MULTIPLE DISEASE DETECTION IN HUMAN USING DEEP LEARNING

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ABSTRACT

As progress in medical technology and artificial intelligence continue to shape the healthcare landscape, this project presents a comprehensive solution for multiple disease detection in humans. Focusing on the integration of deep learning techniques, specifically CNNs, the project introduces a web-based platform designed to streamline the diagnostic process for brain tumour and Alzheimer's disease [1] [2]. *The system incorporates a user-friendly interface accessible to both healthcare professionals and patients. Patients can select the specific disease category (brain tumour or Alzheimer's), and input detailed information including personal data, symptoms, medical history, and crucially, MRI images. For healthcare professionals, the platform provides a centralized portal allowing them to access and analyse patient information securely. The deep learning models, trained on extensive datasets, facilitate accurate and rapid disease prediction based on the provided MRI images. This predictive capability empowers healthcare and treatment plans. The system further supports efficient communication between healthcare professionals and patients, enabling appointment scheduling based on the severity and urgency of the diagnosed condition.*

KEYWORDS: *Brain Tumour and Alzheimer's Detection.*

1. INTRODUCTION

The intersection of healthcare and technology has brought forth a period of transformative possibilities, especially in the domain of disease detection. As medical diagnostics evolve, the integration of deep learning techniques presents a promising avenue for enhancing accuracy and efficiency. This research introduces a web-based solution focused on multiple disease detection, with a specific emphasis on brain tumour and Alzheimer's disease.

In contemporary healthcare, timely and accurate diagnosis is paramount for effective patient care. The conventional methods of disease detection, while valuable, often face limitations in terms of speed and precision. This project seeks to address these challenges by harnessing the power of deep learning, specifically through the implementation of CNN [3].

The backbone of our disease prediction system lies in the utilization of CNNs, trained on extensive datasets to accurately analyze and interpret MRI images. This predictive capability equips healthcare professionals with a rapid and informed assessment of a patient's condition, facilitating prompt decision-making and personalized treatment plans.

By presenting a holistic approach to multiple disease detection, this contributes to the advancement of medical diagnostics and integration of deep learning in healthcare solutions.

2. RELATED WORKS

The exploration of existing literature is paramount to contextualize and build upon the foundations of this research. In this section, we present a comprehensive overview of related work that has significantly Detection in Human using Deep Learning. By critically analyzing and synthesizing findings from various studies, we aim to identify gaps, challenges, contributed to the understanding of Multiple Disease and opportunities that motivate the current investigation. The selected works showcase a diverse range of methodologies and perspectives, providing valuable insights that inform the development and refinement of our research objectives. Through this examination, we establish a robust foundation for our study and contribute to the ongoing discourse within the field of Deep Learning.

Dheiver Santos et al. 2022 [4], approaches the technology of MobileNets, in this they used ANN Model for training and testing data, this model gets 89% of test accuracy and further can be increasing with respect to increasing data.

In this paper [5] 2020, Abhinav Saurabh et al. proposed predicting multiple disease detection using deep learning, in this they proposed a CNN model that reached the accuracy upto 97.84% malaria prediction, 88.7% while predicting for brain tumor and 97.4% for retinal Oct.'s.

Prajakta Tambe et al.2021 [6], has proposed a paper on Deep Learning techniques for effective diagnosis of Alzheimer's disease using MRI images, in this research paper they used 8192 MRI images dataset, The initial training phase involved 40 epochs, resulting in a loss of 0.0934 and a categorical accuracy of 0.9643 for the training dataset, The subsequent exploration of Transfer Learning incorporated ResNet50; however, the model's underwhelming performance, with a training loss of 0.9700 and categorical accuracy of 0.5541, VGG19, another Transfer Learning-based model, demonstrated better results, with a training loss of 0.2194 and a categorical accuracy of 0.9138.

Ercan AVŞAR et al. 2019, in their research paper [13], proposed the use of the R-CNN classifier to expedite both testing and training processes. The dataset consisted of 3,064 MRI images, with 2,452 images utilized for training the model. They reported an impressive 91.66% classification accuracy on the training set. Their conclusion emphasized that the R- CNN algorithm is well-suited for achieving the highest accuracy in this context.

We have summarized all the research papers and read, and the techniques employed by other researchers mentioned in these papers in Table 1.

Table 1: accuracy results in related work methods and the proposed method.

Author	Year	Algorithms	Dataset used	Accuracy
Dheiver Santos, Ewerton Santos	2022	ANN	3,762 MRI images	89.00%
Abhinav Saurabh, Adyasha Sahu, C. Vijayakumaran	2020	CNN model	8000 cell images for Malaria, 6210 images retinal oct and 7022 images of brain tumor	97.84% for malaria prediction, 97.4% for retinal Oct and 88.7% for brain tumor.
Prajakta Tambe, Rutuja Saigaonkar, Nidhi Devadiga, Ms. Pallavi H. Chitte	2021	CNN ResNet50, VGG19, Transfer Learning	8192 MRI images	VGG19: 91.38% Resnet50: 55.41% CNN : 96.43%
Ercan AVŞAR, Kerem SALÇIN	2019	R-CNN	2,452 images	91.66%

3. FUTURE SCOPE

3.1 Expansion of Disease Coverage: the scope of the project can be expanded to include detection capabilities for a wider range of diseases beyond brain tumors and Alzheimer's. This expansion could encompass various cancers, cardiovascular diseases, infectious diseases, and more. By training the deep learning models on diverse datasets specific to each disease.

3.2 Real-Time Monitoring and Prognosis: The future development of real-time monitoring features can enable continuous tracking of disease progression and treatment efficacy. By analyzing temporal patterns in patient data over time, the platform can offer personalized prognostic assessments, allowing healthcare providers to adjust treatment plans accordingly and improve patient outcomes.

3.3 **Enhanced Interoperability and Integration:** Strengthening interoperability with existing healthcare systems and electronic medical records (EMRs) can facilitate seamless data exchange and integration. By interoperating with EMRs, the platform can access historical patient data, facilitating longitudinal analysis and enhancing diagnostic accuracy.

3.4 **Mobile Application Development:** Developing a mobile application version of the platform can extend accessibility to patients, enabling them to input data and communicate with healthcare providers conveniently from their smartphones. A mobile app can enhance patient engagement and empower individuals to take a more proactive role in managing their health.

3.5 **Continuous Improvement and Optimization:** Continuously refining and optimizing the deep learning models through iterative training with new data and feedback from users can ensure ongoing improvement in diagnostic accuracy and performance. By staying abreast of advancements in deep learning research and healthcare technology, the platform can evolve to meet the evolving needs of patients and healthcare providers.

4. IMAGE PROCESSING METHODS

The integration of image processing methods [7] is fundamental to the success of the multiple disease detection system, particularly in the analysis of medical images such as MRI scans. Steps that are used for image processing method are shown in Figure 1.

The following outlines the key stages involved in image processing within the context of disease detection:

4.1 Scanned Image Acquisition:

Purpose: Obtain high-quality scanned images, typically MRI scans, for subsequent processing.
Workflow:

- Patients undergo MRI scans as part of the diagnostic process.
- The resulting digital images are stored securely in the system.

4.2 Preprocessing:

Purpose: Enhance the quality and clarity of the scanned images, mitigating artifacts and noise.
Workflow:

- Apply noise reduction techniques to minimize interference.
- Correct for any distortions or inconsistencies in the scanned images.

4.3 Segmentation:

Purpose: Identify and delineate specific regions or structures of interest within the medical images.
Workflow:

- Utilize segmentation algorithms to isolate relevant anatomical structures.
- Segment brain regions for brain tumor detection or specific regions for Alzheimer's analysis.
- Create a precise delineation of areas for further analysis.

4.4 Feature Selection:

Purpose: Extract relevant features from the segmented regions to characterize disease-specific patterns.
Workflow:

- Identify distinctive features such as shape, texture, and intensity.
- Use feature extraction techniques to capture meaningful information.
- Select features that are discriminative for disease identification.

4.5 Classification:

Purpose: Use machine learning methods to analyze images, extracting important features to identify the presence or absence of diseases.

Workflow:

- Train a classification model (e.g., Support Vector Machines, Random Forests) using a labeled dataset.
- Utilize the selected features as input to the trained model.
- Classify images into disease categories (e.g., brain tumor, Alzheimer's).
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4.6. Detection of Disease:

Purpose: Determine the likelihood and severity of diseases based on the classification results.

Workflow:

- Establish threshold values to interpret the output probabilities from the classification model.
- Generate predictions indicating the presence or absence of diseases.
- Provide healthcare professionals with actionable information for diagnosis anddecision-making. Classify images into disease categories (e.g., brain tumor, Alzheimer's).

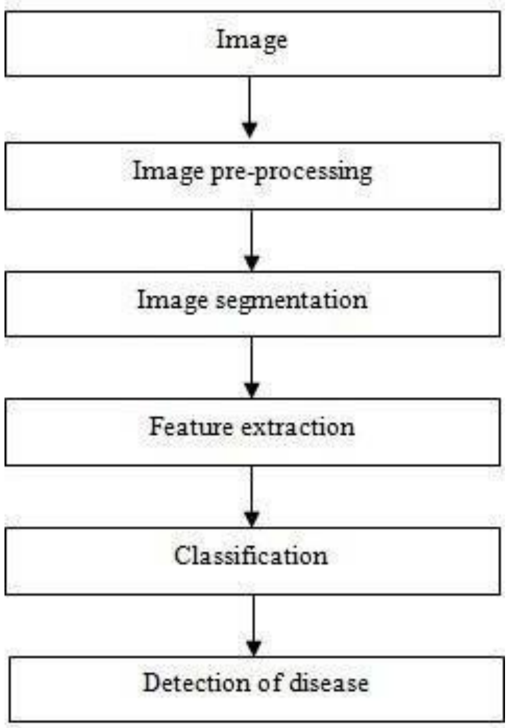

Figure 1: Steps of Digital Image Processing

5. MATERIALS AND METHODS

5.1 Dataset:

- **Brain Tumor** [8]**:** The dataset for brain images consists of 2,947 MRI images, showcasing four distinct types of brain tumors: meningioma, glioma, pituitary, and images without tumor(no-tumor). Figure 2 display sample images from each of these classes, providing a visual representation of what these different tumor types look like. Additionally, Table 2 outlines the distribution of images across the various tumor types, offering a numerical breakdown of how many images belong to each category. This information helps us understand the composition of the dataset and the prevalence of different tumor types within it.

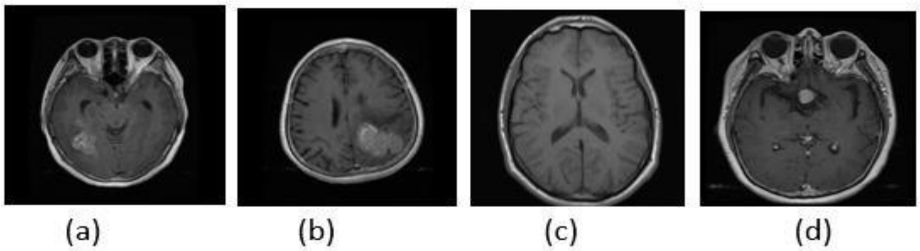

Figure 2: Image containing different types of brain tumors: (a) glioma, (b) meningioma, (c) no-tumor (d) pituitary

Table 2: four classes of brain tumor

Tumour Type	Number of Images
Glioma	775
Meningioma	900
Pituitary	802
No-tumor	470
Total:	**2947**

- **Alzheimer's:** The dataset for Alzheimer's images consists of 6,400 MRI images, featuring four distinct types related to Alzheimer's disease: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. In Figure 3, you can find sample images illustrating each of these classes, giving a visual representation of what different Alzheimer's types look like in the MRI scans. Additionally, Table 3 provides information on the distribution of images across these Alzheimer's types, offering a breakdown of how many images belong to each category. This breakdown helps us understand the composition of the dataset and the prevalence of different Alzheimer's types within it.

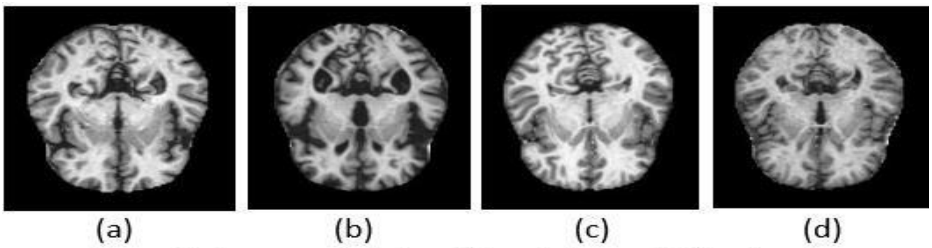

Figure 3: Image containing different types of Alzheimer's: (a) MildDemented, (b) ModerateDemented, (c) NonDemented and (d) VeryMildDemented

Table 3: four classes of Alzheimer's

Alzheimer's Type	Number of Images
MildDemented	896
ModerateDemented	64
NonDemented	3200
VeryMildDemented	2240
Total:	**6400**

5.2 Training:

i) **Brain Tumor:** We have a dataset of images related to brain tumors. To train our computer model, we randomly selected 90% of these images. We made sure to pick an equal number of images from each type of brain tumor to avoid bias. The remaining 10% of images are set aside to test how well our model works [9]. Here are some key details about how we trained the model: No. of iteration:20 (how many times it learns from the data), Softmax_neuron:4, Max-Pooling: Kernel Size- 2x2 (focuses on 2x2 pixel areas) and Stride-2.

ii) **Alzheimer's:** We randomly chose 90% of images for training, making sure to have an equal mix of different cases. The remaining 10% is kept for testing the model. We used a faster CNN for analysing the images. Here are some key details about how we trained the model: No. of iteration:20 (how many times it learns from the data), Softmax_neuron:4 (representing different outcomes), Max-Pooling: Kernel Size- 2x2 (focuses on 2x2 pixel areas) and Stride-2 (skips every other 2x2 area).

5.3 Methodology:

In the field of analyzing medical images, developing a CNN for detecting two specific diseases, brain tumors and Alzheimer's, marks a significant progress in automating diagnostic procedures. The CNN architecture is organized with sequential convolutional layers [10], using rectified linear units (ReLU) to activate features, pooling for downsizing, and flattening to transition to fully connected layers (refer to Fig. 4). This structure empowers the network to identify intricate patterns within medical images, enhancing its ability to make accurate predictions about diseases.

The model is designed to handle a diverse dataset, including different types of brain tumors (glioma, meningioma, pituitary tumor, and cases without tumors) and various stages of Alzheimer's disease (MildDemented, ModerateDemented, Non-Demented, VeryMildDemented). Before training, the dataset undergoes preprocessing, shuffling, and splitting into training and testing sets to ensure a thorough evaluation of the model's performance. During training, the Adam optimizer is used, and the categorical cross-entropy loss function is employed. These choices help fine-tune the model's parameters over multiple iterations, improving its ability to accurately classify and predict outcomes.

The research focuses on combining advanced image processing methods with deep learning in the CNN framework. This approach is designed to address both brain tumors and Alzheimer's disease. The flexibility of CNNs in learning complex disease-related patterns from medical images is crucial for accurate disease prediction. Ethical considerations, especially regarding patient privacy, are fundamental to the research. The overarching objective is to leverage CNNs to significantly improve disease detection, enhancing diagnostic capabilities, and providing personalized patient care for various stages of both brain tumors and Alzheimer's disease.

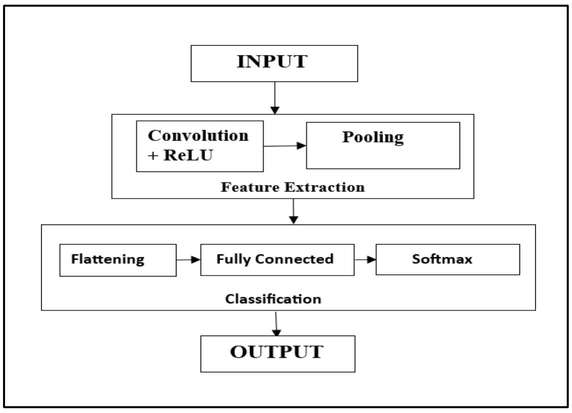

Figure 4: Structure of CNN

6. EXPERIMENTAL RESULT ANALYSIS

6.1. Brain Tumor: Figures 5 and 6 show how well our CNN model performed when applied to both the training and test datasets over twenty rounds of learning [11]. After training the model for twenty rounds, we observed the following results:

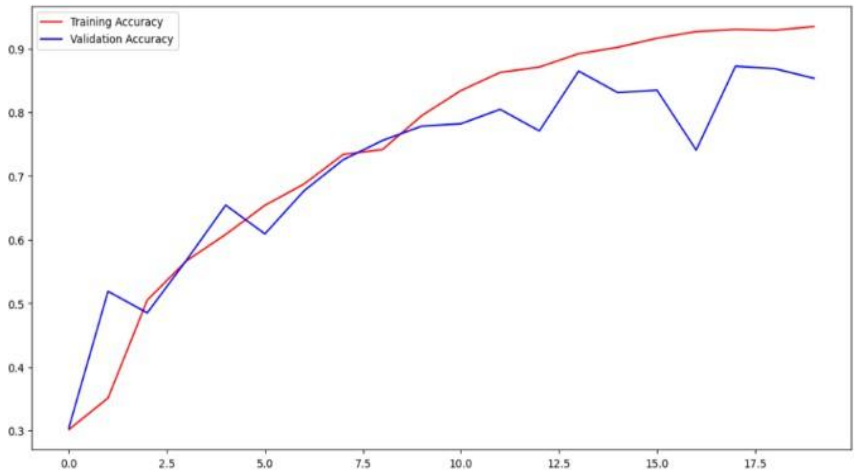

Figure 5: comparing training/Validation accuracy

In the fig. 5, it shows that training and validation accuracy for 20 epochs, in this graph red line represents validation accuracy and blue line represents the training accuracy. Using CNN, in this we achieved training accuracy: 93.46% and validation_accuracy:85.34%.

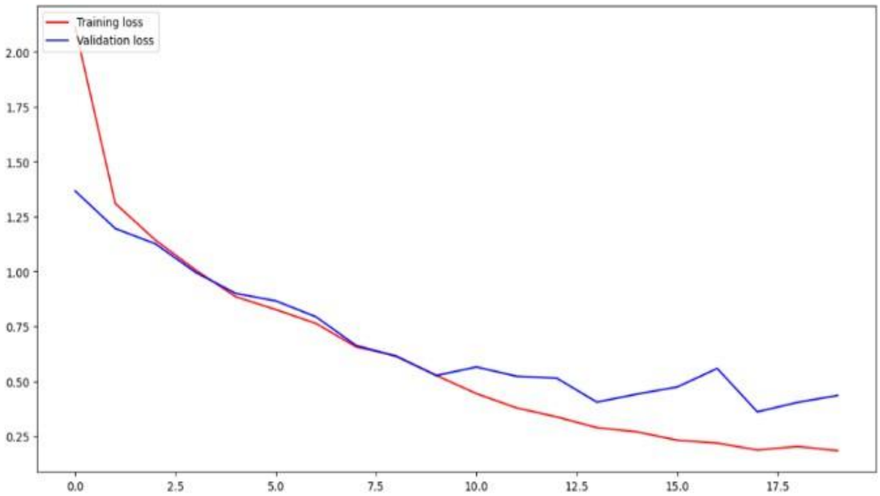

Figure 6: comparing loss/Val_loss

In the fig. 6, for brain tumor it shows that training and validation loss for 20 epochs, in this graph red line represents training loss and blue line represents the validation loss. Using CNN, in this we achieved training loss: 0.1843 and validation loss: 0.8534.

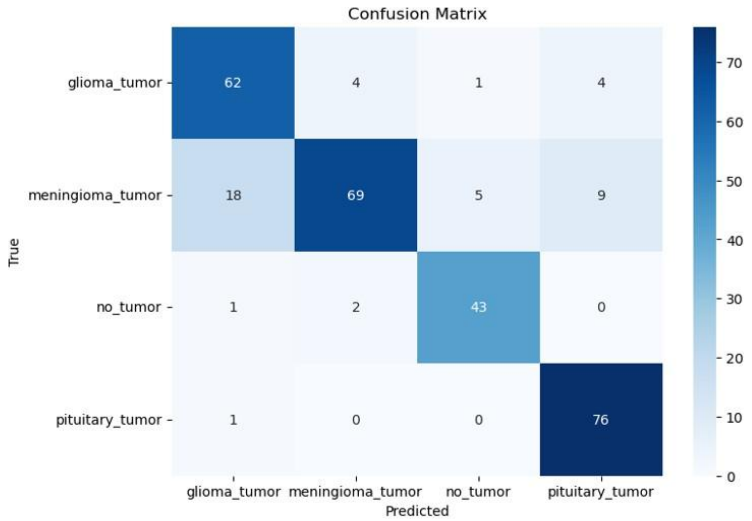

Figure 7: Confusion matrix

Confusion matrix provides a detailed breakdown of how well the model predicts different classes (meningioma, glioma, pituitary adenoma, or no tumor).
The matrix (ref. to fig.7) shows correct predictions along the main diagonal and misclassifications in off-diagonal elements. Analyzing the matrix helps calculate metrics like precision, recall, and accuracy for each class, offering insights into the model's performance strengths and weaknesses.

6.2 Alzheimer's: Figures 8 and 9 display how well our CNN model performed on both the training and test datasets during twenty rounds of training. After these twenty rounds, `we found the following results:

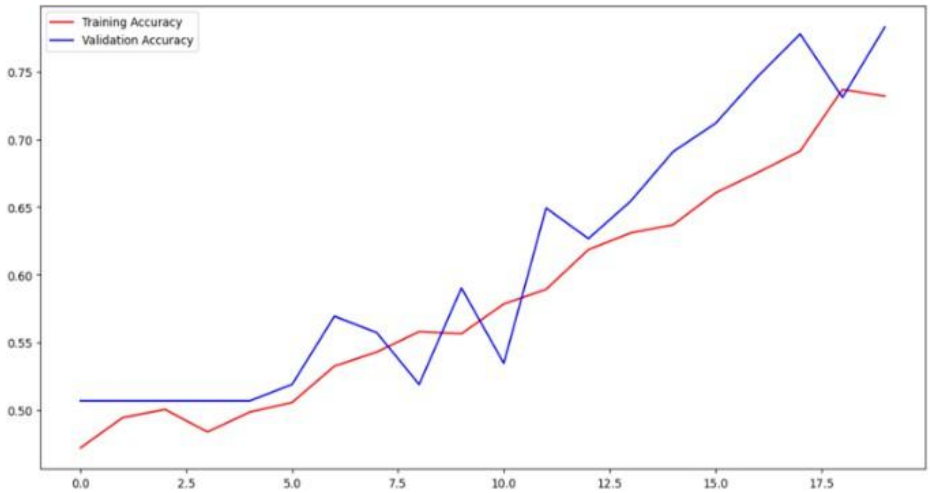

Figure 8: comparing training/Validation accuracy

In this graph (fig.8) of Alzheimer's, it shows that the training and testing accuracy for 20 epoch, the blue line represent the validation accuracy for Alzheimer's and get the validation accuracy:78.30% and red line represent training accuracy for Alzheimer's and get the training accuracy:73.19%.

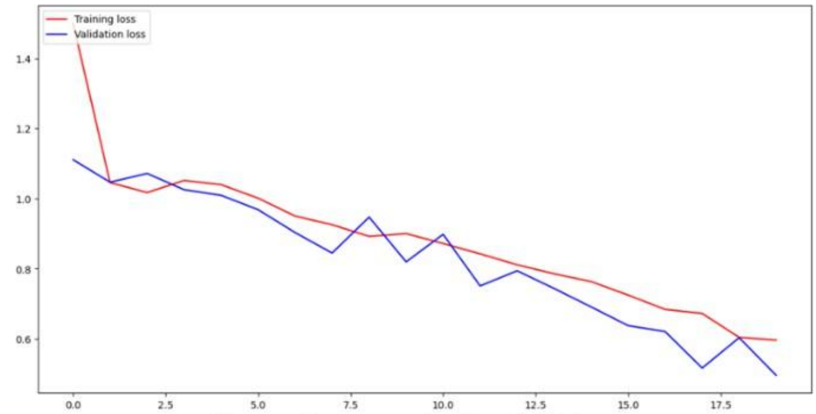

Figure 9: comparing loss/Val_loss

This graph (ref. to fig.9) shows the training and validation loss, the training loss we got for Alzheimer's for 20 epochs using CNN is 0.5967 and validation loss: 0.4962.

7. CONCLUSION

In conclusion, the multiple disease detection system embodies a fusion of technological innovation, user-centric design, and ethical considerations. Image processing and machine learning provides a robust foundation for accurate disease predictions. This study presented a system that incorporates two disease prediction models into a single application. The models take MRI Image input and predict whether there is a chance that the disease is present or not. The system includes models for brain tumor and alzheimer's. To develop the system, the researchers trained each model with CNN using datasets specific to each disease.
The brain tumor model, developed with CNN, demonstrated a loss of 0.1843 and an accuracy of 93.46%. When applied to new, unseen data (validation set), the loss was 0.4359, and the accuracy stood at 85.34%. On the other hand, the Alzheimer's model, also built with CNN, showed a loss of 0.5967 and an accuracy of 73.19%. Its performance on the validation set resulted in a loss of 0.4962 and an accuracy of 78.30%.

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