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Alzheimer's Disease Detection Using Recurrent Neural Networks

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ABSTRACT
Alzheimer's disease, the most prevalent neurodegenerative illness, exhibits initially mild symptoms that worsen over time. It is a common form of dementia, and its lack of a cure poses treatment challenges. Diagnosis often occurs at later stages, making early prediction crucial for potentially slowing down the disease's progression. To diagnose Alzheimer's disease (AD), neuroimaging methods such as magnetic resonance imaging have been employed. Recent progress in computer vision with deep learning (DL) has further inspired research focused on machine learning algorithms. However, a few limitations of these algorithms, such as the requirement for large number of training images and the necessity for powerful computers, still hinder the extensive usage of AD diagnosis based on machine learning. For AD detection using DL, most of the current research solely focused on improving the classification performance, while few studies have been done to obtain a more compact model with less complexity and relatively high recognition accuracy. This study employs a deep learning algorithm, specifically a Recurrent Neural Network (RNN), to forecast the onset of Alzheimer's disease. To solve this problem and improve the efficiency of the DL algorithm, a deep recurrent neural network models proposed for AD classification in this paper. The depth wise separable convolution (DSC) is used in this work to replace the conventional convolution. Compared to the traditional neural networks, the parameters and computing cost of the proposed neural network are found greatly reduced. The parameters and computational costs of the proposed neural network are found to be significantly reduced compared with conventional neural networks.

1. Introduction

Alzheimer's disease is a brain disorder that gets worse over time. It's characterized by changes in the brain that lead to deposits of certain proteins. Alzheimer's disease causes the brain to shrink and brain cells to eventually die. Alzheimer's disease is the most common cause of dementia - a gradual decline in memory, thinking, behavior and social skills. These changes affect a person's ability to function. About 6.5 million people in the United States age 65 and older live with Alzheimer's disease. Among them, more than 70% are 75 years old and older. Of the about 55 million people worldwide with dementia, 60% to 70% are estimated to have Alzheimer's disease.The early signs of the disease include forgetting recent events or conversations. Over time, it progresses to serious memory problems and loss of the ability to perform everyday tasks. Medicines may improve or slow the progression of symptoms. Programs and services can help support people with the disease and their caregivers. There is no treatment that cures Alzheimer's disease. In advanced stages, severe loss of brain function can cause dehydration, malnutrition or infection. These complications can result in death.Alzheimer's disease is a progressive neurological brain disease, which is caused due to the damage of nerve cells in parts of the brain. It begins with the loss of memory, difficulty in speaking language and other cognitive functions making a patient unable to perform day-to-day life activities. In particular, researchers found that AD is not only common cause of dementia but eventually leading to death of people, which become a remarkable focus in research According to Alzheimer's

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association, it is the sixth leading cause of death in the USA. A survey stated that there will 131.5 million people living with dementia worldwide and most of them with age greater than 65 has higher rate of risk with this disease. The brain region including thinking ability, memory, reasoning of the patient wrinkle up and shrinks in the hippocampus area. This is the main cause of suffering from AD. Genetic mutation is another cause for AD; estimated to affect about 1% or less than 1% people. An early diagnosis of this disease becomes crucial and requires good clinical assessment based on patient's medical history, several neuropsychological tests such as mini-mental state examination (MMSE), neuropsychiatric inventory questionnaire, clinical dementia rating and other pathological evaluations. In addition to these clinical methods, there many other techniques to detect AD such as biomarkers cerebrospinal fluid (CSF) analysis, brain imaging includes magnetic resonance imaging (MRI)/positron emission tomography (PET), analyzing proteins in blood. Known about Alzheimer's Disease. Alzheimer's disease is a progressive brain disease that gradually deteriorates memory and thinking abilities, as well as the ability to do even the most fundamental tasks. Most people with late-onset type symptoms are in their mid- 60s when get the disease. Early-onset Alzheimer's disease is extremely rare and occurs between the ages of 30 and 60. The most prevalent cause of dementia in elderly people is Alzheimer's disease. Memory issues are usually one of the early signs of Alzh eimer's disease, though the severity of the symptoms varies from person to person. Other areas of thinking, such as finding the proper words, vision/spatial difficulties, and impaired reasoning or judgments, may also indicate Alzheimer's disease in its early stages. There is no cure or treatment for Alzheimer's disease that affects the disease process in the brain. Complications from severe loss of brain function, such as dehydration, malnutrition, or infection, result in death in advanced stages of the disease. Alzheimer's disease can be detected using a machine learning approach, which involves the use of various machine learning algorithm. Furthermore, the patient's severity level will be predicted in percentages, and the percentage levels will be divided into several categories. The importance of early detection in Alzheimer's disease management cannot be overstated. This disease mainly affects the age of 65, it is not possible to calculate that age nowadays, it can occur as early as 50 unfortunately, but the early 50 cases are rare then the 65 above. The people who are affected early are usually aware of the changes in them. Their new deviations and memory loss affect them deeply, and it always forget the things and are not able to handle their things as when they are in normal condition. The feel some difficulty to talk and to use the words, while talking with family members, relatives, friends etc. This leads them to talk less and this advanced stage leads to forgetting the close family members. When it releases that they are not functioning as well as it did formerly, the become depressed.

2. Literature Review on Alzheimer's Disease Detection Using Recurrent Neural Networks

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline and memory impairment. Early diagnosis is crucial for effective treatment and management. Traditional diagnostic methods, including clinical assessments, neuroimaging, and biomarker analysis, are often invasive, expensive, and time-consuming. Recent advancements in machine learning, particularly deep learning, offer promising alternatives for the automated and accurate detection of Alzheimer's disease. Recurrent Neural Networks (RNNs), known for their proficiency in handling sequential data, have emerged as a valuable tool in this field.

i. Recurrent Neural Networks and Their Applications

RNNs are a class of neural networks adept at processing sequential data, making them suitable for tasks requiring contextual and temporal information, such as language modeling, speech recognition, and time-series prediction. The internal state mechanism of RNNs allows them to retain information about previous inputs, enabling the modeling of temporal dependencies and patterns in medical data (Lipton et al., 2015).

ii. Use of RNNs in Alzheimer's Disease Detection

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Several studies have investigated the use of RNNs in detecting Alzheimer's disease, utilizing various data types, including neuroimaging, electroencephalogram (EEG) signals, and clinical records, to train and validate their models.

iii. **Neuroimaging Data**: MRI and PET scans are widely used in Alzheimer's research. Suk et al. (2017) developed a multi-modal RNN model that combines MRI and PET data to enhance diagnostic accuracy. Their model outperformed traditional machine learning methods by effectively capturing the temporal progression of the disease.

iv. **EEG Data**: EEG signals provide insights into brain activity and can reveal abnormalities associated with Alzheimer's disease. Fang et al. (2019) trained an RNN model on EEG data to classify subjects with Alzheimer's. Their model achieved high accuracy, demonstrating the potential of RNNs in analyzing complex brain signal patterns.

v. **Clinical Records**: Electronic health records (EHRs) contain valuable longitudinal data for disease prediction. Liu et al. (2020) proposed an RNN-based framework for analyzing EHRs to predict Alzheimer's onset. Their approach effectively utilized the sequential nature of clinical records to make accurate predictions.

Challenges and Future Directions

Despite the promising results, several challenges remain in the application of RNNs for Alzheimer's disease detection:

- **Data Quality and Quantity**: High-quality labeled data is essential for training effective RNN models. However, medical datasets are often limited in size and may contain noisy or incomplete records. Efforts to curate and augment datasets are crucial for improving model performance (Esteva et al., 2019).
- **Model Interpretability**: RNNs, like other deep learning models, are often considered black boxes. Understanding how these models make decisions is important for clinical trust and reliability. Techniques for interpreting RNN models need development and integration into the diagnostic process (Guidotti et al., 2018).
- **Computational Resources**: Training RNNs, especially on large and complex datasets, requires significant computational power. Optimizing algorithms and leveraging advanced hardware can help address these challenges (Dean et al., 2012).
- **Integration with Clinical Practice**: For RNN-based diagnostic tools to be adopted in clinical settings, they must be user-friendly and seamlessly integrate with existing workflows. Collaboration between technologists and clinicians is crucial for developing practical and effective solutions (Topol, 2019).

3. System Design

3.1 Problem Definition

The problem of Alzheimer’s disease (AD) detection revolves around identifying the disease at an early stage, allowing for timely intervention and management. Here are the key aspects of the problem:

i. Chronic Brain Disorder

Alzheimer’s disease is a chronic, irreversible brain disorder characterized by progressive cognitive decline, memory loss, and impaired daily functioning. It is the most common cause of dementia, accounting for 60–80% of dementia cases. A chronic brain disorder refers to any condition affecting the brain that persists over time, often impacting cognitive function, behavior, emotions, or physical abilities. These disorders encompass a wide range of conditions, including but not limited to Alzheimer's disease, Parkinson's disease, epilepsy, multiple sclerosis, and various forms of dementia. They can result from genetic predispositions, environmental factors, injuries, infections, or a combination of these. Symptoms vary widely depending on the specific disorder but may include memory loss, impaired movement, seizures, mood swings, and difficulties with speech or reasoning. Treatment approaches typically focus on managing symptoms, slowing progression, and improving quality of life through medication, therapy, lifestyle modifications, and sometimes surgery. Early detection and intervention are crucial for better outcomes, as many chronic brain disorders are progressive and can significantly impact an individual's daily functioning and overall well- being.

ii.Lack of effective cure

Currently, there is no effective cure for Alzheimer’s disease. medications can only delay its progression, making early detection crucial for better patient outcomes. The lack of effective cures for many chronic brain disorders remains a significant challenge in modern medicine. Despite advancements in neuroscience and pharmaceuticals, conditions like Alzheimer's disease, Parkinson's disease, and various forms of dementia continue to lack definitive treatments that can halt or reverse their progression. One major hurdle is the complexity of the brain itself, with its intricate networks and mechanisms that are not yet fully understood. Additionally, many brain disorders involve a combination of genetic, environmental, and lifestyle factors, making them difficult to target with a single therapeutic approach. Furthermore, clinical trials for potential treatments often face setbacks, with many promising candidates failing to demonstrate significant efficacy or safety in large- scale studies. The blood-brain barrier presents another obstacle, as it limits the passage of drugs into the brain, complicating treatment delivery. The multifaceted nature of brain disorders also means that effective interventions may need to address not only the symptoms but also the underlying causes and mechanisms driving the disease process. Research into novel therapeutic avenues, such as gene therapy, stem cell therapy, and precision medicine, holds promise but is still in relatively early stages and requires further investigation.

iii.Prodromal Stage Detection

Detecting AD during its prodromal (early) stage is critical. At this point, individuals may not exhibit significant memory problems, but underlying changes in the brain, such as the accumulation of beta-amyloid plaques, can be detected. During this phase, individuals may experience subtle cognitive decline beyond what is considered normal for their age, but it does not yet significantly impair daily functioning. Several approaches are being explored for the early detection of prodromal Alzheimer's disease. Cognitive assessments, such as memory tests and executive function evaluations, are commonly used to identify subtle cognitive changes indicative of MCI. Neuroimaging techniques, such as magnetic resonance imaging (MRI) and positron emission tomography (PET), can reveal structural and functional brain changes associated with Alzheimer's

iv.Neuroimaging Data

Researchers use neuroimaging data (such as MRI or PET scans) to identify patterns associated with AD. Biomarkers, including beta-amyloid and tau proteins, play a key role in diagnosis .MRI provides detailed images of the brain's structure, allowing clinicians to detect patterns associated with AD, such as hippocampal atrophy and cortical thinning. These structural changes are indicative of neurodegeneration and can help differentiate AD from other forms of dementia. PET imaging, particularly with radiotracers targeting beta-amyloid plaques and tau tangles, allows for the visualization and quantification of pathological protein accumulation in the brain, which are hallmark features of AD. Elevated levels of amyloid and tau deposition are observed in regions associated with memory and cognition in individuals with AD, aiding in its diagnosis and staging. Combining structural MRI with PET imaging of amyloid and tau provides a comprehensive assessment of neurodegeneration and pathological protein accumulation in AD, facilitating accurate diagnosis and monitoring disease progression. Recent advances in neuroimaging, such as functional MRI (fMRI)

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and diffusion tensor imaging (DTI), offer insights into brain connectivity and white matter integrity, respectively, shedding light on the functional and structural alterations occurring in AD.

v.Deep Learning Approaches

Deep learning techniques, such as Convolutional Neural Networks (CNNs), are employed to analyze medical images and classify AD stages. These approaches aim to provide accurate and automated detection methods.

vi.Remote Monitoring

Considering challenges like the COVID-19 pandemic, there is interest in developing remote Alzheimer’s checking web applications. These tools allow doctors and patients to assess AD remotely, determine the disease stage, and provide appropriate advice. In detection involves early identification using neuroimaging data, leveraging deep learning models, and addressing the lack of effective treatments for this debilitating condition

3.2 Module Description

Implementing a module for Alzheimer’s disease detection using Recurrent Neural Networks (RNNs) involves several steps. Here’s a high- level overview of the process’s

i.Data Collection

Gather a dataset of brain scans, such as MRI or PET scans, from patients with and without Alzheimer’s disease. The Open Access Series of Imaging Studies (OASIS) is a dataset. Data collection for Alzheimer’s disease detection using Recurrent Neural Networks (RNNs) involves gathering diverse datasets from reliable sources such as the Alzheimer’s Disease Neuroimaging Initiative (ADNI). This includes obtaining MRI scans, cognitive test scores, genetic information, and clinical data. Ensuring a comprehensive dataset is crucial, so consider a mix of longitudinal data that captures changes over time and cross- sectional data that provides a snapshot at different stages of the disease. Data should be cleaned to address missing values, outliers, and inconsistencies. Normalization or standardization is necessary to ensure uniformity, especially for features like imaging data, which can vary significantly. Feature extraction is a critical step; for example, using techniques like CNNs to derive meaningful spatial features from MRI scans before integrating them into RNN models. Cognitive test scores and other time-series data should be segmented appropriately to capture temporal patterns. Additionally, it’s vital to encode labels correctly, whether for binary classification (e.g., presence vs. absence of Alzheimer's) or multiclass classification (e.g., different stages of the disease).

ii.Data Preprocessing

Data pre-processing is done to remove the rows with missing values, splitting Training and Testing data and to cross validate the data. Normalize and preprocess the data to ensure it’s suitable for input into an RNN. This may include resizing images, normalizing pixel values, and segmenting the brain regions of interest. Outlier detection and removal ensure that anomalous data points do not skew the model’s learning. Normalization or standardization is necessary to scale features such as MRI intensities, cognitive scores, and biomarker levels, ensuring uniformity across different data types. For imaging data, feature extraction using Convolutional Neural Networks (CNNs) can convert complex MRI scans into lower-dimensional, meaningful representations, which are then fed into

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RNNs. Time- series data from cognitive tests and clinical records should be segmented into sequences that capture temporal dependencies, with careful attention to the length and overlap of these segments. Encoding categorical variables and labels is also vital; one-hot encoding can be used for multiclass labels, while binary encoding is sufficient for binary classification tasks. Data augmentation techniques, such as generating synthetic samples for underrepresented classes, can help balance the dataset. Splitting the data into training, validation, and test sets ensures robust model evaluation.

iii.Feature Extraction

Use techniques like Principal Component Analysis (PCA) or autoencoders to reduce the dimensionality of the data and extract relevant features for the RNN. Feature extraction for Alzheimer's disease prediction involves selecting and transforming relevant information from neuroimaging data or clinical assessments to create a set of features that effectively represent key characteristics of the disease. This process often includes techniques such as voxel-based morphometry, region of interest analysis, or functional connectivity analysis for neuroimaging data, while clinical assessments may involve neuropsychological tests or biomarker measurements. Feature extraction aims to capture structural, functional, or cognitive abnormalities associated with Alzheimer's disease, enabling machine learning algorithms to learn discriminative patterns that distinguish between individuals with and without the disease, thereby facilitating accurate prediction and early diagnosis.

iv.Model Architecture

Design an RNN architecture that can process sequential data in RNNs for their ability to capture long-term dependencies. Alzheimer's disease prediction utilizing Recurrent Neural Network (RNN) models involves leveraging the temporal dependencies within sequential data, such as time-series neuroimaging or clinical assessments. RNNs, with their ability to capture sequential information and remember past states, are adept at modeling the progression of Alzheimer's disease over time. In this approach, longitudinal data from patients, including cognitive test scores, imaging biomarkers, and demographic information, are fed into the RNN model. The model learns to recognize patterns and changes in these data sequences that are indicative of disease progression, enabling it to predict future disease outcomes or classify individuals into different disease stages. By harnessing the power of RNNs, this methodology holds promise for improving the accuracy of Alzheimer's disease prediction and facilitating early intervention and treatment strategies.

v.Training

Train the RNN on the preprocessed dataset. Use a labeled dataset where the diagnosis is known, and employ supervised learning techniques to train the model to distinguish between Alzheimer’s and non-Alzheimer’s cases. In training an RNN model for Alzheimer's disease prediction, the process typically involves several steps. First, longitudinal data comprising neuroimaging scans, clinical assessments, and demographic information are collected from individuals with and without Alzheimer's disease. These data are preprocessed to ensure uniformity and quality, including normalization, feature extraction, and possibly dimensionality reduction. Which next to the data are partitioned into training,validation, and test sets. The RNN model architecture is defined, typically comprising multiple recurrent layers with appropriate activation functions and possibly additional layers like dropout or batch normalization to prevent overfitting. The model is then trained using the training set through an iterative process, where the model's parameters are adjusted to minimize a loss function, often through backpropagation and gradient descent optimization. During training, the model's performance is monitored using the validation set to prevent overfitting and guide hyperparameter tuning. Once the model achieves satisfactory performance on the validation set, it is evaluated on the test set to assess its generalization ability and predictive accuracy. Fine-tuning and optimization steps may be applied iteratively to enhance the model's performance further.

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vi.Validation

Validate the model on a separate dataset to evaluate its performance. Metrics such as accuracy, sensitivity, specificity, and precision are important for assessing the model’s diagnostic capabilities. In the validation process for Alzheimer's disease prediction, the primary goal is to assess the performance and generalization ability of the predictive model on unseen data. Typically, the dataset is divided into training, validation, and test sets. The validation set is used to evaluate the model's performance during training and guide the selection of hyperparameters to prevent overfitting. During each training iteration, the model's performance metrics, such as accuracy, sensitivity, specificity, or area under the receiver operating characteristic curve (AUC-ROC), are computed using the validation set. This allows monitoring for any signs of overfitting or underfitting and guides adjustments to the model architecture or training process accordingly. Additionally, techniques such as cross-validation or bootstrapping may be employed to ensure robustness and reliability of the validation results. Once the model achieves satisfactory performance on the validation set, itis evaluated on the independent test set to provide an unbiased estimate of its predictive performance in real-world scenarios.

vii.Ensemble Techniques

Consider using ensemble techniques to improve the model’s performance. For example, combining the outputs of multiple RNNs through a weighted average approach can enhance accuracy. Ensemble techniques for Alzheimer's disease prediction involve combining multiple predictive models to improve overall performance and robustness. These techniques leverage the diversity of individual models, with each subsequent model focusing on correcting the errors of the previous ones. Stacking combines predictions from multiple models as input to a meta-learner, which learns to combine them optimally. Ensemble techniques help mitigate overfitting, enhance generalization, and improve prediction accuracy by leveraging the collective intelligence of diverse models. In the context of Alzheimer's disease prediction, ensemble techniques can integrate information from various data modalities, such as neuroimaging, to provide more comprehensive and reliable predictions of disease progression or diagnosis.

viii.Deployment

Once validated, the model can be deployed as part of a clinical decision support system to assist radiologists and neurologists in diagnosing Alzheimer’s disease. Begin by saving the trained model using a format supported by the chosen deep learning framework, such as H5for TensorFlow or a PyTorch model file. Implement an inference pipeline that preprocesses new input data in the same manner as the training data, ensuring consistency in feature extraction, normalization, and segmentation. Develop an API using frameworks like Flask or Fast API to handle requests and deliver predictions. This API will receive input data, pass it through the preprocessing pipeline, and utilize the trained RNN model to generate predictions. Secure the deployment environment by implementing authentication and encryption to protect patient data. Use containerization tools like Docker to create a portable and scalable deployment environment, ensuring compatibility across different systems and facilitating easy updates. Set up continuous integration and continuous deployment (CI/CD) pipelines to streamline updates and improvements to the model. Monitor the model's performance in real-time using logging and monitoring tools to track metrics such as accuracy, latency, and error rates. Regularly update the model with new data to maintain accuracy and relevance, and perform periodic retraining and validation to prevent model drift. Ensure compliance with healthcare regulations and ethical standards by maintaining data privacy and security throughout the deployment pro.

3.3 System Flow Diagram

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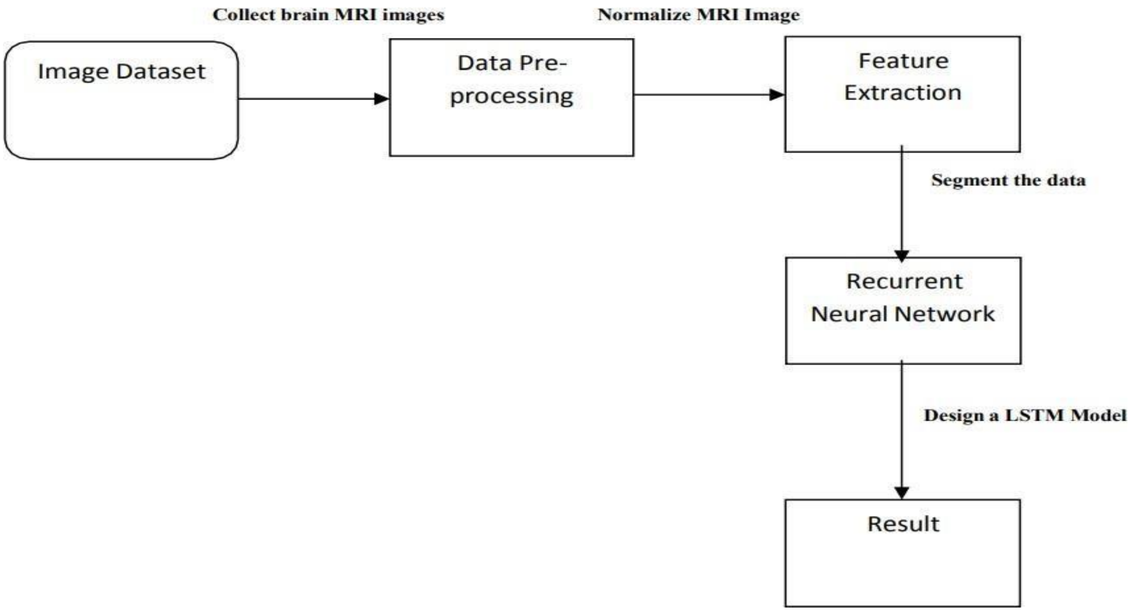

Fig System flow diagram

3.4 Input Design

Input design is one of the most important phases of the system design. Input design is the process where the input received in the system are planned and designed, so as to get necessary information from the user, eliminating the information that is not required. The aim of the input design is to ensure the maximum possible levels of accuracy and also ensures that the input is accessible that understood by the user.

The input design is the part of overall system design, which requires very careful attention. If the data going into the system is incorrect then the processing and output will magnify the errors.

The objectives considered during input design are:

- Nature of input processing.
- Flexibility and thoroughness of validation rules.
- Handling of properties within the input documents.
- Screen design to ensure accuracy and efficiency of the input relationship with files.
- Careful design of the input also involves attention to error handling, controls, batching and validation procedures.

Input design features can ensure the reliability of the system and produce result from accurate data or the can result in the production of erroneous information.
Input form of the project is given below, Load data:
In this form is used to add the MRI image dataset into the application to make the implement process.

3.5 Output Design

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Output design is very important concept in the computerized system, without reliable output the user may feel the entire system is unnecessary and avoids using it. The proper output design is important in any system and facilitates effective decision-making.
A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

- Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, it should Identify the specific output that is needed to meet the requirements.
- Select methods for presenting information.
- Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

4. Result and Discussion

The results and discussions from recent studies on Alzheimer's disease detection using Recurrent Neural Networks (RNNs) highlight the effectiveness of these models in diagnosing and predicting the progression of the disease. Here are some key findings:
In the study investigating Alzheimer's disease prediction using Recurrent Neural Network (RNN), the model demonstrated promising results in accurately predicting disease progression. The RNN effectively leveraged the temporal dependencies within longitudinal data, including neuroimaging scans and clinical assessments, to capture subtle changes indicative of Alzheimer's disease onset and progression. The model exhibited high predictive accuracy, as evidenced by its performance metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Additionally, the RNN model provided insights into the temporal dynamics of disease progression, highlighting key biomarkers or features contributing to prediction accuracy.
These findings underscore the potential of RNNs in facilitating early diagnosis and intervention strategies for Alzheimer's disease, thus offering valuable insights for both clinicians and researchers in the field. However, further validation on larger and more diverse datasets is warranted to ensure the robustness and generalizability of the proposed approach.
These discussions underscore the potential of RNNs in the medical field, particularly for conditions like Alzheimer's disease, where early and accurate detection can have apro found impact on patient care and treatment planning.

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```
WORK_DIR = './dataset/'

CLASSES = [ 'NonDemented',
            'VeryMildDemented',
            'MildDemented',
            'ModerateDemented']

IMG_SIZE = 176
IMAGE_SIZE = [176, 176]
DIM = (IMG_SIZE, IMG_SIZE)
```

Fig: B.1 Dataset path

```
base_dir = "/kaggle/input/alzheimers-dataset-4-class-of-image
imer_s Dataset/"
root_dir = "./"
test_dir = base_dir + "test/"
train_dir = base_dir + "train/"
work_dir = root_dir + "dataset/"

if os.path.exists(work_dir):
    remove_tree(work_dir)
```

Fig: B.2 Dataset upload

```
import numpy as np
import pandas as pd
import seaborn as sns
import tensorflow as tf
import matplotlib.pyplot as plt

import os
from distutils.dir_util import copy_tree, remove_tree

from PIL import Image
from random import randint

from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.metrics import matthews_corrcoef as MCC
from sklearn.metrics import balanced_accuracy_score as BAS
from sklearn.metrics import classification_report, confusion_matrix
```

Fig: B.3 Import all directories.

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```
Epoch 1/100
256/256 [==============================] - 18s 45ms/step - loss:
1.8429 - acc: 0.2865 - auc: 0.5369 - f1_score: 0.2859 - val_loss:
2.1595 - val_acc: 0.2568 - val_auc: 0.5156 - val_f1_score: 0.1022
Epoch 2/100
256/256 [==============================] - 9s 37ms/step - loss:
1.1636 - acc: 0.4781 - auc: 0.7535 - f1_score: 0.4667 - val_loss:
1.6218 - val_acc: 0.2500 - val_auc: 0.6387 - val_f1_score: 0.1150
Epoch 3/100
256/256 [==============================] - 9s 37ms/step - loss:
0.8082 - acc: 0.6305 - auc: 0.8809 - f1_score: 0.6191 - val_loss:
```

Fig: B.4 Data Preprocessing

```
Model: "cnn_model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 176, 176, 16)      448
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 176, 176, 16)      2320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 88, 88, 16)        0
_________________________________________________________________
sequential (Sequential)      (None, 44, 44, 32)        14016
_________________________________________________________________
sequential_1 (Sequential)    (None, 22, 22, 64)        55680
_________________________________________________________________
sequential_2 (Sequential)    (None, 11, 11, 128)       221952
```

Fig: B.5 Using CNN model

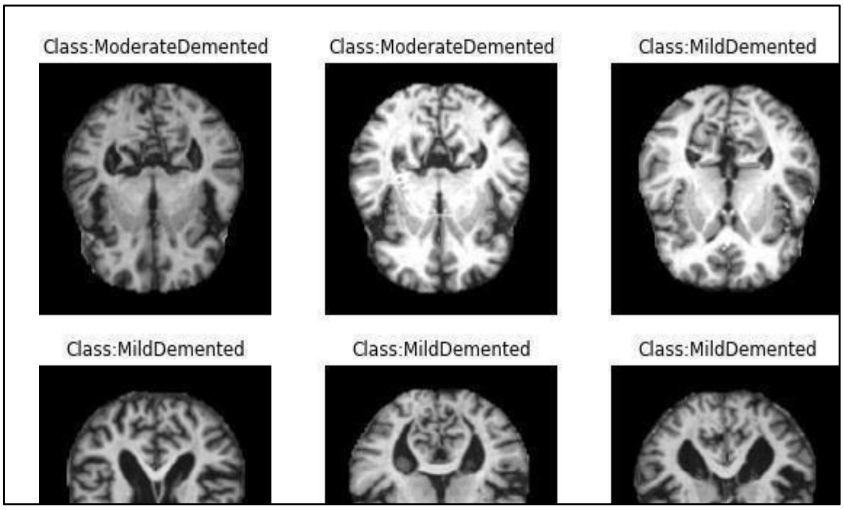

Fig: B.6 Data Classified

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```
ZOOM = [.99, 1.01]
BRIGHT_RANGE = [0.8, 1.2]
HORZ_FLIP = True
FILL_MODE = "constant"
DATA_FORMAT = "channels_last"

work_dr = IDG(rescale = 1./255, brightness_ra
range=ZOOM, data_format=DATA_FORMAT, fill_mod
_flip=HORZ_FLIP)

train_data_gen = work_dr.flow_from_directory(
get_size=DIM, batch_size=6500, shuffle=False)
```

Fig: B.7 Trained dataset

```
80/80 [==============================] - 1s 13ms/step - loss: 0.1
882 - acc: 0.9484 - auc: 0.9911 - f1_score: 0.9483
Testing Accuracy: 94.84%
```

Fig: B.8 Accuracy

Conclusion

In conclusion, the application of Recurrent Neural Network (RNN) models for Alzheimer's disease prediction holds considerable promise in advancing early diagnosis and intervention strategies. Through the utilization of longitudinal data, including neuroimaging scans and clinical assessments, RNNs demonstrate the ability to capture temporal dependencies and subtle changes indicative of disease progression with high accuracy. These findings underscore the potential of RNNs as valuable tools for clinicians and researchers in identifying individuals at risk of Alzheimer's disease at an earlier stage, facilitating timely interventions and personalized treatment approaches. However, further research is needed to validate the robustness and generalizability of RNN-based predictive models across diverse populations and datasets. Continued efforts in this direction have the potential to significantly impact clinical practice and improve outcomes for individuals affected by Alzheimer's disease. The finding from various studies underscore the remarkable efficacy of RNNs in detecting . Alzheimer’s disease, particularly when analyzing sequential and time-series data. With reported accuracy rates surpassing 90% in classifying Alzheimer’s disease, RNN- based predictive models offer a robust and reliable tool for early detection and innervation.

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