Enhancing the Efficiency of Diagnosing and Managing Mental Disorders using Machine Learning

SLIIT FACULTY OF COMPUTING

Group ID: 24-25J-322

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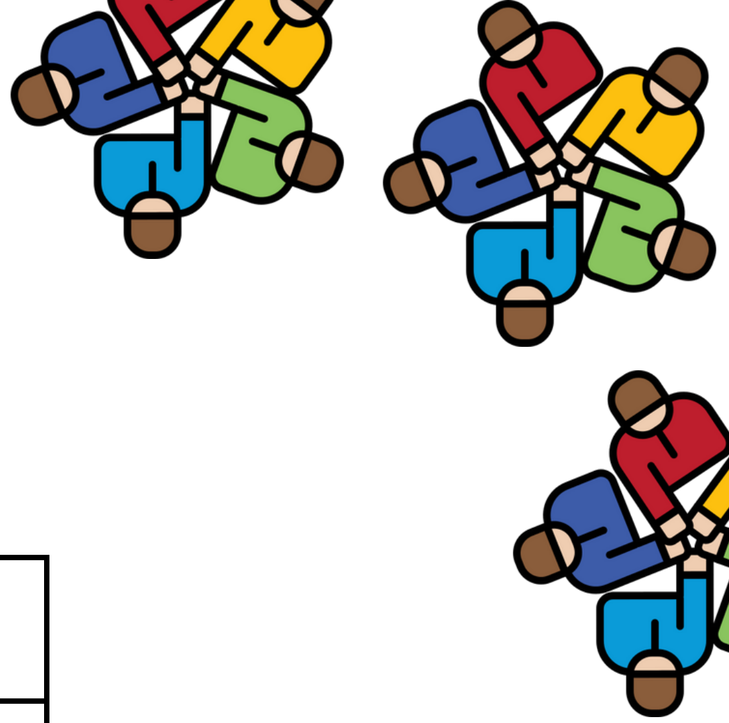

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INTRODUCTION

According to the World Health Organization **1 in every 8 people** in the world live with a mental disorder.

Mental disorders, significantly impact an individual's cognitive, emotional, and social functioning.

Early diagnosis is crucial for effective intervention, as it can greatly improve long-term outcomes.

INTRODUCTION

- According to world's Alzheimer's association 1 out of 9 adults (>65) have Alzheimer's.
- Over 700,000 lives have been lost all over the world due to depression. (Global suicide statistics IASP)
- Approximately 1 out of 13 children are being diagnosed with autism. Data and Statistics on Autism Spectrum Disorder | Autism Spectrum Disorder (ASD) | CDC
- Parkinson foundation estimates that by the year 2030 the patients with Parkinson's disease will be rise to 1.2 million (https://www.parkinson.org/understanding-parkinsons/statistics)
- These diseases needed to be identified at the first stages to ensure immediate treatment. That helps patients' family members to plan their lives and keep the situation under control.

Research Problem

- How to leverage machine and deep learning techniques to enhance mental care?
- Up to what extent machine and deep learning can be used to diagnose and analyze mental disorders like Autism, Alzheimer's, Parkinson's, and Depression?
- How trustworthy and useful are the built models?
- How to monitor patients effectively?

Research Objectives

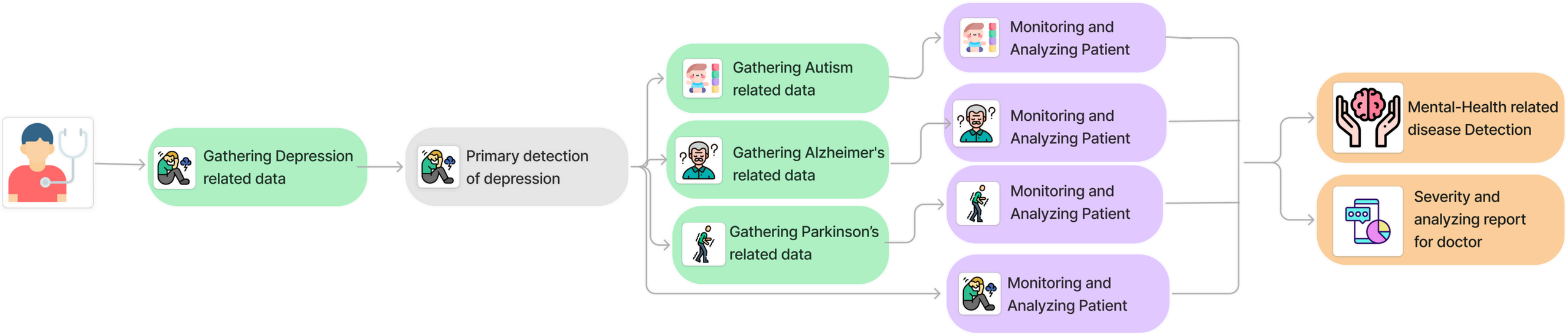
Diagnosing and Analyzing Alzheimer’s Risk through Machine Learning Techniques

Early Detection of Parkinson's: Harnessing Machine Learning for Predictive Risk Modeling.

Early Autism Spectrum Disorder Detection Using Facial Images and Text Analysis

Diagnosing and Analyzing Depression through Text and Facial Images

Overall System Diagram



Diagnosing and Analyzing Alzheimer's Risk through Machine Learning Techniques

IT21180934 | Dilshan G.A.M

Bachelor of Science (Hons) in Information Technology
Specializing in Data Science

Background

Component 1

What is Alzeihmers?

- Alzheimer's disease is a progressive neurological disorder that leads to memory loss, cognitive decline, and behavioral changes.

Research Question

- How to get patient sleep quality measures?
- How to develop a solution to integrate all these components in one application?
- How to feed MRI scan images into the system?
- How to manage the patient status with the medications and treatments through out the time?
- How to make clear visualizations for doctors to evaluate patients' medical history with the treatments?

Research Gap

- **Works Well Only on Ideal Data**

AI models are trained on clean, perfect datasets. They don’t work as well with real-world hospital data.

- **Not Easy to Understand**

Many models are like “black boxes.” Doctors can't see how the AI made a decision.

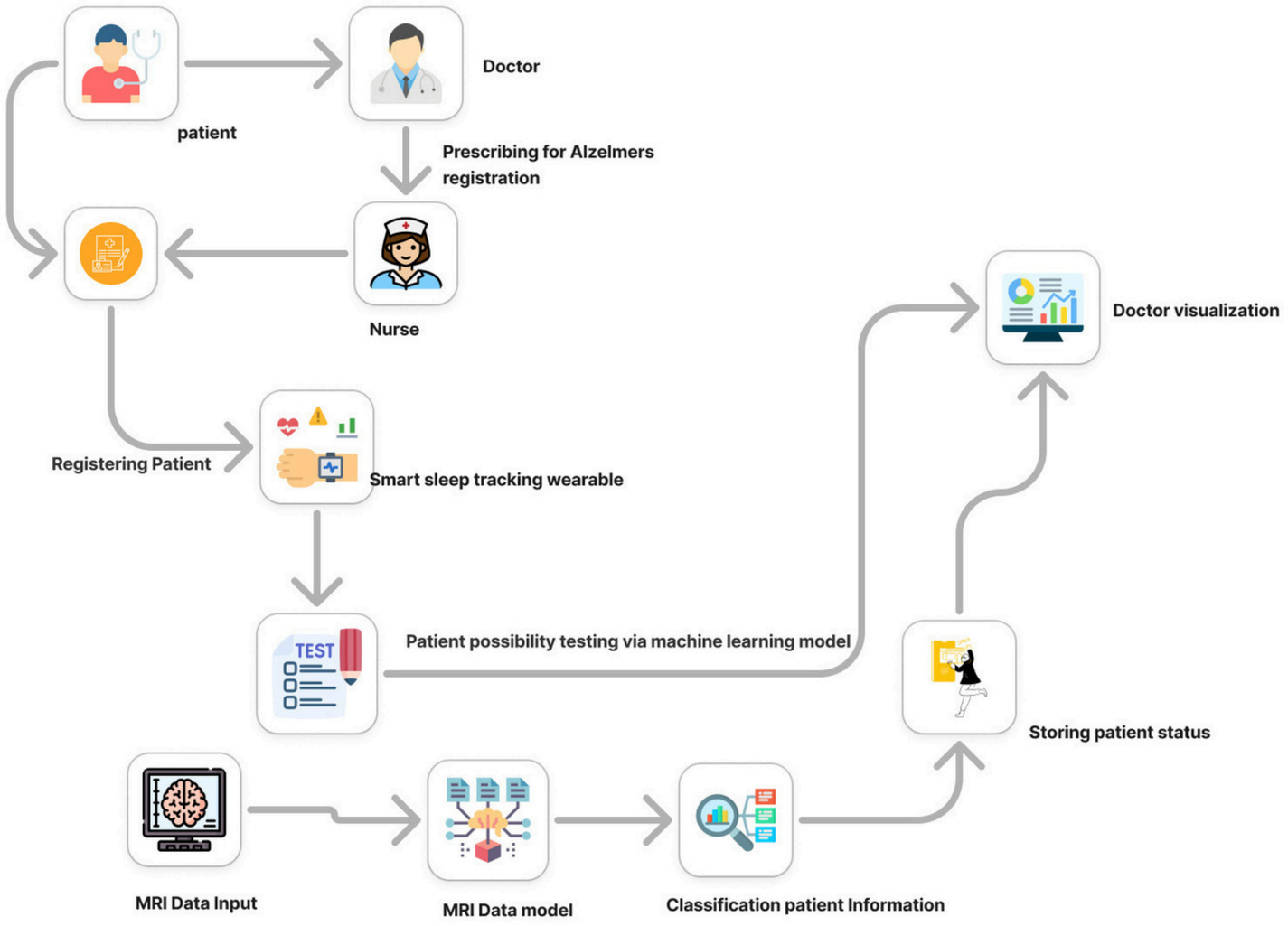
- **Ignores Disease Over Time**

Most systems look at one-time data. They don’t track how Alzheimer’s develops or predict future changes.

Specific & Sub Objectives

- Classifying patients’ severity using MRI scans.
- Identifying possibility of a patient having Alzheimer's using general information.
- Visualizing patient possibilities and levels of the disease through out the time.

Methodology



Requirements

Personal Requirements

- Dr. Anuradha Baminiwatta from Ragama hospital

Functional Requirements

- Identifying patients possibility of having the disease using general information inputs.
- Identify and classify the patients disease status using MRI scans
- Visualizing patients' medical history to the doctor.

Non-Functional Requirements

- Create easy to use user interfaces.
-
- Fast user interaction.
-
- Reliable and stable application behaviour.

Tools & Technologies

Technologies

- Flutter
- Python
- ReactJS
- Firebase
- Docker
- Google colab
- ChartJS

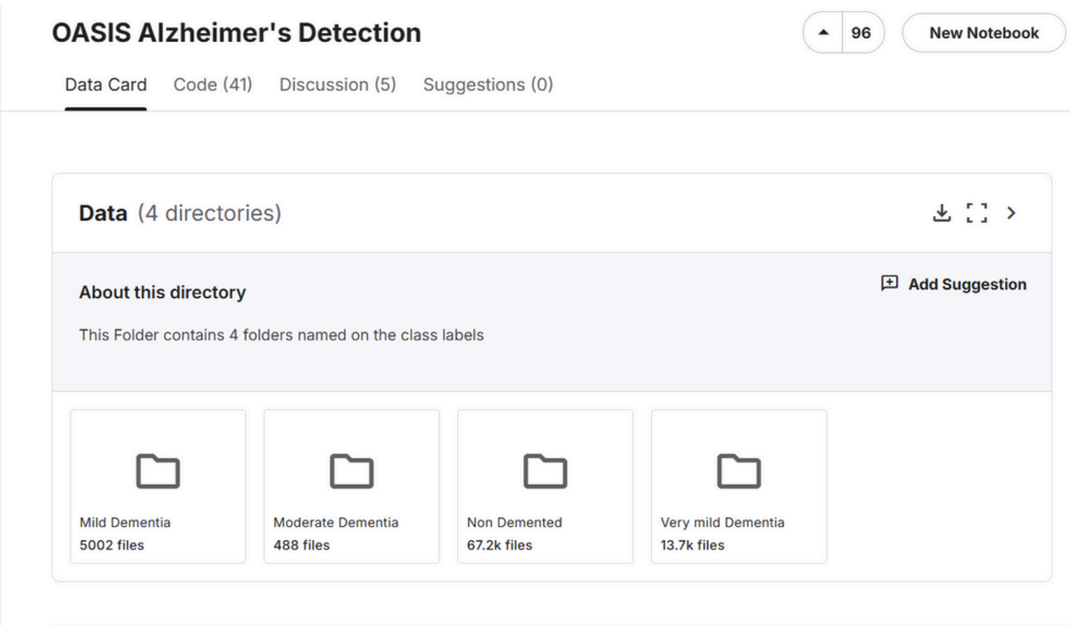
Algorithms

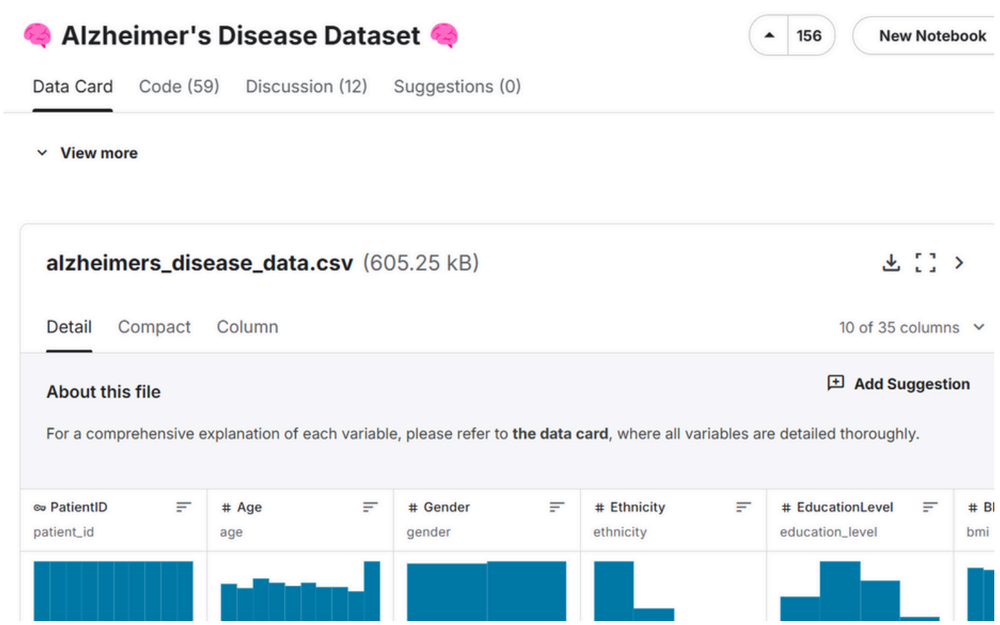
- CNN models.
- Random forest and other suitable machine learning algorithms

Techniques

- Sleep quality detection.
- Image classification.

Data gathering



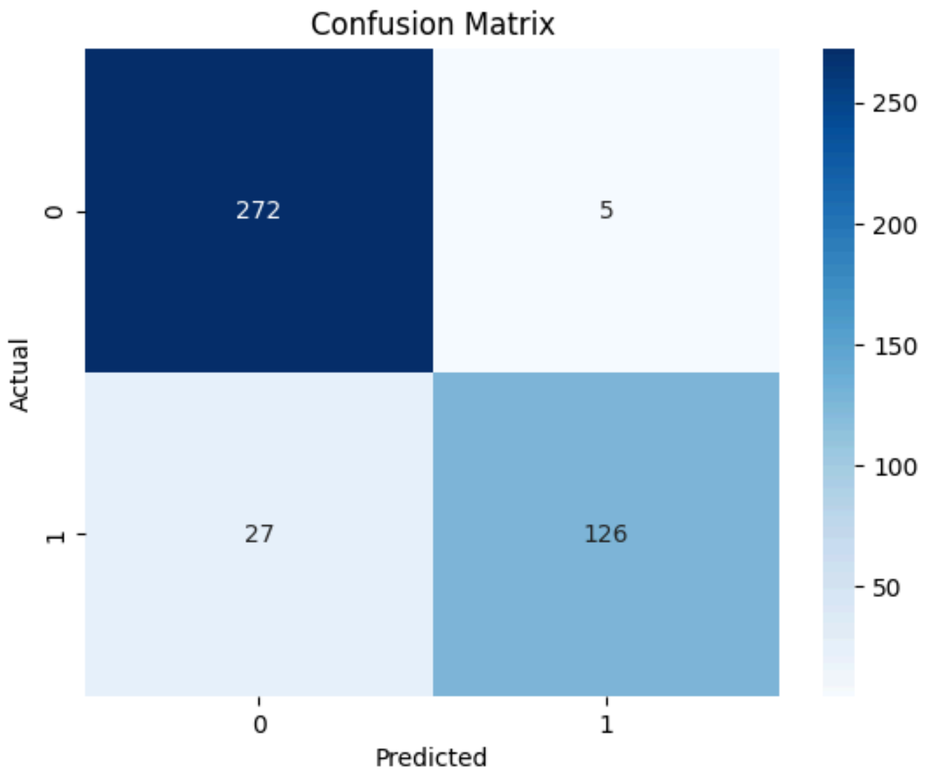


Data Preprocessing

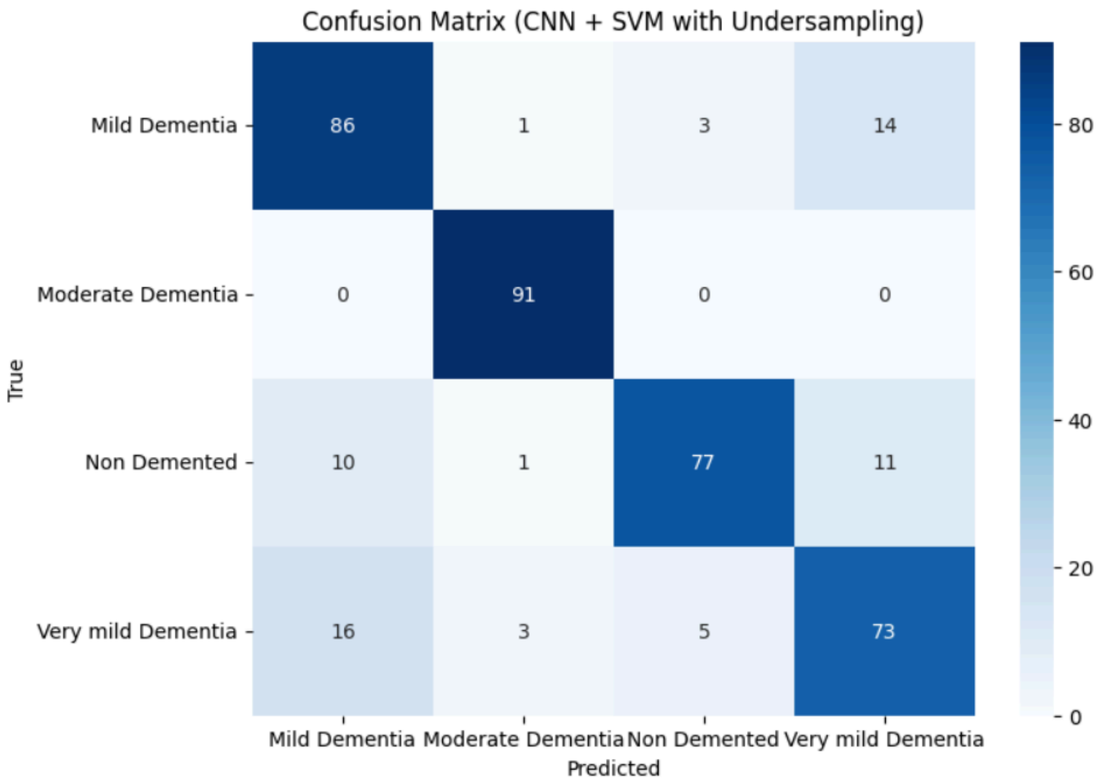
```python
# Check for missing values
print("\nMissing Values:")
print(data.isnull().sum())

# Handle missing values (drop rows with missing values for simplicity)
data = data.dropna()

# Encode categorical variables (if any)
label_encoders = {}
for column in data.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    data[column] = le.fit_transform(data[column])
    label_encoders[column] = le

# Feature selection and splitting the dataset
X = data.drop('Diagnosis', axis=1)  # Features (all columns except target)
X = X.drop('PatientID', axis=1)  # Drop the 'Patient ID' column
X= X.drop('DoctorInCharge', axis=1)  # Drop the 'DoctorInCharge' column
```

```python
# Import necessary libraries
import numpy as np
from imblearn.over_sampling import RandomOverSampler
from collections import Counter

# Reshape the labels to match the requirements of RandomOverSampler
labels = train_generator.classes
labels = labels.reshape(-1, 1)  # Reshape to 2D array as required by RandomOverSampler

# Initialize the RandomOverSampler
oversampler = RandomOverSampler(random_state=42)

# Get the filenames and labels for oversampling
filenames = np.array(train_generator.filepaths)  # Get filepaths of images

# Perform oversampling
oversampled_filenames, oversampled_labels = oversampler.fit_resample(filenames.reshape(-1, 1), labels)

# Flatten the oversampled_filenames back to a 1D array
oversampled_filenames = oversampled_filenames.flatten()

# Display the new distribution
oversampled_class_counts = Counter(oversampled_labels.flatten())
print(f"Original class counts: {class_counts}")
print(f"New class counts after oversampling: {oversampled_class_counts}")

# Update the train_datagen to use the oversampled data
from tensorflow.keras.preprocessing.image import array_to_img, img_to_array, load_img
```

Modal validation

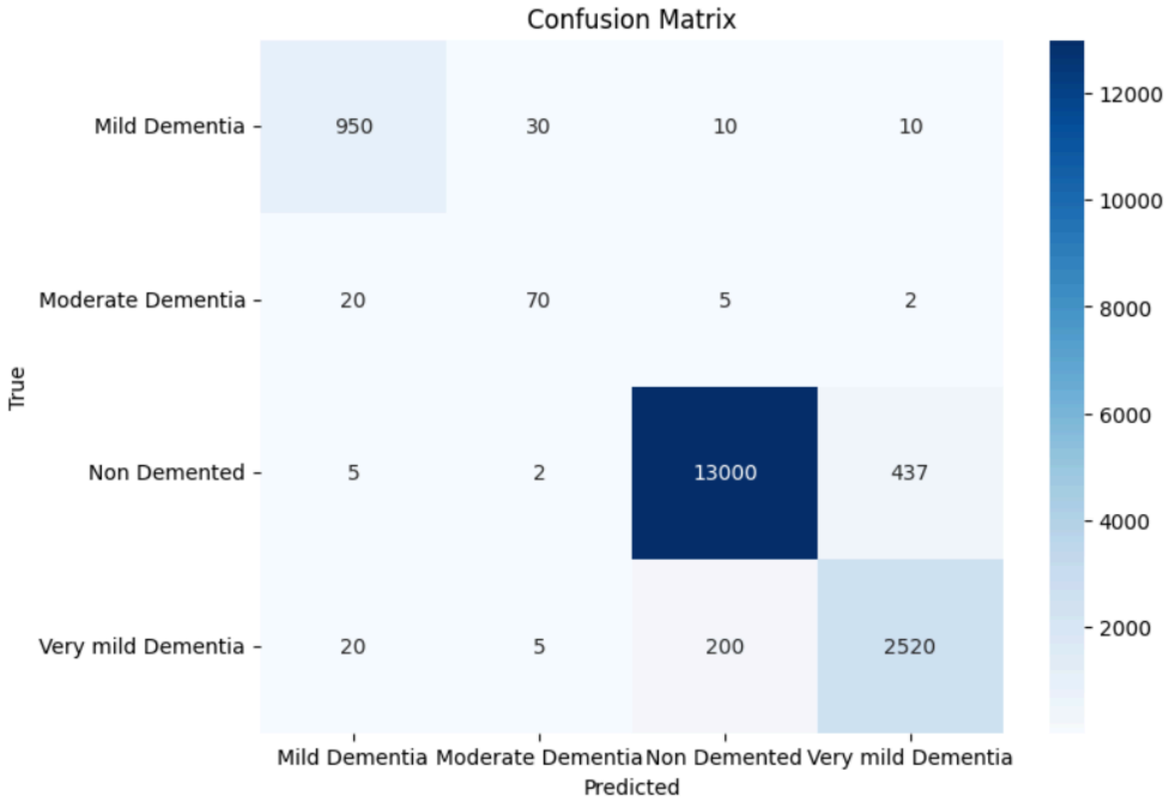


Data CNN + SVM model summary




```
...
    Classification Report:

                       precision    recall  f1-score   support

         Mild Dementia       0.77      0.83      0.80       104
     Moderate Dementia       0.95      1.00      0.97        91
          Non Demented       0.91      0.78      0.84        99
    Very mild Dementia       0.74      0.75      0.75        97

              accuracy                           0.84       391
             macro avg       0.84      0.84      0.84       391
          weighted avg       0.84      0.84      0.84       391


...  ['feature_scaler.pkl']
```

EfficientNetB0 Modal summary



References

[1] *A. Ebrahimi-Ghahnavieh, S. Luo and R. Chiong, "Transfer Learning for Alzheimer's Disease Detection on MRI Images," 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT), Bali, Indonesia, 2019, pp. 133-138*

[2] *C. -E. Kuo, Y. -C. Liu, D. -W. Chang, C. -P. Young, F. -Z. Shaw and S. -F. Liang, "Development and Evaluation of a Wearable Device for Sleep Quality Assessment," in IEEE Transactions on Biomedical Engineering, vol. 64, no. 7, pp. 1547-1557*

[3] *Simon A., Deo M., Selvam V., and Babu R., An overview of machine learning and its applications, International Journal of Electrical Sciences & Engineering. (2016)* ***1****, 22–24.*

Early Detection of Parkinson's: Harnessing Machine Learning for Predictive Risk Modeling

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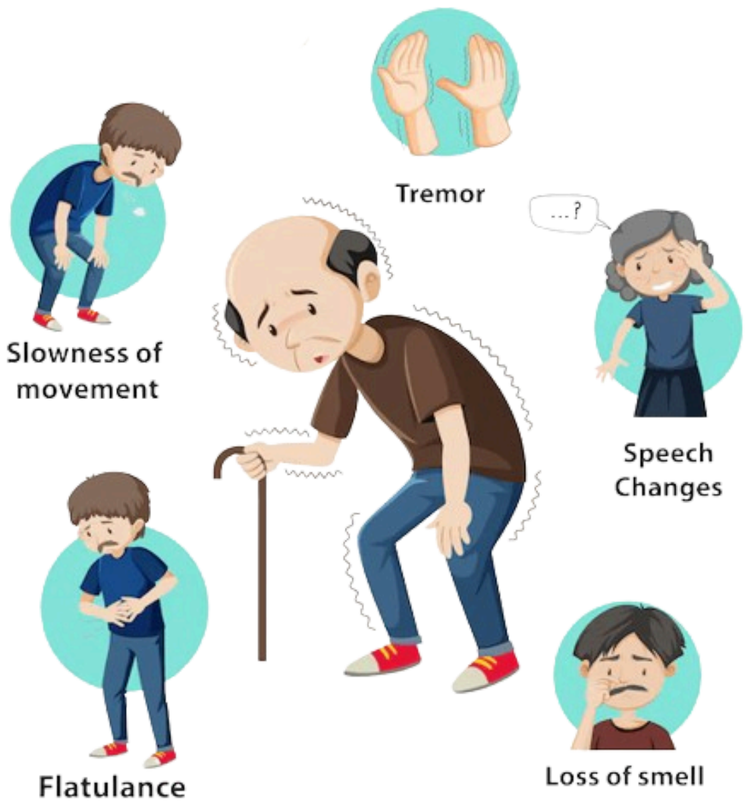
Bachelor of Science (Hons) in Information Technology
Specializing in Data Science

Introduction & Background

Component 2

What is Parkinson’s disease?

- Parkinson's disease is a progressive neurodegenerative disorder affecting millions worldwide. It primarily impacts motor functions due to the loss of dopamine-producing neurons in the brain.



Identified Research Gaps

-Most existing works focus on a single data modality

-Limited research on real-world integration of multimodal inputs for Parkinson’s detection.

-Lack of practical models that provide stage-wise risk assessment.

-Few studies utilize smart data acquisition methods.

-Real-time deployment through web-based application

Proposed Creative Solution

Multimodal ML Framework for Parkinson's Detection

Uses separately trained models for each modality

-Clinical
-Voice
-Handwriting

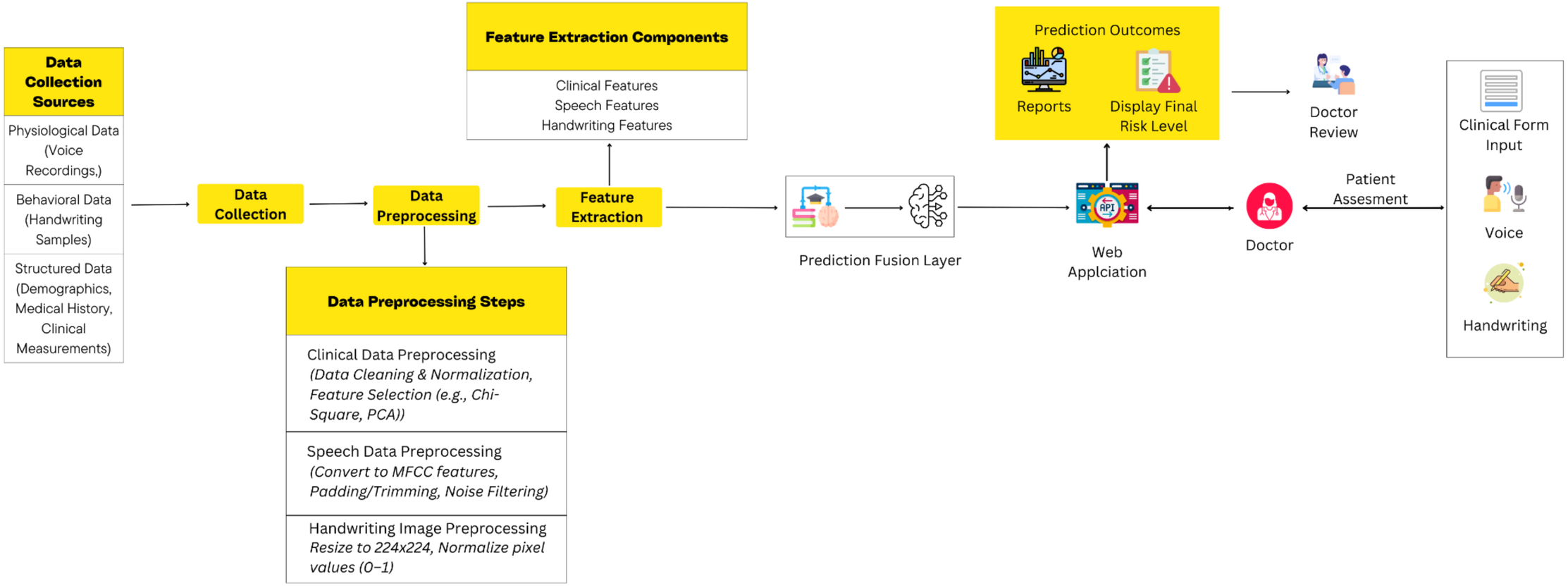
Designed for Real-World Use

Designed for practical usage in healthcare environments

Allows doctors to upload patient voice, handwriting, and fill clinical form via a web application

Produces a final risk prediction for Parkinson's disease to support early diagnosis

Methodology



Requirements

Personal Requirements

- Guidance from Dr. Anuradha Baminiwatta

Functional Requirements

- Data Collection and Preprocessing
- Predictive Modeling
- Feature Extraction and Selection
- Integration and Real-Time Analysis
- Reporting and Visualization

Non-Functional Requirements

- Performance
- Scalability
- Reliability
- Security
- Usability

Tools & Technologies

Technologies

- Flutter
- Python
- ReactJS
- Firebase
- Docker
- Google colab
- ChartJS

Algorithms

- Support Vector Machines (SVM)
- Random Forest
- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN) / Long Short-Term Memory (LSTM)

Techniques

- Voice Classification
- Voice Activity Detection (VAD)
- Image Classification
- Multimodal Fusion

Separation of Feature Domains

Each dataset represents a distinct feature domain.

•Handwriting Samples Model: Focuses on motor-related symptoms (e.g., tremors or irregularities in handwriting)

•DVoice Audio Model: Targets speech-related symptoms (e.g., monotone speech, voice tremors).

•Clinical Data Model: Leverages demographic and lifestyle factors for broader risk prediction.

Evidence Of Completion

Predictive Model for Early Identification of Parkinson's Disease Risk Using Clinical Data

Overview of the Dataset

This dataset contains clinical records of Parkinson's patients, including:

- Demographic details (Age, Gender, etc.)
- Clinical test results (UPDRS score, Tremor severity, MoCA scores, etc.)
- Lifestyle & medical history factors

-2,105 patient records and 35 features

-Reads the dataset from a CSV file and displays the first 5 rows

-Checking missing values

```
df.shape
```

```
(2105, 35)
```

```
[ ] #load the dataset
    df = pd.read_csv('parkinsons_disease_data.csv')
    df.head()
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption	PhysicalActivity	DietQuality	...	FunctionalA
0	3058	85	0	3	1	19.619878	0	5.108241	1.380660	3.893969	...	
1	3059	75	0	0	2	16.247339	1	6.027648	8.409804	8.513428	...	
2	3060	70	1	0	0	15.368239	0	2.242135	0.213275	6.498805	...	
3	3061	52	0	0	0	15.454557	0	5.997788	1.375045	6.715033	...	
4	3062	87	0	0	1	18.616042	0	9.775243	1.188607	4.657572	...	

5 rows × 35 columns

```
df.isnull().sum()
```

	0
PatientID	0
Age	0
Gender	0
Ethnicity	0
EducationLevel	0
BMI	0
Smoking	0
AlcoholConsumption	0

Data Preprocessing

```
[ ] #Label Encoding the Target Variable

    from sklearn.preprocessing import LabelEncoder


    le = LabelEncoder()
    df['Diagnosis'] = le.fit_transform(df['Diagnosis'])
```

```
[ ] df['Diagnosis'].head()
```

	Diagnosis
0	0
1	1
2	1
3	1
4	0

dtype: int64

Encode categorical labels into numerical format

-Used LabelEncoder()

```
#Drop Unrelated Columns
df.drop(['PatientID','DoctorInCharge'],axis=1,inplace=True)
df.head()
```

	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption	PhysicalActivity	DietQuality	SleepQuality	...	MoCA	FunctionalAssessment	Tr
0	85	0	3	1	19.619878	0	5.108241	1.380660	3.893969	9.283194	...	29.181289	1.572427	
1	75	0	0	2	16.247339	1	6.027648	8.409804	8.513428	5.602470	...	12.332639	4.787551	
2	70	1	0	0	15.368239	0	2.242135	0.213275	6.498805	9.929824	...	29.927783	2.130686	
3	52	0	0	0	15.454557	0	5.997788	1.375045	6.715033	4.196189	...	21.304268	3.391288	
4	87	0	0	1	18.616042	0	9.775243	1.188607	4.657572	9.363925	...	8.336364	3.200969	

5 rows × 33 columns

Removing unnecessary columns that do not contribute to the model's prediction.

Data Preprocessing

Feature Selection

-Using the Chi-Square (χ^2) statistical test

```python
#Feature selection using Chi-Square
from sklearn.feature_selection import chi2
from sklearn.feature_selection import SelectKBest

# Assume X is the feature matrix and y is the target
X = df.drop(columns=['Diagnosis'])
y = df['Diagnosis']

# Select top 10 features using chi2
chi2_selector = SelectKBest(chi2, k=10)
X_selected = chi2_selector.fit_transform(X, y)
print("Selected Features:", chi2_selector.get_feature_names_out())
```

```
Selected Features: ['Age' 'AlcoholConsumption' 'CholesterolTriglycerides' 'UPDRS' 'MoCA'
 'FunctionalAssessment' 'Tremor' 'Rigidity' 'Bradykinesia'
 'PosturalInstability']
```

Spliit the dataset

-Splits the dataset into training and testing sets before model training

```python
#Train-Test Split (80%-20%)
from sklearn.model_selection import train_test_split

X = df[['Age' , 'AlcoholConsumption' ,'CholesterolTriglycerides', 'UPDRS' ,'MoCA',
 'FunctionalAssessment', 'Tremor' ,'Rigidity', 'Bradykinesia',
 'PosturalInstability']]
y = df['Diagnosis']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```python
y_train
```

	Diagnosis
874	0
650	0
1596	1
1578	1
1560	0
...	...
1638	1
1095	0
1130	1
1294	0
860	1

Model Training

```python
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

#Define hyperparameter grids
param_grids = {
    "Decision Tree": {
        "criterion": ["gini", "entropy"],
        "max_depth": [3, 5, 10, None],
        "min_samples_split": [2, 5, 10],
        "min_samples_leaf": [1, 2, 4]
    },
    "Random Forest": {
        "n_estimators": [100, 200, 300],
        "max_depth": [5, 10, None],
        "min_samples_split": [2, 5, 10],
        "min_samples_leaf": [1, 2, 4]
    },
    "XGBoost": {
        "n_estimators": [100, 200, 300],
        "max_depth": [3, 5, 10],
        "learning_rate": [0.01, 0.1, 0.2],
        "subsample": [0.6, 0.8, 1.0],
        "colsample_bytree": [0.6, 0.8, 1.0]
    }
}
```

Defines hyperparameter tuning grids for three classifiers:

- Decision Tree Classifier
- Random Forest Classifier
- XGBoost Classifier

Model Training

```python
[ ]
grid_search.fit(X_train, y_train)

# Get the best model and evaluate
best_model = grid_search.best_estimator_
best_models[model_name] = best_model

# Make predictions
train_pred = best_model.predict(X_train)
test_pred = best_model.predict(X_test)

# Calculate metrics
train_accuracy = accuracy_score(y_train, train_pred)
test_accuracy = accuracy_score(y_test, test_pred)

results[model_name] = {
    "Best Params": grid_search.best_params_,
    "Train Accuracy": train_accuracy,
    "Test Accuracy": test_accuracy,
    "Classification Report": classification_report(y_test, test_pred, output_dict=True)
}

print(f"{model_name} - Train Accuracy: {train_accuracy:.4f}, Test Accuracy: {test_accuracy:.4f}")
print(f"Best Parameters: {grid_search.best_params_}")
```

```
Optimizing Decision Tree...
Fitting 3 folds for each of 72 candidates, totalling 216 fits
Decision Tree - Train Accuracy: 0.9181, Test Accuracy: 0.8670
Best Parameters: {'criterion': 'entropy', 'max_depth': 5, 'min_samples_leaf': 1, 'min_samples_split': 10}
Optimizing Random Forest...
Fitting 3 folds for each of 81 candidates, totalling 243 fits
Random Forest - Train Accuracy: 0.9792, Test Accuracy: 0.9145
Best Parameters: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 300}
Optimizing XGBoost...
Fitting 3 folds for each of 243 candidates, totalling 729 fits
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [09:12:36] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
XGBoost - Train Accuracy: 0.9572, Test Accuracy: 0.9145
Best Parameters: {'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 100, 'subsample': 1.0}
```

Performs model training and hyperparameter tuning using Grid Search CV for three models:

- **Decision Tree**
- **Random Forest**
- **XGBoost**

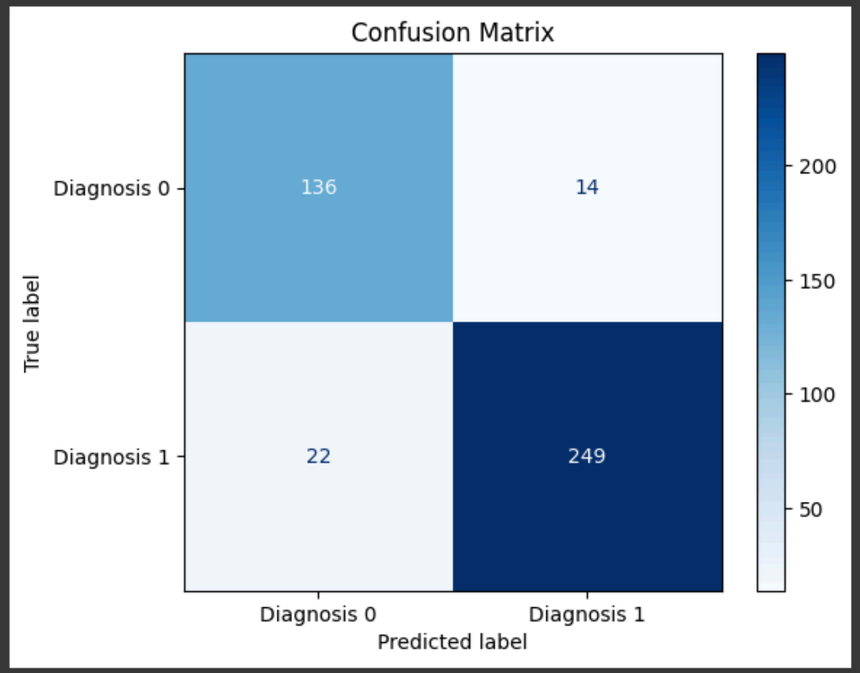
```python
[ ] # Find the best model based on Test Accuracy
best_model_name = max(results, key=lambda x: results[x]["Test Accuracy"])
best_model = best_models[best_model_name]

print(f"\nBest Model: {best_model_name} with Test Accuracy: {results[best_model_name]['Test Accuracy']:.4f}")
print(f"Best Hyperparameters for {best_model_name}: {results[best_model_name]['Best Params']}")
```

```
Best Model: Random Forest with Test Accuracy: 0.9145
Best Hyperparameters for Random Forest: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 300}
```

Random Forest outperformed the others, achieving a test accuracy of **91.45%**

Performance Evaluation

```python
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# Assuming best_model is your trained model
y_pred = best_model.predict(X_test)

# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred, labels=[0, 1])

# Display confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Diagnosis 0", "Diagnosis 1"])
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix")
plt.show()
```



Confusion Matrix

True Positives (TP) = 249

True Negatives (TN) = 136

False Positives (FP) = 14

False Negatives (FN) = 22

Key Performance Metrics

Precision - 94.68%

Recall - 91.89%

F1-score - Around 93%

Speech-Based Predictive Model for Early Parkinson's Disease Risk Identification

Overview of the Dataset

There are 2 types of category files:

Helathy vs. Parkinson's

-Ensures the dataset is correctly structured before feature extraction.

-Helps detect missing or unbalanced data early.

```python
import os
import pandas as pd

# Define the dataset path
dataset_path = "/content/drive/MyDrive/speech_dataset/Audio"

# Define paths for Healthy and Parkinson's audio folders
healthy_audio_path = os.path.join(dataset_path, "HC_AH - Healthy/HC_AH")
parkinson_audio_path = os.path.join(dataset_path, "PD_AH - With Parkinson/PD_AH")

# Get list of files in each folder
healthy_files = os.listdir(healthy_audio_path)
parkinson_files = os.listdir(parkinson_audio_path)

# Create a DataFrame for overview
df_overview = pd.DataFrame({
    "Category": ["Healthy", "Parkinson's"],
    "Total Files": [len(healthy_files), len(parkinson_files)],
    "Sample Files": [healthy_files[:3], parkinson_files[:3]]  # Display first 3 sample files
})

# Print dataset summary
print("\n=== Dataset Overview ===")
print(df_overview)

from IPython.display import display
display(df_overview)
```

```
=== Dataset Overview ===
      Category  Total Files                                       Sample Files
0      Healthy           41  [AH_114S_A89F3548-0B61-4770-B800-2E26AB3908B6....
1  Parkinson's           40  [AH_545622718-C052AD58-5E6B-4ADC-855C-F76B66BA...
```

	Category	Total Files	Sample Files
0	Healthy	41	[AH_114S_A89F3548-0B61-4770-B800-2E26AB3908B6....
1	Parkinson's	40	[AH_545622718-C052AD58-5E6B-4ADC-855C-F76B66BA...

```python
# Display in table format (for Colab)
from IPython.display import display
display(df_files)
```

```
=== List of All Audio Files ===
                                                Filename     Category
0    AH_114S_A89F3548-0B61-4770-B800-2E26AB3908B6.wav      Healthy
1    AH_064F_7AB034C9-72E4-438B-A9B3-AD7FDA1596C5.wav      Healthy
2    AH_264Z_593C20CD-0A54-4177-B031-26EE147080A3.wav      Healthy
3    AH_195B_39DA6A45-F4CC-492A-80D4-FB79049ACC22.wav      Healthy
4    AH_325J_7F5F27AA-5A93-43CF-AB17-FC53940BF4B0.wav      Healthy
..                                                ...          ...
76  AH_545812846-0C14B32A-6C50-4B62-BC89-0A815C2DE...  Parkinson's
77  AH_545841227-5C77713A-66F1-49D0-BC8A-702C152E6...  Parkinson's
78  AH_545789682-7554E0C7-4E25-49C3-9E6C-04D525455...  Parkinson's
79  AH_545806325-8A17002B-CFD3-4DCF-8854-04F0F2BFF...  Parkinson's
80  AH_545834603-857E007F-1CCF-4249-8160-3A0F3F5AB...  Parkinson's

[81 rows x 2 columns]
```

	Filename	Category
0	AH_114S_A89F3548-0B61-4770-B800-2E26AB3908B6.wav	Healthy
1	AH_064F_7AB034C9-72E4-438B-A9B3-AD7FDA1596C5.wav	Healthy
2	AH_264Z_593C20CD-0A54-4177-B031-26EE147080A3.wav	Healthy
3	AH_195B_39DA6A45-F4CC-492A-80D4-FB79049ACC22.wav	Healthy
4	AH_325J_7F5F27AA-5A93-43CF-AB17-FC53940BF4B0.wav	Healthy
...	...	...
76	AH_545812846-0C14B32A-6C50-4B62-BC89-0A815C2DE...	Parkinson's
77	AH_545841227-5C77713A-66F1-49D0-BC8A-702C152E6...	Parkinson's
78	AH_545789682-7554E0C7-4E25-49C3-9E6C-04D525455...	Parkinson's
79	AH_545806325-8A17002B-CFD3-4DCF-8854-04F0F2BFF...	Parkinson's
80	AH_545834603-857E007F-1CCF-4249-8160-3A0F3F5AB...	Parkinson's

Data Preprocessing

```python
def match_audio_with_metadata(metadata, hc_audio_dir, pd_audio_dir):
    audio_data = []
    for _, row in metadata.iterrows():
        sample_id = row['Sample ID']
        label = row['Label']
        age = row['Age']
        sex = row['Sex']


        if label == 'HC':
            file_path = os.path.join(hc_audio_dir, f"{sample_id}.wav")
        else:
            file_path = os.path.join(pd_audio_dir, f"{sample_id}.wav")

        if os.path.exists(file_path):
            audio_data.append({
                'Sample ID': sample_id,
                'File Path': file_path,
                'Label': label,
                'Age': age,
                'Sex': sex
            })
        else:
            print(f"Audio file missing: {sample_id}.wav")

    return pd.DataFrame(audio_data)
```

```python
[ ] # Match audio files with metadata
    audio_metadata = match_audio_with_metadata(metadata, hc_audio_dir, pd_audio_dir)
```

Audio File Matching & Metadata Integration

- Matched audio files with metadata (Sample ID, Age, Sex).
- Identified and handled missing files.
- Structured the dataset into a DataFrame for feature extraction.

Data Preprocessing

Enhancing Model Generalization Through Audio Data Augmentation

Augmentation Techniques Used

-Noise Addition -Time Stretching -Pitch Shifting

```python
# Augment audio with noise, pitch shift, and time stretch
def augment_audio(file_path):
    audio, sr = librosa.load(file_path, sr=None)

    # Augmentation methods
    augmented_audios = [
        audio + np.random.normal(0, 0.02, audio.shape),
        librosa.effects.time_stretch(audio, rate=1.2),
        librosa.effects.pitch_shift(y=audio, sr=sr, n_steps=2),
    ]
    return augmented_audios, sr

# Save augmented audio files
def augment_dataset(audio_metadata, output_dir):
    if not os.path.exists(output_dir):
        os.makedirs(output_dir)

    augmented_metadata = []
    for _, row in audio_metadata.iterrows():
        file_path = row['File Path']
        label = row['Label']
        augmented_audios, sr = augment_audio(file_path)

        # Save augmented audios
        for i, augmented_audio in enumerate(augmented_audios):
            augmented_file = os.path.join(output_dir, f"{os.path.basename(file_path).split('.')[0]}_aug{i}.wav")
            sf.write(augmented_file, augmented_audio, sr)  # Save using soundfile
            augmented_metadata.append({
                'Sample ID': f"{row['Sample ID']}_aug{i}",
                'File Path': augmented_file,
                'Label': label
            })

    return pd.DataFrame(augmented_metadata)
```

Feature Extraction

Used YAMNet pre-trained audio feature extraction model

```python
import tensorflow_hub as hub
import tensorflow as tf

# Load YAMNet
yamnet_model = hub.load('https://tfhub.dev/google/yamnet/1')

def extract_yamnet_features(file_path):
    audio, sr = librosa.load(file_path, sr=16000)
    waveform = tf.convert_to_tensor(audio, dtype=tf.float32)
    scores, embeddings, spectrogram = yamnet_model(waveform)
    return embeddings.numpy().mean(axis=0)


def extract_features(audio_metadata):
    features = []
    labels = []
    for _, row in audio_metadata.iterrows():
        features.append(extract_yamnet_features(row['File Path']))
        labels.append(row['Label'])
    return np.array(features), np.array(labels)

features, labels = extract_features(audio_metadata)
```

Data Preprocessing

Dataset Splitting & Label Encoding for Speech Classification

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2, random_state=42)

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Fit and transform labels to numerical values
y_train = label_encoder.fit_transform(y_train).astype('float32')
y_test = label_encoder.transform(y_test).astype('float32')
```

- Split dataset into 80% training and 20% testing.
- Encoded categorical labels (HC, PD) into numerical values (0,1).

Model Training

```python
def create_transfer_learning_model(input_shape):
    model = models.Sequential([
        layers.Dense(128, activation='relu', input_shape=input_shape),
        layers.Dropout(0.5),
        layers.Dense(64, activation='relu'),
        layers.Dense(1, activation='sigmoid')  # Binary classification
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

model = create_transfer_learning_model((features.shape[1],))
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argumen
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

-Used a Fully Connected Neural Network (Dense Layers).

Built a deep learning model using transfer learning (YAMNet embeddings).

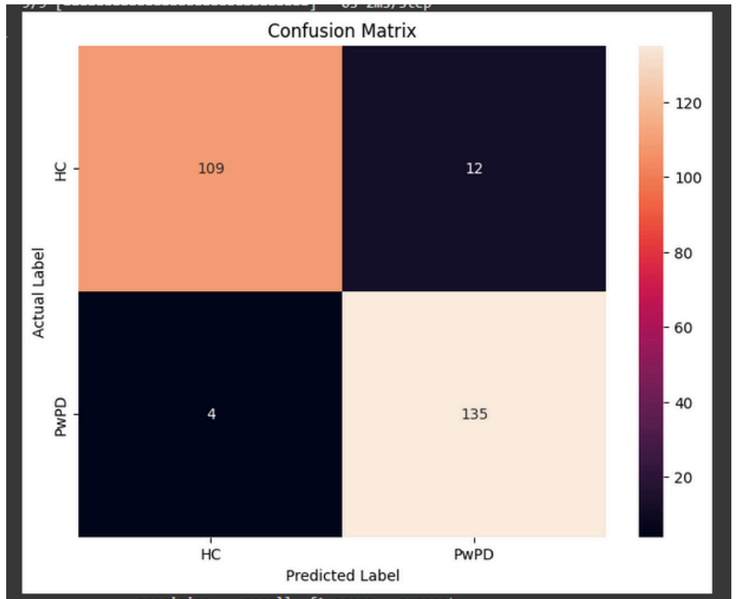
```python
[ ] history = model.fit(
        X_train, y_train,
        epochs=20,
        batch_size=16,
        validation_data=(X_test, y_test)
    )
```

```
65/65 [==============================] - 0s 4ms/step - loss: 0.1574 - accuracy: 0.9431 - val_loss: 0.1999 - val_accuracy: 0.9308
Epoch 16/20
65/65 [==============================] - 0s 4ms/step - loss: 0.1300 - accuracy: 0.9517 - val_loss: 0.2014 - val_accuracy: 0.9308
Epoch 17/20
65/65 [==============================] - 0s 4ms/step - loss: 0.1421 - accuracy: 0.9479 - val_loss: 0.1881 - val_accuracy: 0.9308
Epoch 18/20
65/65 [==============================] - 0s 4ms/step - loss: 0.1399 - accuracy: 0.9402 - val_loss: 0.1995 - val_accuracy: 0.9346
Epoch 19/20
65/65 [==============================] - 0s 4ms/step - loss: 0.1231 - accuracy: 0.9517 - val_loss: 0.1667 - val_accuracy: 0.9423
Epoch 20/20
65/65 [==============================] - 0s 4ms/step - loss: 0.1199 - accuracy: 0.9546 - val_loss: 0.1907 - val_accuracy: 0.9385
```

- Training Accuracy (Final Epoch 20): **95.46%**
- Validation Accuracy (Final Epoch 20): **93.85%**

Performance Evaluation

```python
[ ] from sklearn.metrics import confusion_matrix, classification_report
    import seaborn as sns
    import matplotlib.pyplot as plt

    # Evaluate model
    y_pred = (model.predict(X_test) > 0.5).astype(int).ravel()

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)

    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt="d", xticklabels=['HC', 'PwPD'], yticklabels=['HC', 'PwPD'])
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("Actual Label")
    plt.show()

    # Classification Report
    print(classification_report(y_test, y_pred, target_names=['HC', 'PwPD']))
```




```
              precision    recall  f1-score   support

          HC       0.96      0.90      0.93       121
        PwPD       0.92      0.97      0.94       139

    accuracy                           0.94       260
   macro avg       0.94      0.94      0.94       260
weighted avg       0.94      0.94      0.94       260
```

- True Negatives (TN = 109)
- True Positives (TP = 135)
- False Positives (FP = 12)
- False Negatives (FN = 4)

- HC Precision: 96%, Recall: 90%
- PwPD Precision: 92%, Recall: 97%

Hand-Writing Samples Predictive Model for Early Parkinson's Disease Risk Identification

Overview of the Dataset

```
[6]  # Get list of images
     healthy_images = [f for f in os.listdir(healthy_path) if f.lower().endswith(('.png', '.jpg', '.jpeg'))]
     parkinson_images = [f for f in os.listdir(parkinson_path) if f.lower().endswith(('.png', '.jpg', '.jpeg'))]
```

```
[7]  # Create a DataFrame for overview
     df_overview = pd.DataFrame({
         "Category": ["Healthy", "Parkinson"],
         "Total Images": [len(healthy_images), len(parkinson_images)],
         "Sample Filenames": [healthy_images[:3], parkinson_images[:3]]  # Show 3 samples
     })
```

```
# Print dataset summary
print("\n=== Dataset Overview ===")
print(df_overview)
display(df_overview)
```

```
=== Dataset Overview ===
    Category  Total Images                                   Sample Filenames
0    Healthy          1632  [Healthy1482.png, Healthy1490.png, Healthy1597...
1  Parkinson          1632  [Parkinson1617.png, Parkinson1481.png, Parkins...
```

	Category	Total Images	Sample Filenames
0	Healthy	1632	[Healthy1482.png, Healthy1490.png, Healthy1597...
1	Parkinson	1632	[Parkinson1617.png, Parkinson1481.png, Parkins...

There are 2 catogries.

- Healthy
- Parkinson

3264 Total Images

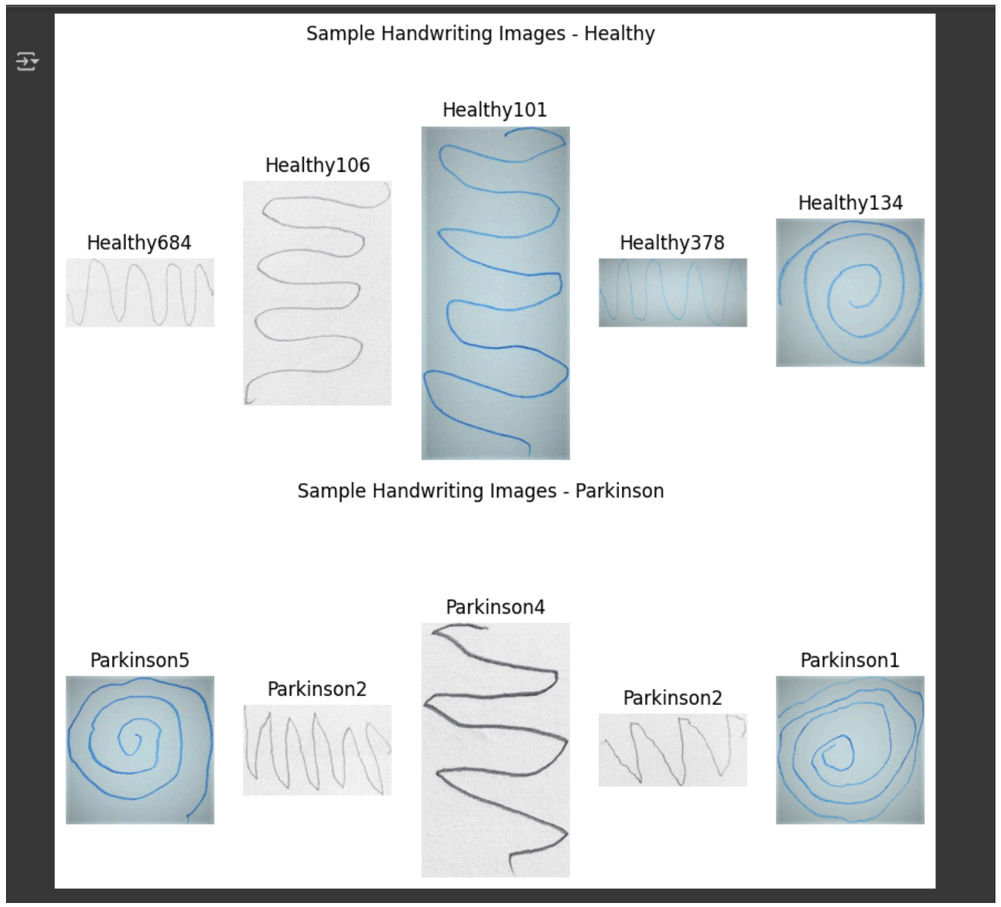
- Healthy - 1632
- Parkinson - 1632

Hand-Writing Samples Predictive Model for Early Parkinson's Disease Risk Identification

Overview of the Dataset

Displays 5 random sample images from each category

```
[9]  # Show random sample images from each category
     def show_sample_images(folder_path, image_list, title):
         plt.figure(figsize=(10, 5))
         random_images = random.sample(image_list, min(5, len(image_list)))  # Pick 5
         for i, img_name in enumerate(random_images):
             img_path = os.path.join(folder_path, img_name)
             img = cv2.imread(img_path)
             img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
             plt.subplot(1, 5, i+1)
             plt.imshow(img)
             plt.axis("off")
             plt.title(img_name[:10])  # Show first 10 characters of filename
         plt.suptitle(title)
         plt.show()

     # Display 5 random sample images from each category
     show_sample_images(healthy_path, healthy_images, "Sample Handwriting Images - Hea
     show_sample_images(parkinson_path, parkinson_images, "Sample Handwriting Images -
```



Data Preprocessing

Dtaset loading & Splitting

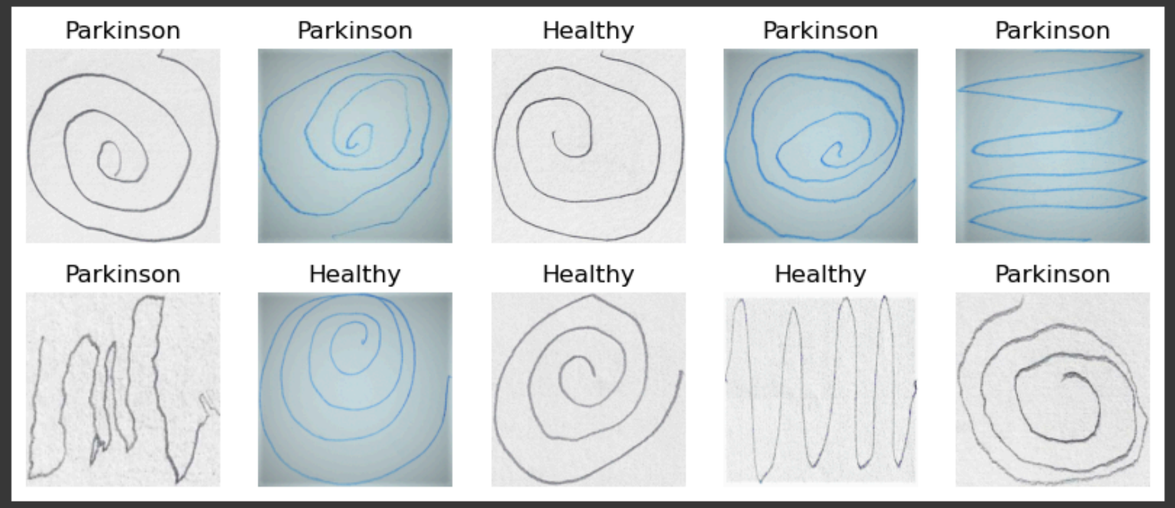
```
BATCH_SIZE = 32
IMG_SIZE = (224, 224)
```

```
[ ] from re import sub

    train_data = tf.keras.utils.image_dataset_from_directory(
        dir,
        image_size=IMG_SIZE,
        batch_size=BATCH_SIZE,
        subset='training',
        validation_split=0.1,
        seed=42
    )
    validation_data = tf.keras.utils.image_dataset_from_directory(
        dir,
        image_size=IMG_SIZE,
        batch_size=BATCH_SIZE,
        subset='validation',
        validation_split=0.1,
        seed=42
    )

    test_data = tf.keras.utils.image_dataset_from_directory(
        dir,
        image_size=IMG_SIZE,
        batch_size=BATCH_SIZE,
        subset='validation',
        validation_split=0.1,
        seed=42
    )
```

Image Normalization

Normalizes pixel values in the training & validation dataset from [0,255] to [0,1].

```
plt.figure(figsize=(10, 4))
for image,label in train_data.take(1) :
  for i in range(10):
    ax = plt.subplot(2,5, i+ 1)
    plt.imshow(image[i].numpy().astype("uint8"))
    plt.title(class_names[label[i]])
    plt.axis("off")

plt.show()
```




```
[ ] train_data = train_data.map(lambda x, y: (x / 255, y))
    validation_data = validation_data.map(lambda x, y: (x / 255, y))
    test_data = test_data.map(lambda x, y: (x / 255, y))
```

Model Training

Used Transfer Learning Model

```python
base_model = tf.keras.applications.MobileNetV2(
    input_shape=(224, 224, 3),
    include_top=False,
    weights='imagenet'
)


base_model.trainable = False


model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(1, activation='sigmoid')
])


model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# Summary of the model
model.summary()

model.compile(optimizer=tf.keras.optimizers.Adam(),
              loss=tf.keras.losses.BinaryCrossentropy(),
              metrics=['accuracy'])
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #

Load Pretrained MobileNetV2 for Feature Extraction

-Used MobileNetV2 as a feature extractor with frozen layers.

Added Custom Fully Connected Layers for Handwriting Classification

-Applied GlobalAveragePooling2D to convert feature maps into a single feature vector.

Compiled and Trained the Model

-Optimizer: Adam

Performance Evaluation

Training Accuracy & Validation Accuracy

```python
    restore_best_weights=True
)

model_checkpoint = ModelCheckpoint(
    'best_model.keras',
    monitor='val_loss',
    save_best_only=True,
    verbose=1
)

history = model.fit(train_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=[early_stopping, model_checkpoint],
                    batch_size = 32
                    )


model.save('parkinson_detection_model.h5')
```

```
Epoch 1/5
92/92 ━━━━━━━━━━━━━━━━━━━━ 0s 622ms/step - accuracy: 0.7383 - loss: 0.5226
Epoch 1: val_loss improved from inf to 0.24858, saving model to best_model.keras
92/92 ━━━━━━━━━━━━━━━━━━━━ 76s 763ms/step - accuracy: 0.7390 - loss: 0.5217 - val_accuracy: 0.8988 - val_loss: 0.2486
Epoch 2/5
92/92 ━━━━━━━━━━━━━━━━━━━━ 0s 600ms/step - accuracy: 0.8755 - loss: 0.2946
Epoch 2: val_loss improved from 0.24858 to 0.17169, saving model to best_model.keras
92/92 ━━━━━━━━━━━━━━━━━━━━ 62s 672ms/step - accuracy: 0.8757 - loss: 0.2943 - val_accuracy: 0.9479 - val_loss: 0.1717
Epoch 3/5
92/92 ━━━━━━━━━━━━━━━━━━━━ 0s 592ms/step - accuracy: 0.9026 - loss: 0.2295
Epoch 3: val_loss improved from 0.17169 to 0.15361, saving model to best_model.keras
92/92 ━━━━━━━━━━━━━━━━━━━━ 62s 667ms/step - accuracy: 0.9026 - loss: 0.2294 - val_accuracy: 0.9448 - val_loss: 0.1536
Epoch 4/5
92/92 ━━━━━━━━━━━━━━━━━━━━ 0s 603ms/step - accuracy: 0.9230 - loss: 0.1991
Epoch 4: val_loss improved from 0.15361 to 0.11844, saving model to best_model.keras
92/92 ━━━━━━━━━━━━━━━━━━━━ 62s 673ms/step - accuracy: 0.9231 - loss: 0.1990 - val_accuracy: 0.9632 - val_loss: 0.1184
Epoch 5/5
92/92 ━━━━━━━━━━━━━━━━━━━━ 0s 577ms/step - accuracy: 0.9377 - loss: 0.1572
Epoch 5: val_loss improved from 0.11844 to 0.10694, saving model to best_model.keras
92/92 ━━━━━━━━━━━━━━━━━━━━ 60s 649ms/step - accuracy: 0.9378 - loss: 0.1571 - val_accuracy: 0.9755 - val_loss: 0.1069
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is consider
```

Used MobileNetV2 with transfer learning, and the training process was enhanced with Early Stopping and Model Checkpointing.

Training Accuracy

93.8%

Validation Accuracy

97.6%

Performance Evaluation

Training Accuracy & Validation Accuracy

```
[ ] evaluation = model.evaluate(validation_data)
    print(f"Validation Loss: {evaluation[0]}, Validation Accuracy: {evaluation[1]}")

11/11 ━━━━━━━━━━━━━━━━━━━━ 6s 562ms/step - accuracy: 0.9821 - loss: 0.0953
Validation Loss: 0.10693712532520294, Validation Accuracy: 0.9754601120948792
```

Model Evaluation on Validation Data

Final Validation Accuracy: 97.6%

Final Validation Loss: 0.1069

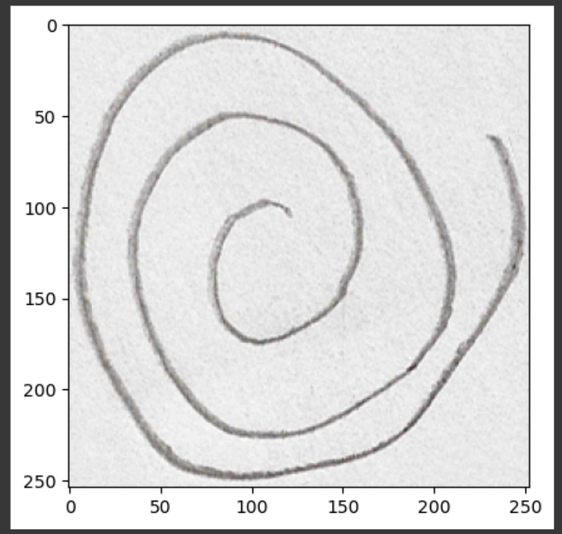
Performance Evaluation

Training Accuracy & Validation Accuracy

Prediction Process

```
[ ] image = cv2.imread('../../DataSets/hehe/Healthy/Healthy80.png')
```

```
[ ] plt.imshow(image)
    plt.show()
```




```
resized_img = tf.image.resize(image, (IMG_SIZE))
scaled_img = resized_img / 255
```

```
[ ] np.expand_dims(scaled_img, axis=0).shape
```

```
(1, 224, 224, 3)
```

```
[ ] y_hat = model.predict(np.expand_dims(scaled_img, axis=0))
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
```

```
[ ] y_hat
```

```
array([[0.08288653]], dtype=float32)
```

```
[ ] class_names
```

```
['Healthy', 'Parkinson']
```

```
[ ] if y_hat > 0.5:
        print(f'Predicted class is healthy')
    else:
        print(f'Predicted class is parkinson')
```

```
Predicted class is parkinson
```

Multimodal Late Fusion for Parkinson's Prediction

```python
def get_clinical_prediction(input_data):
    # Get predictions from the clinical model
    clinical_pred = clinical_model.predict_proba([input_data])[0]  # [Low, Moderate, High]
    return clinical_pred

def get_speech_prediction(audio_file):
    # Extract MFCC features and get predictions from the speech model
    y, sr = librosa.load(audio_file, sr=22050)
    mfcc = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=32)
    mfcc = mfcc.T  # Transpose the MFCC matrix

    # Flatten the MFCCs to a 1D array with 1024 features
    mfcc = mfcc.flatten()[:1024]  # Trim or pad to 1024

    # Reshape to match the expected input shape (None, 1024)
    mfcc = mfcc.reshape(1, -1)  # -1 infers the dimension

    # Check the input shape expected by the speech model
    print("Input shape expected by the model:", speech_model.input_shape)
    print("Shape of MFCCs:", mfcc.shape)
    speech_pred = speech_model.predict(mfcc)[0]  # [Low, Moderate, High]
    return speech_pred

def get_handwriting_prediction(img_path):
    # Preprocess handwriting image and get predictions from the handwriting model
    img = image.load_img(img_path, target_size=(224, 224))
    img_array = image.img_to_array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)
    handwriting_pred = handwriting_model.predict(img_array)[0]  # [Low, Moderate, High]
    return handwriting_pred
```

Defines functions for getting predictions from each individual model (clinical, speech, handwriting) before applying late fusion.

get_clinical_prediction(input_data)

get_speech_prediction(audio_file)

get_handwriting_prediction(img_path)

Multimodal Late Fusion for Parkinson’s Prediction

```python
[ ] def apply_late_fusion(clinical_pred, speech_pred, handwriting_pred):
        """Combine predictions using Weighted Averaging (adjusted weights)."""

        weights = [0.4, 0.3, 0.3]

        final_score = [
            (clinical_pred[0] * weights[0]) + (speech_pred[0] * weights[1]) + (handwriting_pred[0] * weights[2]),
            (clinical_pred[1] * weights[0]) + (speech_pred[1] * weights[1]) + (handwriting_pred[1] * weights[2]),
            (clinical_pred[2] * weights[0]) + (speech_pred[2] * weights[1]) + (handwriting_pred[2] * weights[2])
        ]

        risk_levels = ["Low Risk", "Moderate Risk", "High Risk"]
        final_prediction = risk_levels[np.argmax(final_score)]

        return final_prediction
```

Define Weights

Assigns higher weight (0.4) to clinical predictions

Assigns moderate weight (0.3) to speech model

Assigns lower weight (0.3) to handwriting model

Compute Weighted Scores

Computes the final probability score for each risk level (Low, Moderate, High).

Multimodal Late Fusion for Parkinson’s Prediction

Takes patient input from three sources (clinical, speech, handwriting).

Each model predicts Parkinson’s risk levels (Low, Moderate, High).

Late fusion integrates all three outputs using weighted averaging.

Final prediction is selected based on the highest probability.

```
[ ] # Example inputs (replace with real values)
    clinical_sample = [53, 16.902, 270.33, 134.18, 3.09, 8.40, 0, 0, 0, 0]  # Example clinical features
    speech_file = "AH_064F_7AB034C9-72E4-438B-A9B3-AD7FDA1596C5.wav"  # Replace with actual speech file path
    handwriting_img = "Healthy1.png"  # Replace with actual handwriting image path

    # Get individual predictions
    clinical_pred, speech_pred, handwriting_pred = get_predictions(clinical_sample, speech_file, handwriting_img)

    # Verify Shapes Again
    print("Final Clinical Prediction Shape:", clinical_pred.shape)
    print("Final Speech Prediction Shape:", speech_pred.shape)
    print("Final Handwriting Prediction Shape:", handwriting_pred.shape)

    # Ensure all models return exactly 3 probabilities
    if clinical_pred.shape[0] != 3 or speech_pred.shape[0] != 3 or handwriting_pred.shape[0] != 3:
        raise ValueError("One or more models are not returning 3 probability values. Check model outputs.")

    # Apply Late Fusion
    final_risk_level = apply_late_fusion(clinical_pred, speech_pred, handwriting_pred)

    print("✅ Final Parkinson’s Risk Level:", final_risk_level)
```

```
⚠️ Warning: Clinical model only returned 2 probabilities. Fixing output.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted wi
  warnings.warn(
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
Fixed Clinical Prediction Shape: (3,)
Fixed Speech Prediction Shape: (3,)
Fixed Handwriting Prediction Shape: (3,)
Final Clinical Prediction Shape: (3,)
Final Speech Prediction Shape: (3,)
Final Handwriting Prediction Shape: (3,)
✅ Final Parkinson’s Risk Level: Low Risk
```

References

[1] *Prashanth, R., & Roy, S. D. (2018). Early detection of Parkinson's disease through patient questionnaire and predictive modelling. International journal of medical informatics, 119, 75-87.*

[2] *Govindu, A., & Palwe, S. (2023). Early detection of Parkinson's disease using machine learning. Procedia Computer Science, 218, 249-261.*

[3] *Wang, W., Lee, J., Harrou, F., & Sun, Y. (2020). Early detection of Parkinson's disease using deep learning and machine learning. IEEE Access, 8, 147635-147646.*

[4] *Shaban, M. (2023). Deep learning for Parkinson's disease diagnosis: a short survey. Computers, 12(3), 58.*

Early Autism Spectum Disorder Detection Using Facial Images and Text Analysis

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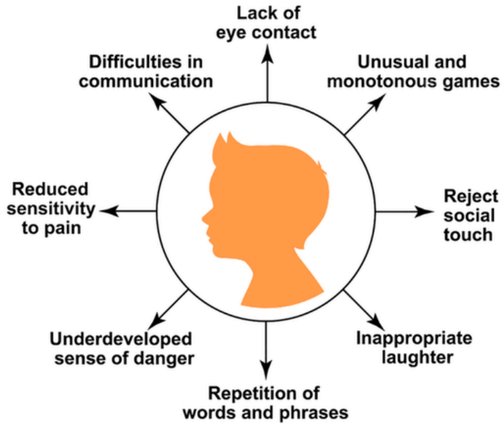
Bachelor of Science (Hons) in Information Technology
Specializing in Data Science

Introduction & Background



What is ASD?

A neurodevelopmental disorder affecting social interaction, communication, and behavior.

Why Early Identification of ASD?

- ***Reduces Clinical Burden*** – Helps doctors focus on real cases, avoiding unnecessary tests.
- ***Helps children get support early*** – Early therapy improves learning and development
- ***Supports parents and families*** – Families can understand the child's needs and help better
- ***Faster and smarter diagnosis*** – AI tools help doctors identify autism early and more reliably

Research Question?

Challenges in Existing ASD Detection Methods

- Delayed Diagnosis
  - Early detection is essential, but often children are diagnosed too late, which reduces the impact of therapy.
- Inaccuracy in Questionnaire-Based Systems
  - Many current methods rely only on questionnaire data or visual features separately.
  - Questionnaire responses may be biased or misunderstood by parents.

Why Combine Facial Images & Questionnaire Data?

- Improves Accuracy
- Captures More Features & Faster Screening

Research Gap

- Insufficient use of multimodal fusion combining both textual/demographic and visual cues.
- Lack of deep fusion techniques like Multimodal Factorized Bilinear (MFB) pooling.
- Few studies explore feature importance over time or integrate advanced architectures like attention-based BiLSTM with Xception hybrids.

Proposed Creative Solution

- Develop a deep learning-based system for early ASD detection using multimodal data.
- Combine textual/numerical (demographic) and visual (facial image) features.
- Implement a four-module framework:
    - Attention-based Stacked BiLSTM for text features
    - Attention-based Xception for facial features
    - MFB (Multimodal Factorized Bilinear) pooling for feature fusion
    - Dense Classifier for final prediction

SPECIFIC & SUB OBJECTIVE

Design and develop an end-to-end multimodal ASD detection framework

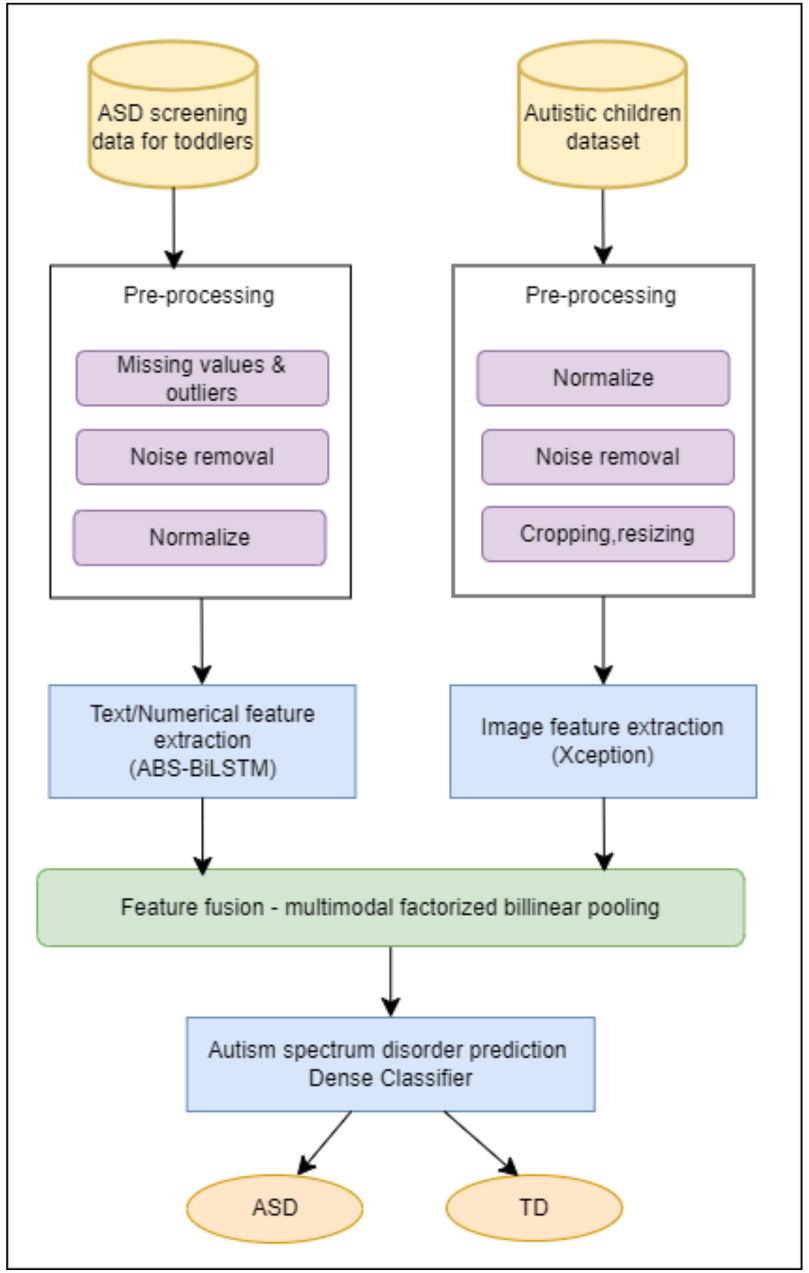
My novel deep learning framework integrates demographic and facial features using Multimodal Factorized Bilinear (MFB) pooling

Validate model performance across multiple datasets and scenarios.

Contribute to practical, scalable, and low-resource ASD screening tools.

Improve early diagnosis accuracy using deep learning and feature fusion.

ASD Prediction Framework Flow Diagram



Tools & Technologies

Technologies

- Flutter
- Python
- ReactJS
- Firebase
- Docker
- Google colab
- ChartJS

Algorithms

- CNN models
- VGG-16 deep learning model
- Random forest
- Naïve bayes and other related machine learning algorithms

Techniques

- Image classification
- Object detection

Requirements

Personal Requirements

- Dr. Anuradha Baminiwatta from Ragama hospital

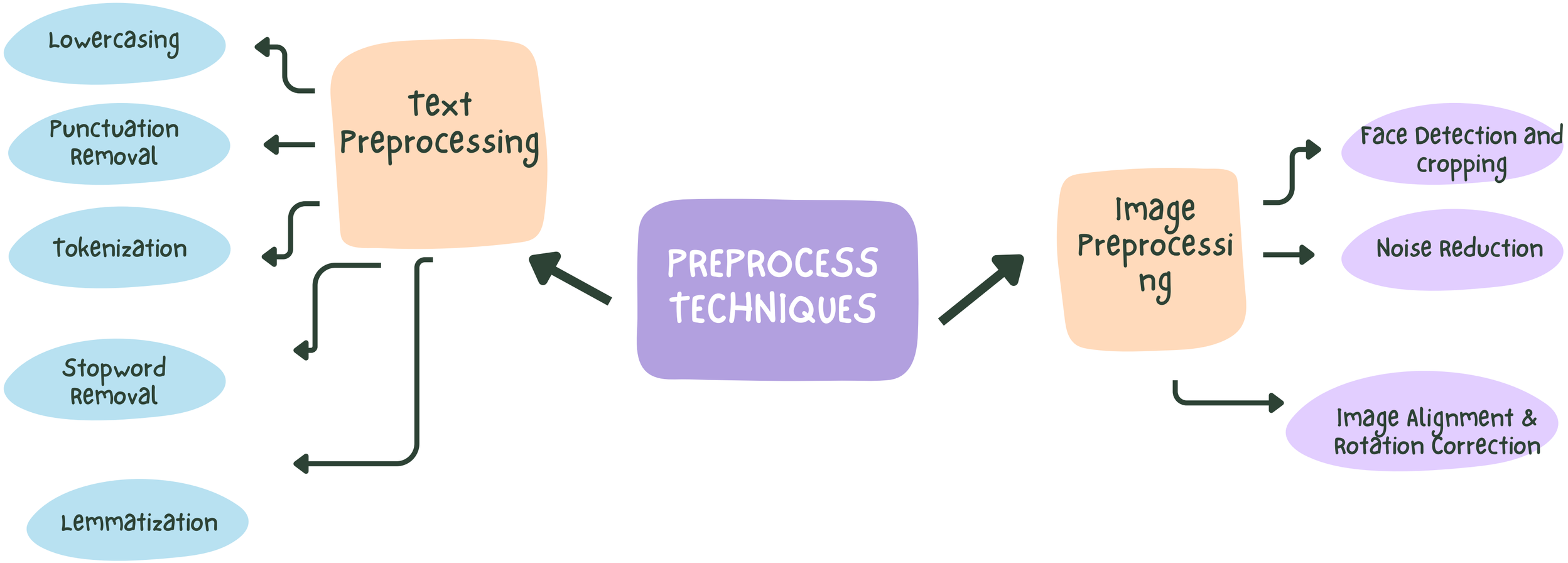
Functional Requirements

- Detecting the facial images
- Identifying the variables to getting rawdata
- Getting the prediction level whether having ASD or not

Non-Functional Requirements

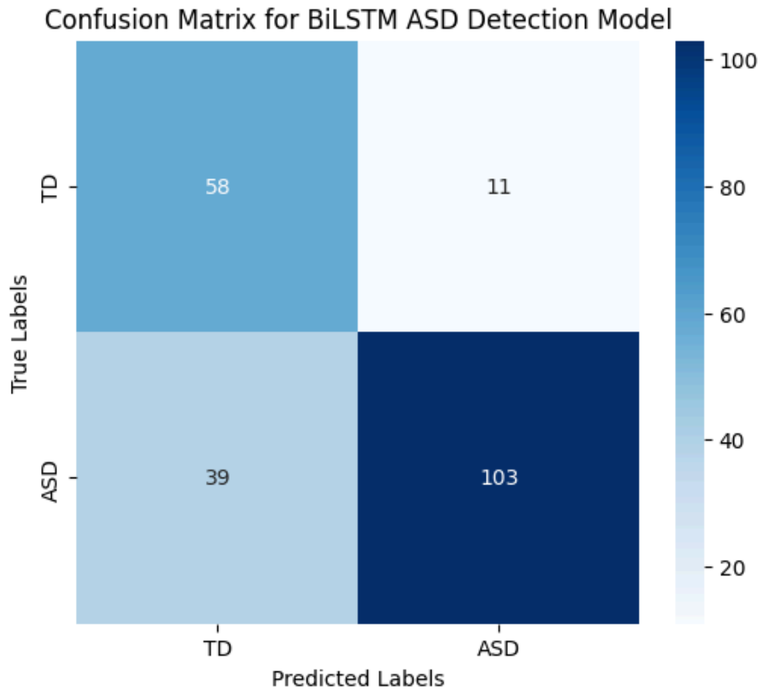
- Interfaces should be User-friendly
- Faster result
- Application should properly work for cross platform

Evidence of Completion


PREPROCESS TECHNIQUES
Text Preprocessing
Lowercasing
Punctuation Removal
Tokenization
Stopword Removal
Lemmatization
Image Preprocessing
Face Detection and cropping
Noise Reduction
Image Alignment & Rotation Correction

BiLSTM-Based ASD Trait Classification

Confusion Matrix



Accuracy

```
26/26 ━━━━━━━━━━━━━━━━━━━━ 2s 49ms/step
              precision    recall  f1-score   support

          TD       0.62      0.80      0.70       264
         ASD       0.89      0.76      0.82       556

    accuracy                           0.78       820
   macro avg       0.75      0.78      0.76       820
weighted avg       0.80      0.78      0.78       820

Accuracy: 0.78
```

Facial Feature Extraction Using Xception with Multimodal Bilinear Fusion

Architecture	Accuracy
InceptionV3	0.83
Xception	0.89
VGG16	0.80
VGG19	0.77

→ Best Architecture Xception

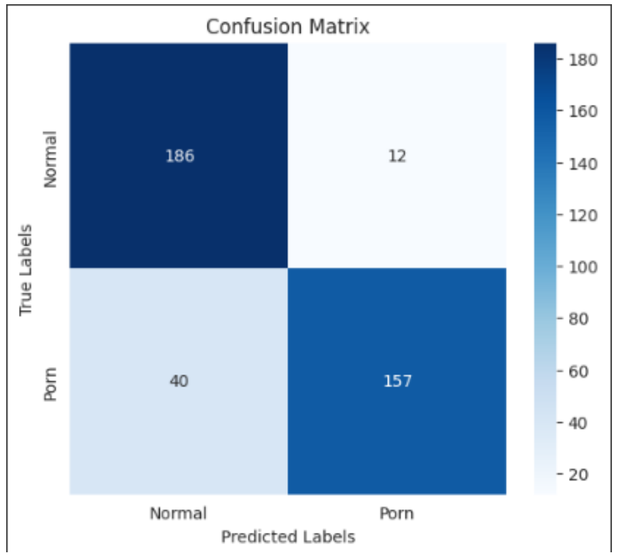
Accuracy Score

```
25/25 ━━━━━━━━━━━━━━━━━━━━ 98s 4s/step
              precision    recall  f1-score   support

           0       0.89      0.90      0.89       198
           1       0.90      0.89      0.89       197

    accuracy                           0.89       395
   macro avg       0.89      0.89      0.89       395
weighted avg       0.89      0.89      0.89       395
```

Confusion Matrix



MFB Fusion Using for Combination of Xception and BiLSTM Features

Autism eye tracking Image Data

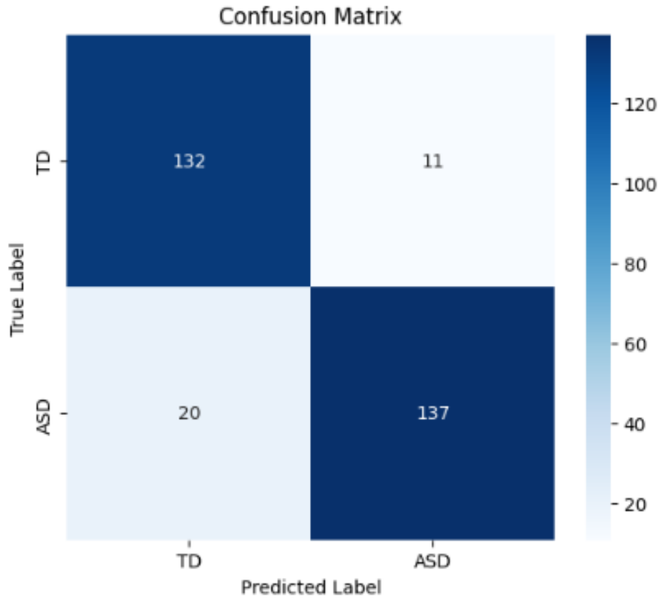
Accuracy Score

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
Classification Report:
              precision    recall  f1-score   support

          TD       0.87      0.92      0.89       143
         ASD       0.93      0.87      0.90       157

    accuracy                           0.90       300
   macro avg       0.90      0.90      0.90       300
weighted avg       0.90      0.90      0.90       300
```

Confusion Matrix



Autism Facial Image Data

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
Classification Report:
              precision    recall  f1-score   support

          TD       0.65      0.69      0.67       151
         ASD       0.66      0.62      0.64       149

    accuracy                           0.66       300
   macro avg       0.66      0.66      0.66       300
weighted avg       0.66      0.66      0.66       300

Confusion Matrix:
[[104  47]
 [ 56  93]]
```

Accuracy Score with Confusion Matrix

References

[1] Uddin, M. Z., Shahriar, M. A., Mahamood, M. N., Alnajjar, F., Pramanik, M. I., & Ahad, M. A. R. (2024). Deep learning with image-based autism spectrum disorder analysis: A systematic review. Engineering Applications of Artificial Intelligence, 127, 107185.

[2] Rasul, R. A., Saha, P., Bala, D., Karim, S. R. U., Abdullah, M. I., & Saha, B. (2024). An evaluation of machine learning approaches for early diagnosis of autism spectrum disorder. Healthcare Analytics, 5, 100293.

[3] *Rashid, A., & Shaker, S. (2023). Autism spectrum disorder detection using face features based on deep neural network. Wasit Journal of Computer and Mathematics Sciences, 2(1), 74-83.*

Diagnosing and Analyzing Depression Through Text and Facial Images

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Specializing in Data Science

Introduction & Background

Component 4

What is Depression?

- Depression is a common mental disorder.
- Globally, an estimated 5% of adults suffer from depression.
- It involves a depressed mood or loss of pleasure or interest in activities **for long periods of time.**
- Depression can lead to suicide.

Research Questions

- How general practitioners can easily diagnose mental disorder like Depression?
- How can practitioners monitor and examine depression patients' behaviors effectively?

Specifics and Sub Objectives

- Initially determining whether a patient is at risk of having depression.
- Monitoring patients' behavior daily by analyzing text inputs and facial images together.
- Give analysis/summary about patients’ current status to doctor.

What I have done?

Depression Diagnosis using Multi-Modal Inputs (Text + Images)

Key Components:

1. **Initial Survey**
2. **Separate models:**
   - Text Model: You're using Bi-LSTM and BERT for depression classification.
   - Image Model: Using VGG19 (or considering ResNet) to analyze facial expressions.
3. **Objective:** Combine both model predictions to enhance accuracy.

What I have done?

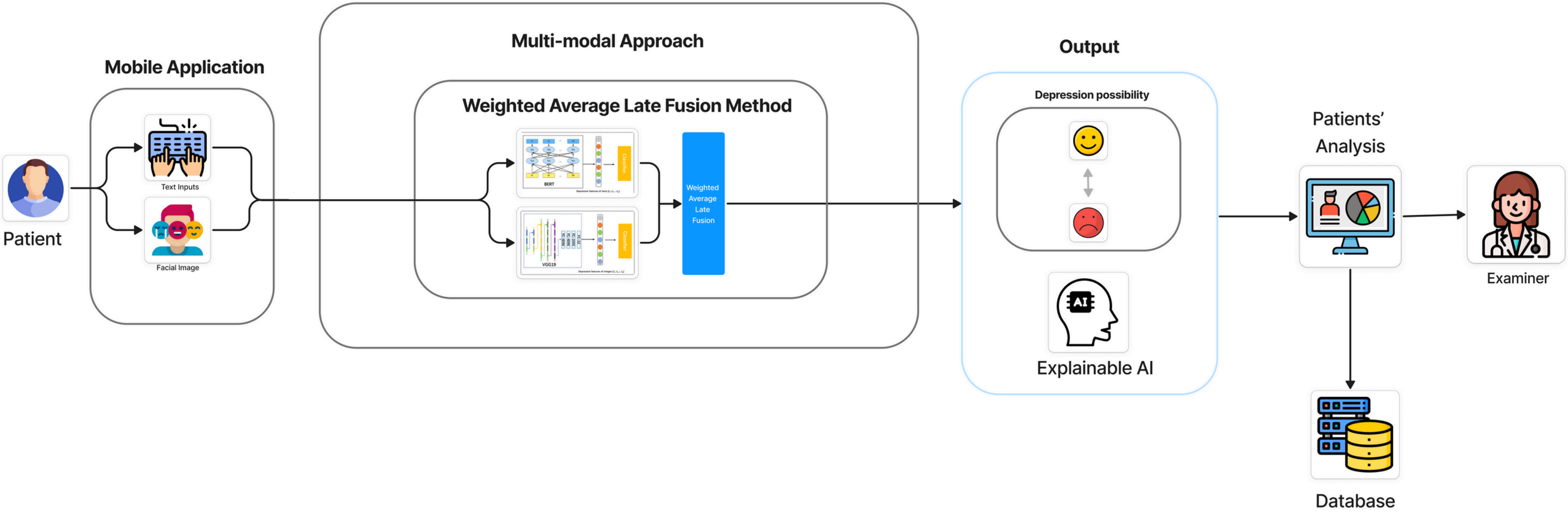
Tried Two Multi-Modal Fusion Approaches:

- Weighted Average (Late Fusion) – combine predictions from both models.
- Multi-Modal Neural Network – combine features from both modalities before classification.

Additional Features:

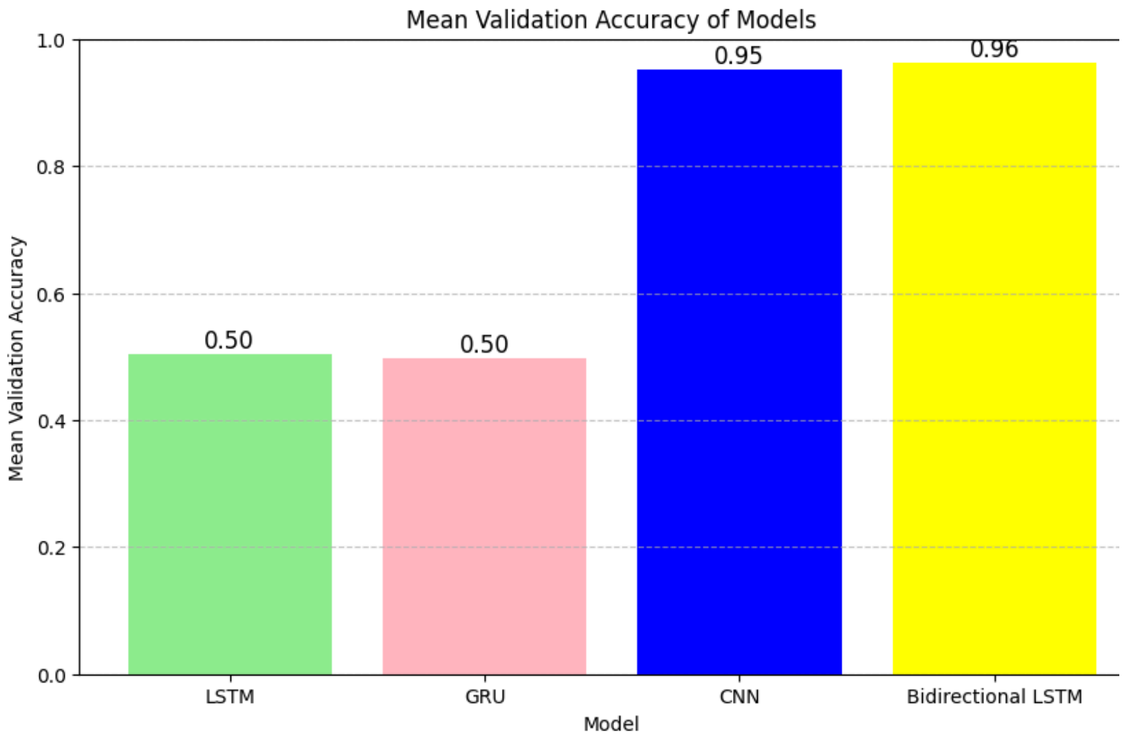
- Use of Explainable AI (XAI) to give doctors understandable model output.
- Implement User-friendly system for the component

Methodology

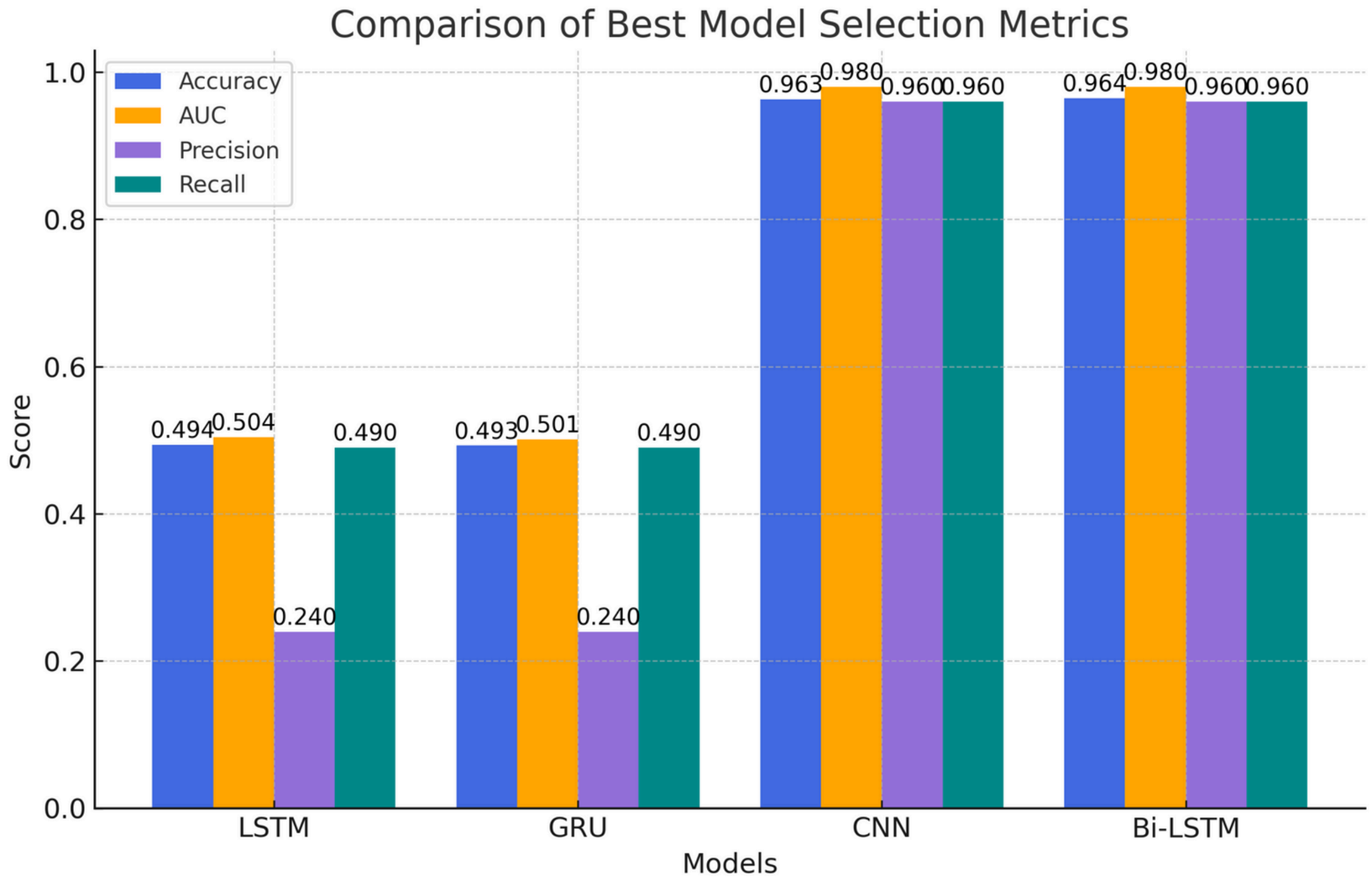


Text Models Comparison

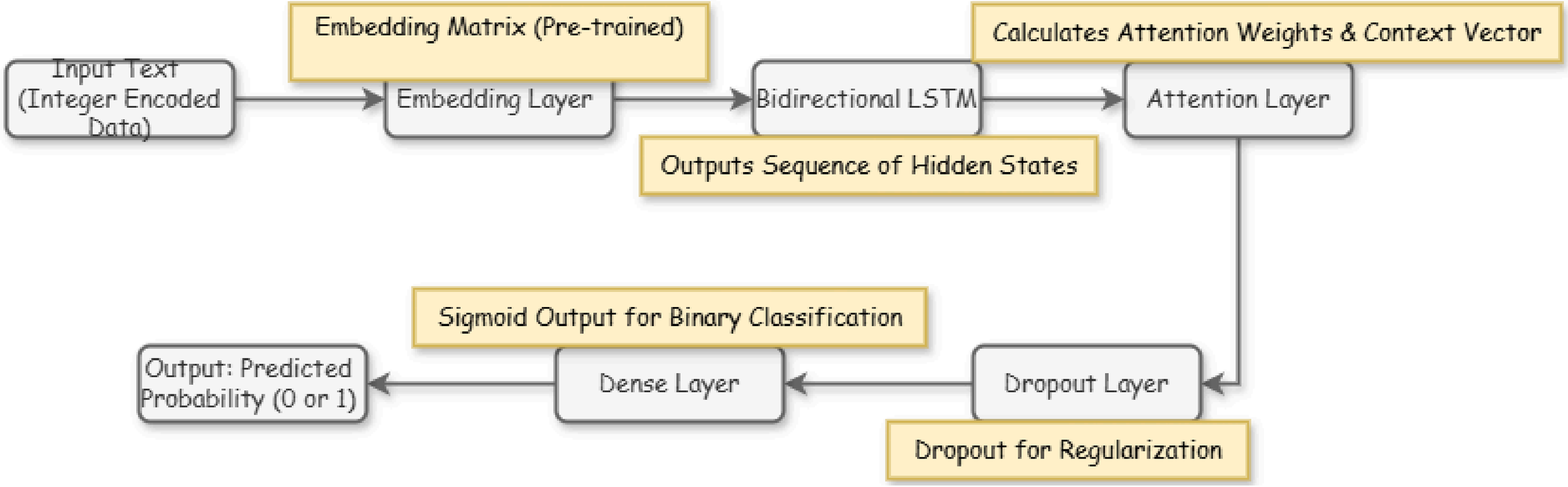
Model	Accuracy
Bidirectional LSTM	0.96
LSTM	0.50
CNN	0.95
GRU	0.50



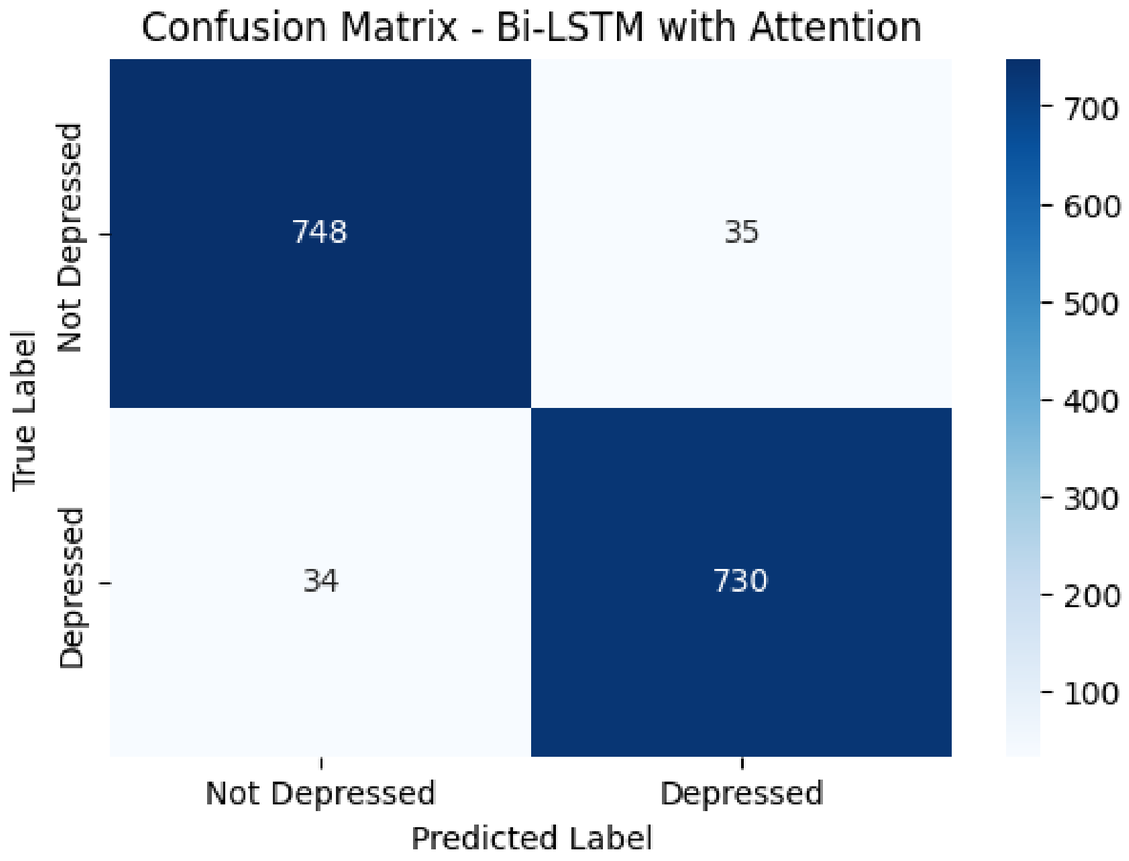
Text Model Selection

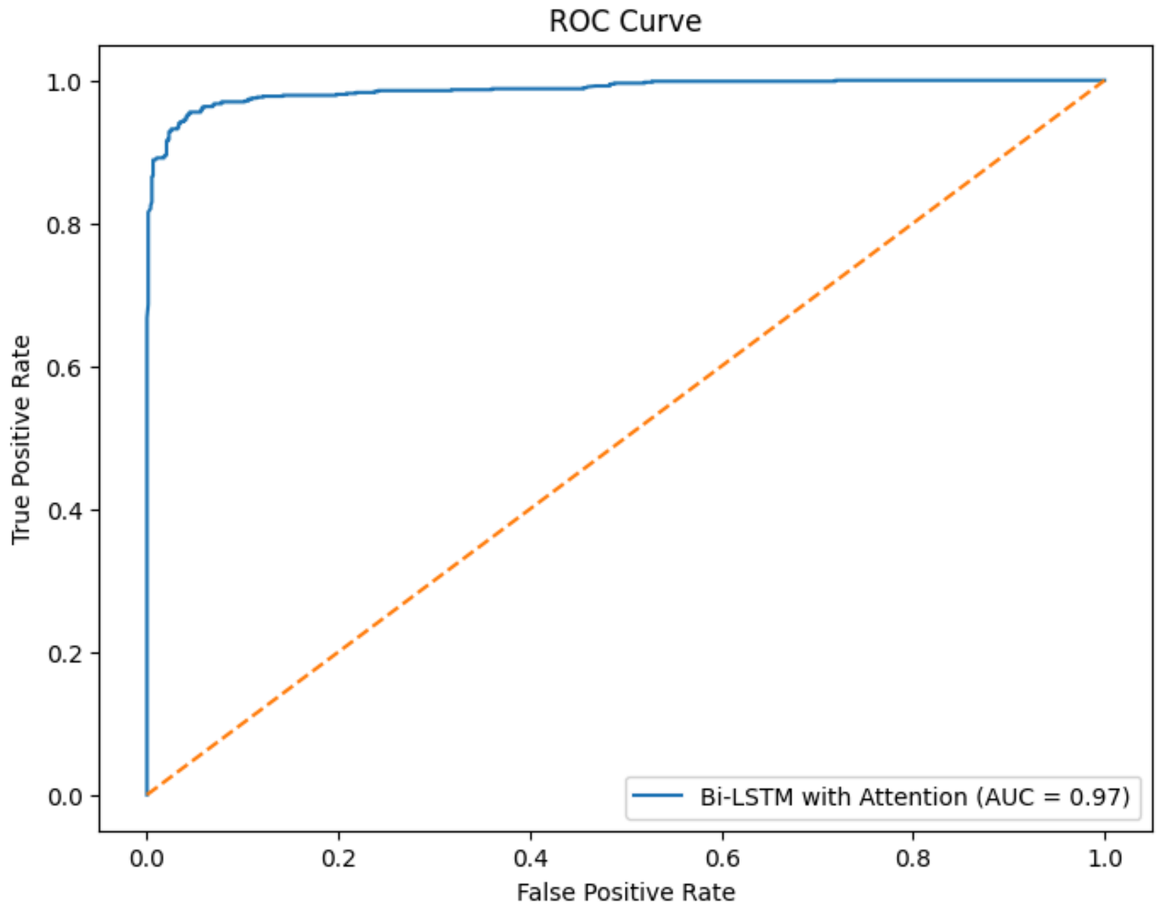


Text Model Architecture



Text Model Performance Evaluation





Text Model Performance Evaluation

```
Bi-LSTM with Attention:
Accuracy: 0.9625, AUC: 0.9764
              precision    recall  f1-score   support

           0       0.94      0.98      0.96       783
           1       0.98      0.94      0.96       764

    accuracy                           0.96      1547
   macro avg       0.96      0.96      0.96      1547
weighted avg       0.96      0.96      0.96      1547

Confusion Matrix:
 [[770  13]
 [ 45 719]]
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step
Text: I feel so down and hopeless every day. Nothing makes sense anymore.
Predicted Probability: 0.9961
Predicted Class: Depressed
--------------------------------------------------
Text: Life is awesome! I am feeling super happy and excited about my future.
Predicted Probability: 0.0008
Predicted Class: Not Depressed
--------------------------------------------------
Text: I have been feeling so lost and empty inside.
Predicted Probability: 0.0007
Predicted Class: Not Depressed
--------------------------------------------------
Text: I am okay, just going through some normal stress.
Predicted Probability: 0.0035
Predicted Class: Not Depressed
--------------------------------------------------
Text: My anxiety keeps getting worse. I don't know what to do.
Predicted Probability: 0.9880
Predicted Class: Depressed
--------------------------------------------------
```

Model Comparison

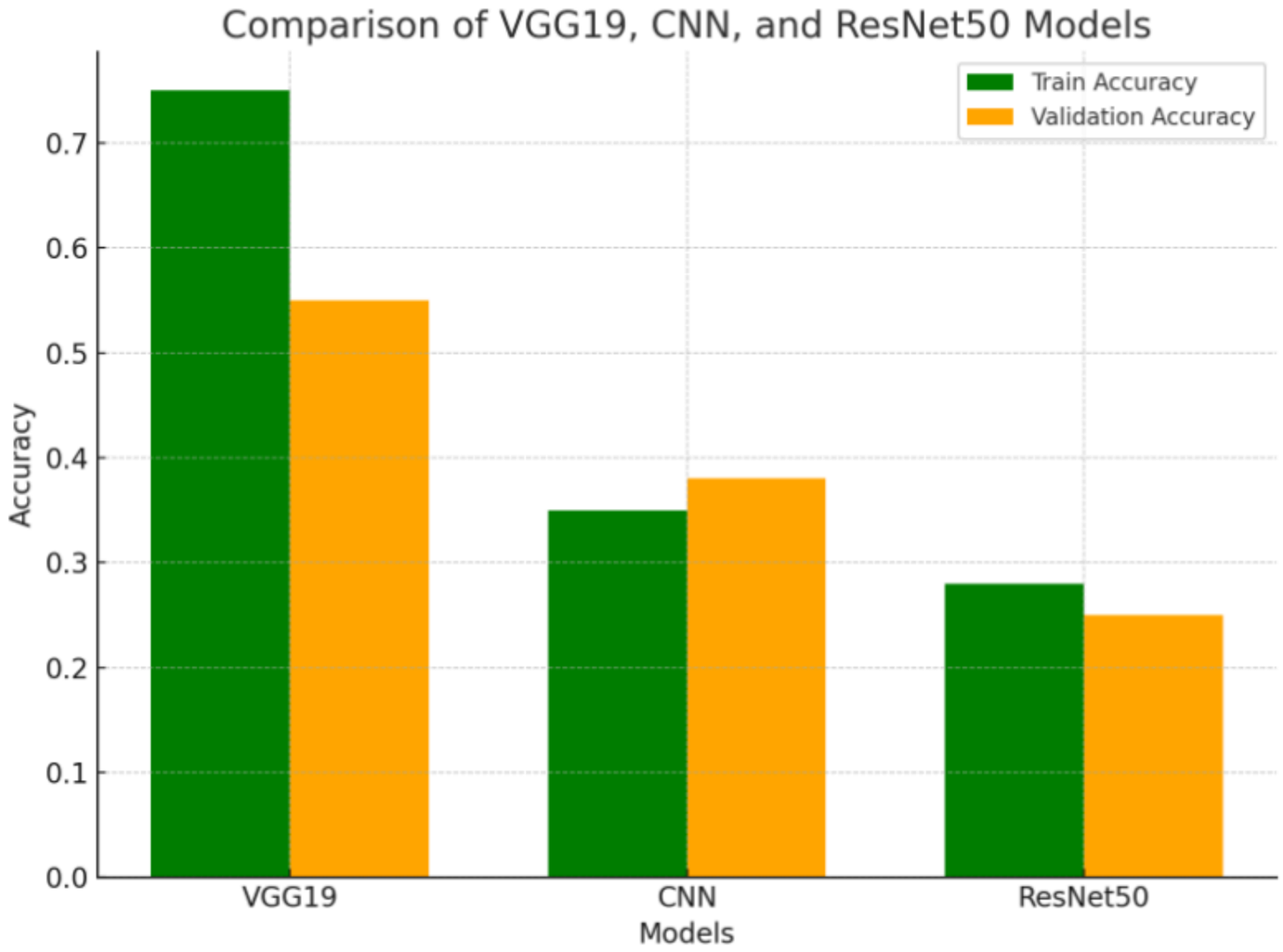


Image Model Performance & Evaluation

```python
# Step 10: Predict a Single Image
from tensorflow.keras.preprocessing.image import load_img, img_to_array

def predict_image(image_path):
    img = load_i (import) img_to_array: Any 224, 224))
    img_array = img_to_array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)

    prediction = model_vgg19.predict(img_array)
    predicted_class = np.argmax(prediction)
    class_labels = list(test_data.class_indices.keys())

    print(f"Predicted Class: {class_labels[predicted_class]} with {np.max(prediction) * 100:.2f}% confidence")

# Example usage
predict_image("D:\\VS Code\\New folder\\train\\neutral\\im1.png")
```

```
1/1 [==============================] - 0s 165ms/step
Predicted Class: neutral with 98.28% confidence
```

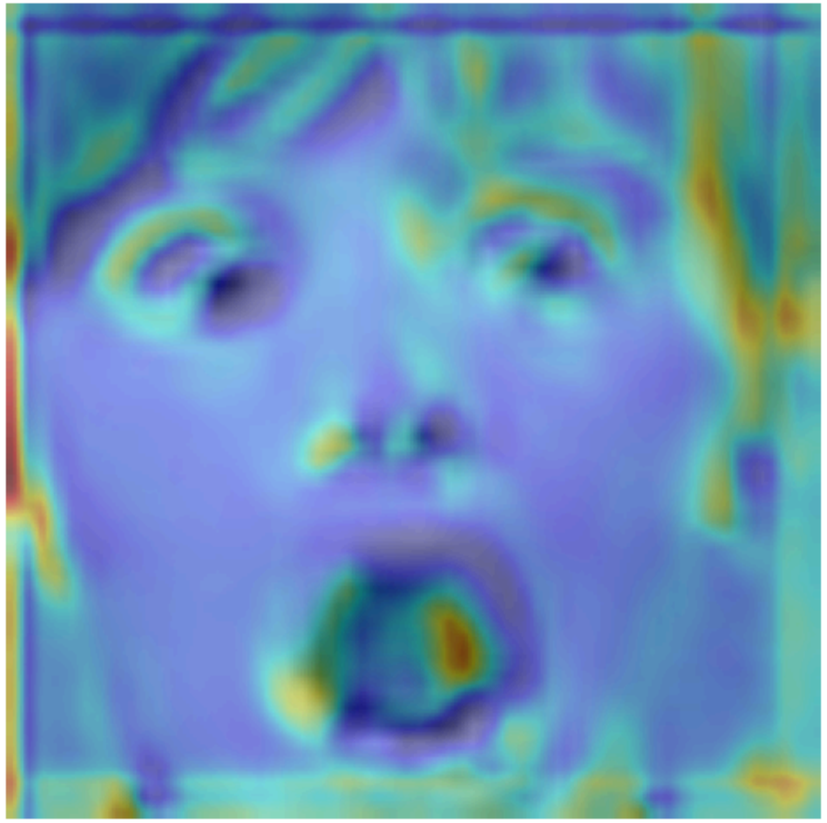
Explainable AI for Model Outputs

```python
# Load and preprocess image
image_path = "D:\\VS Code\\New folder\\test\\surprised\\im11.png"
input_image = preprocess_image(image_path)

# Get predictions
predictions = model.predict(input_image)
predicted_class = np.argmax(predictions)
confidence = np.max(predictions) * 100

# Print prediction result
print(f"Predicted Class: {class_labels[predicted_class]} with {confidence:.2f}% confidence")

# Generate Grad-CAM heatmap
last_conv_layer_name = "block3_conv4"  # Replace with the correct layer name in your model
heatmap = generate_gradcam_heatmap(model, input_image, last_conv_layer_name)

# Overlay heatmap on original image
overlay_heatmap(image_path, heatmap)

```

✓ 2.3s

```
1/1 [==============================] - 1s 514ms/step
Predicted Class: surprised with 99.22% confidence
```

Explainable AI - Grad-CAM



Explainable AI for Model Outputs

```python
# Step 10: Predict a Single Image
from tensorflow.keras.preprocessing.image import load_img, img_to_array

def predict_image(image_path):
    img = load_img(image_path, target_size=(224, 224))
    img_array = img_to_array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)

    prediction = model_vgg19.predict(img_array)
    predicted_class = np.argmax(prediction)
    class_labels = list(test_data.class_indices.keys())

    print(f"Predicted Class: {class_labels[predicted_class]} with {np.max(pre

# Example usage
predict_image("D:\\VS Code\\New folder\\test\\fearful\\im0.png")
```

```
1/1 [==============================] - 0s 172ms/step
Predicted Class: fearful with 52.66% confidence
```

Explainable AI - Grad-CAM

Mutlimodal Fusion - Weighted Average Approach

Multimodal Fusion:

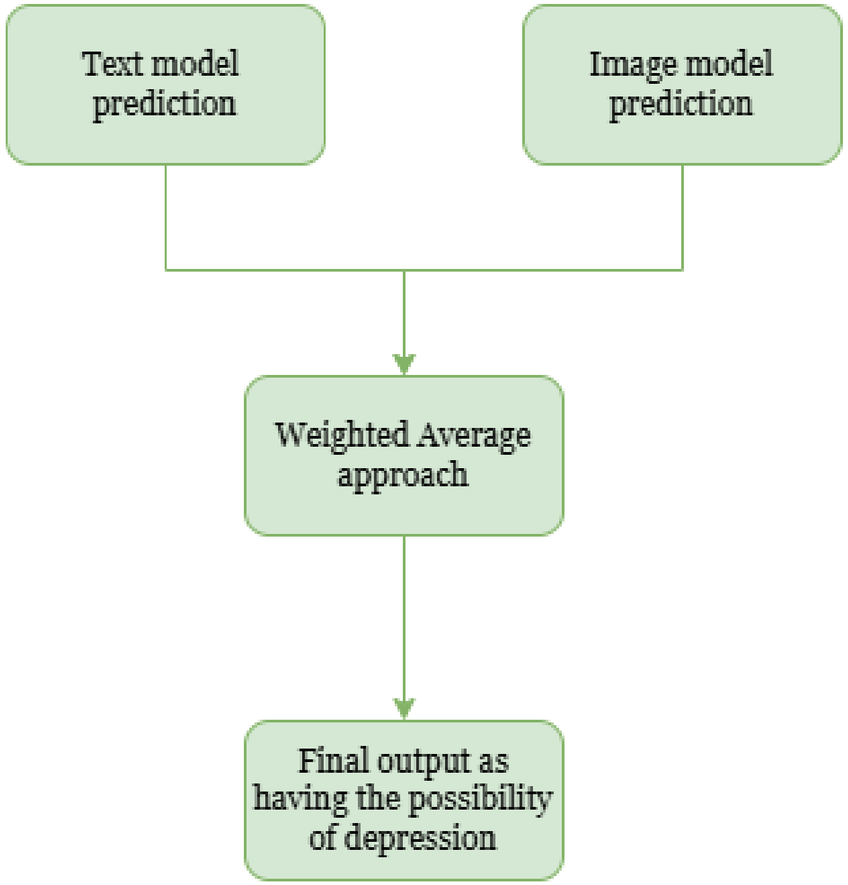
- To combine the text and image prediction probabilities.
- The weights for the text and image probabilities are adjustable.
- The formula used is:

$$\textit{Final Score} = (w\ \textit{text} \times \textit{Text Prediction}) + (w\ \textit{image} \times \textit{Image Prediction})$$

Final Output:

- The final prediction is made based on the fused probabilities (using weighted average).
- If the final probability exceeds 0.5, the result is classified as "Depressed," otherwise "Not Depressed."

Mutlimodal Fusion - Weighted Average Approach



Mutlimodal Fusion - Weighted Average Approach

```python
# Example Image Prediction
P_image = predict_image("/content/drive/MyDrive/Colab Notebooks/Research/emotions/test/happy/im.png")
print("Prob of image: ", P_image)

# Multimodal Fusion: Weighted Average
def weighted_average(P_text, P_image, w_text=0.5, w_image=0.5):
    return w_text * P_text + w_image * P_image

# Final Prediction
P_final = weighted_average(P_text, P_image)
print("Final prob using weighted avg: ", P_final)

if P_final > 0.5:
    print("Depressed")
else:
    print("Not Depressed")
```

```python
# Define emotion class indices
class_indices = {
    'angry': 0,
    'disgusted': 1,
    'fearful': 2,
    'happy': 3,
    'neutral': 4,
    'sad': 5,
    'surprised': 6
}
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compi
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compi
WARNING:absl:Error in loading the saved optimizer state. As a result, your model is starting with a
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
Text Input: I feel very satisfying.
Prob of text:  0.010250252
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
Probabilities of emotions:  [0.02920195 0.00413914 0.05542067 0.83891743 0.04600881 0.014124
 0.01218805]
Image Path: /content/drive/MyDrive/Colab Notebooks/Research/emotions/test/happy/im0.png
Prob of image:  0.09874662
Final prob using weighted avg:  0.054498434
Not Depressed
```

References

[1] *K. Shah, U. Patel and Y. Kumar, "Machine Learning-Based Approaches for Early Prediction of Depression," 2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bangalore, India, 2024, pp. 1-7, doi: 10.1109/IITCEE59897.2024.10467234. keywords: {Computational modeling;Medical treatment;Mental health;Forestry;Predictive models;Depression;Risk management;depression detection;machine learning;random forest;ensemble method},*

[2] *A. Agrawal, S. Dey and G. C. Jana, "Depressive and Non-depressive Tweets Classification using a Sequential Deep Learning Model," 2023 International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC), Silchar, India, 2023, pp. 1-6, doi: 10.1109/ISACC56298.2023.10083981. keywords: {Deep learning;Social networking (online);Computational modeling;Mental health;Media;Depression;Intelligent systems;Depression Detection;Sequential Deep Learning Model;ID-Convolution;LSTM;Social Media},*

References

[3] *M. k. Jha, R. Ranjan, G. K. Dixit and K. Kumar, "An Efficient Machine Learning Classification with Feature Selection Techniques for Depression Detection from Social Media," 2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI), Greater Noida, India, 2023, pp. 481-486, doi: 10.1109/ICCSAI59793.2023.10421064. keywords: {Sensitivity;Social networking (online);Machine learning;Mental health;Depression;Feature extraction;Web sites;Depression Detection;Random Forest;Machine Learning;Gredient Boosting;Recursive Feature Elimination;ADASYN;Linear Regression},*

Business Plan of MENTCARE AI

April 2024
Project Initiation

August 2024
Finalize Architecture

September 2024
Model Development and Implementation

October 2024
Begin development of platform

Q1 2025
Complete development of platform and have a working prototype

Q2 2025
Release Mentcure to the market

Q2 2025
Begin marketing campaigns and outreach programs for user acquisition

Q3 2025
Expand the functionality of the platform and focus on new features

SLIIT FACULTY OF COMPUTING

Group ID: 24-25J-322

Commercialization

Target Market

General Practitioners of the MOH centers

Institutes who learn about mental disorders

General population who wish to take self mental care

Market Size

~12.5% of the world population

Market Access Points

MOH Center

Mentcare Web

Q & A Session

Thank you for your attention