden ofthis debilitating illness, we have seen the growing significance of early and precise Alzheimer's detection. With its capacity to handle deep learning has developed intoa highly promising technique that can analyze massive quantities of data and spot subtle patterns that may be early indicators of Alzheimer's. The examined research emphasises how deep learning algorithms can be usedto better utilise clinical, genetic, and neuroimaging data, among other forms of medical data, to increase predictionand diagnostic accuracy.

Our proposed methodology and system architecture rep- resent a significant step toward saddressing the challenges associated with Alzheimer's detection. By building upon the existing knowledge and innovations in this field, we aim to contribute to the ongoing efforts to develop more effective diagnostic tools. While the full implementation and validation of our proposed approach are beyond the scope of this research paper, we believe that it holdspromise for future research and application.

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