Team 4: Homework 5 Report

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CSCI 5622-001

1 Homework 5 - Report

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Link To Github Repo

1.1 Data Background and Preprocessing Steps

The data provided was in separate CSV files for each participant, with each record representing the participant's turn and the corresponding features. The train folder contained 87 files, while the test folder had 20 files. To simplify the process, all CSVs from the train folder were combined into a single file. The participant ID was extracted from the CSV file name and added as a feature to the consolidated data. The "labels.csv" file was used to map the participant ID to their corresponding gender and depression labels. The test data underwent a similar treatment. As a result, two files were generated: "final_training_data" with 13,625 records and 91 columns, and "final_testing_data" with 3,280 records and 91 columns. In addition to the 88 audio features provided, three columns were added: "participant_id," "gender," and "depression".

[ ]:
```
#import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
↪RepeatedStratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import mutual_info_classif
from sklearn.tree import DecisionTreeClassifier

from keras import models, layers, optimizers, regularizers
```

[ ]:
```
def data_fetch(file_path):
    '''
```

```python
    Fetch the data and remove NAs

    Returns:
    1. Dataframe
    '''
    df = pd.read_csv(file_path, index_col=0)

    #After data exploring we found that one of the data sample's turn was all␣
 ↪NA. So we removed it
    df.dropna(inplace=True)

    return df

def prep_X_y(df,target):
    '''
    Prepare X and y sets for the given dataframe and the specified target␣
 ↪(Depression or Gender)
    Scales the features using Standard Scaler

    Returns:
    1. Scaled X as an array
    2. y as a Pandas series
    3. Gender values as a Pandas series
    4. Feature names from filtered X as a Pandas Index
    '''

    #Prepare X
    X = df.drop(['Depression', 'Gender', 'participant_id'], axis=1)

    #Get features for X set
    features = X.columns

    #Normalize X using standard scaler
    scaler = StandardScaler()
    X = scaler.fit_transform(X)

    #Prepare y
    y = df[target]

    #Get Gender flags
    gender = df['Gender']

    return X,y,gender,features
```

1.2 (a.i) Depression classification

[ ]:
```
def hyperparameter_tuning_rf(X_train, y_train, X_val, y_val):
    param_grid = {
        'n_estimators': [100, 200, 300, 400, 500, 600, 800, 1000, 1200], 
 ↪#Number of trees in the forest
        'max_features': ['sqrt', 'log2'],  #Number of features to consider at␣
 ↪every split
        'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100],  #Maximum␣
 ↪number of levels in tree
        'min_samples_split': [2, 5, 10]  #Minimum number of samples required to␣
 ↪split a node
    }

    #Initialize the classifier
    rf = RandomForestClassifier(random_state=42)

    print("Initializing the evaluator")
    #Define cross-validation evaluation for the search space
    cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=42)

    #Setup the random search space with repeated stratified k fold␣
 ↪cross-validation
    random_search = RandomizedSearchCV(estimator=rf,␣
 ↪param_distributions=param_grid, cv=cv,
                                       scoring='accuracy', verbose=1,␣
 ↪random_state=42, n_jobs=-1)

    print("Fitting the random search cv on the training data")
    #Fit random_search to the data
    random_search.fit(X_train, y_train)

    #Best parameters
    best_params = random_search.best_params_
    print("Best parameters:", best_params)

    #Best model from random search
    best_rf = random_search.best_estimator_

    #Predict on the validation set
    y_pred = best_rf.predict(X_val)

    #Calculate accuracy
    accuracy = accuracy_score(y_val, y_pred)
    print("Validation Accuracy:", accuracy)

    return best_params
```

After experimenting with both Feed Forward Neural Network (FNN) and Random Forest Classifier (RF), we decided to model the Depression classification using Random Forest due to its ease of interpretability and faster processing speed. Although the FNN had a slight advantage in terms of accuracy, the Random Forest Classifier proved to be a more suitable choice for this particular task, offering a balance between performance and practicality.

Moving forward with this choice, we used a Randomized Search CV to identify the best hyperparameters for the Random Forest Classifier. Our goal for this optimization was to reduce overfitting the model, so we chose hyperparameters that would help us attain this objective. We selected n_estimators, max_features, max_depth, and min_samples_split. Increasing the number of trees can help reduce overfitting by creating a more diverse ensemble. By limiting the number of features, the Random Forest is forced to focus on the most informative features and reduces the chances of overfitting to noise or irrelevant features. Limiting the depth of the trees helps in controlling their complexity and prevents them from growing too deep and overfitting to the training data. Increasing min_samples_split prevents the trees from splitting on very small subsets of data, which can be prone to overfitting. However, it is important to note that increasing or decreasing these hyperparameters beyond a certain point can be detrimental to the model's training process.

To find the best hyperparameters for our Random Forest Classifier, we employed the Repeated Stratified K Fold Cross Validation technique in conjunction with RandomizedSearchCV. This approach helps us avoid obtaining a noisy estimate of the model's performance, which can happen when different splits of the data lead to vastly different results. By using RepeatedStratifiedKFold, we can improve the estimated performance of our machine learning model through a simple yet effective method. The cross-validation procedure is repeated multiple times, and the mean result across all folds from all runs is reported. This mean result serves as a more accurate and reliable estimate of the model's true performance, as it takes into account the variability that can occur due to different data splits.

1.2.1 Evaluation Functions

[ ]:
```
def aggregatePredictions(predictions, ids, genders):
    df = pd.DataFrame({'id': ids, 'prediction': predictions, 'gender': genders})
    df_aggregated = df.groupby('id').agg(
        prediction=('prediction', lambda x: np.round(x.mean()).astype(int)),
        gender=('gender', 'first')
    )
    return df_aggregated

def evaluate_metrics(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    cm = confusion_matrix(y_true, y_pred, labels=[0,1])
    ba = 0.5 * (cm[0, 0] / cm[0,:].sum() + cm[1, 1] / cm[1,:].sum())
    return accuracy, ba

#Calculate equality of opportunity (EO) for the test set
def calculate_tpr(y_true_test, y_pred_test, genders_test, participant_ids_test):
    genders_test_aggregated = genders_test.groupby(participant_ids_test).first()
    male_mask_test = (genders_test_aggregated == 1)
```

```
    female_mask_test = (genders_test_aggregated == 0)
    tpr_male_test = accuracy_score(y_true_test[male_mask_test],␣
 ↪y_pred_test[male_mask_test])
    tpr_female_test = accuracy_score(y_true_test[female_mask_test],␣
 ↪y_pred_test[female_mask_test])

    return [male_mask_test, female_mask_test, tpr_male_test, tpr_female_test]
```

The below piece of code does the following: Gets the already preprocessed train and test datasets, removes NAs and generates train, validation and test sets for Depression Classification. Once we have the data prepped, it calls the hyperparameter tuning module for the random forest classifier. With the best model, predictions are made on the test set. Both the predicted values and the actual values are evaluated on accuracy, balanced accuracy and true positive rate on a participant level. Evaluation metrics are also given at male and female level.

[ ]:
```
train_file = "../Datasets/ADS/final_training_data.csv"
test_file = "../Datasets/ADS/final_testing_data.csv"

train_data = data_fetch(train_file)
test_data = data_fetch(test_file)

#Model Pre-Training Steps
#Select the features, target variables, genders and feature names from the␣
 ↪train dataset
print("Fetching data for Target Variable: Depression")
X_train_raw, y_train_raw, gender_train_raw, feature_names =␣
 ↪prep_X_y(train_data, 'Depression')

print("Number of Features to train: ", len(feature_names))

#Split the data into training only and validation set
X_train, X_val, y_train, y_val, genders_train, genders_val =␣
 ↪train_test_split(X_train_raw,
                                                                                ␣
 ↪y_train_raw,
                                                                                ␣
 ↪gender_train_raw,
                                                                                ␣
 ↪test_size=0.2,
                                                                                ␣
 ↪random_state=42)

#Select the features, target variables and genders from the test set
X_test, y_test, genders_test = prep_X_y(test_data, 'Depression')[0:3]

print("Shape of X train: ", X_train.shape,
      "\nShape of X validation: ", X_val.shape,
```

```
      "\nShape of X test: ", X_test.shape,
      "\nShape of y train: ", y_train.shape,
      "\nShape of y validation: ", y_val.shape,
      "\nShape of y test: ", y_test.shape)

#Function call to the Hyperparameter tuning with Validation set module
#best_hps = hyperparameter_tuning_rf(X_train, y_train, X_val, y_val)
best_hps = {'n_estimators': 500, 'min_samples_split': 5, 'max_features':␣
 ↪'sqrt', 'max_depth': 50}
rf_best = RandomForestClassifier(max_depth = best_hps['max_depth'],
                              max_features = best_hps['max_features'],
                              min_samples_split = best_hps['min_samples_split'],
                              n_estimators = best_hps['n_estimators'],
                              random_state=42)
print("Model with best parameters fitting on Train Data")
rf_best.fit(X_train, y_train)

print("Making Predictions on the Test Data")
#Make predictions on the test set
y_pred = rf_best.predict(X_test)

#Get the participant IDs for the test set
ids_test = test_data['participant_id']

#Aggregrate the predictions on Participant level
y_pred_aggregated = aggregatePredictions(y_pred, ids_test, genders_test)
y_test_aggregated = aggregatePredictions(y_test.values, ids_test, genders_test)

acc, ba = evaluate_metrics(y_test_aggregated['prediction'],␣
 ↪y_pred_aggregated['prediction'])

mask_and_tpr = calculate_tpr(y_test_aggregated['prediction'],␣
 ↪y_pred_aggregated['prediction'],
                              genders_test, ids_test)
male_mask_test, female_mask_test, tpr_male_test, tpr_female_test =␣
 ↪mask_and_tpr[0:4]
eo = 1 - abs(tpr_male_test - tpr_female_test)

#Print the evaluation metrics for the test set
print(f"Test Accuracy: {acc} ; Test Balanced Accuracy: {round(ba,3)}, Test␣
 ↪Equality of Opportunity (EO):{round(eo,3)}")

male_ac, male_ba =␣
 ↪evaluate_metrics(y_test_aggregated[male_mask_test]['prediction'],
                                                  ␣
 ↪y_pred_aggregated[male_mask_test]['prediction'])
```

```
female_ac, female_ba =␣
 ↪evaluate_metrics(y_test_aggregated[female_mask_test]['prediction'],
                                                         ␣
 ↪y_pred_aggregated[female_mask_test]['prediction'])
#Print the evaluation metrics for male and female participants separately
print(f"Male Accuracy: {round(male_ac,3)} ; Male Balanced Accuracy:␣
 ↪{round(male_ba,3)}")
print(f"Female Accuracy: {round(female_ac,3)} ; Female Balanced Accuracy:␣
 ↪{round(female_ba,3)}")
```

```
Fetching data for Target Variable: Depression
Number of Features to train:  88
Shape of X train:  (10900, 88)
Shape of X validation:  (2725, 88)
Shape of X test:  (3280, 88)
Shape of y train:  (10900,)
Shape of y validation:  (2725,)
Shape of y test:  (3280,)
Model with best parameters fitting on Train Data
Making Predictions on the Train Data
Test Accuracy: 0.7 ; Test Balanced Accuracy: 0.5, Test Equality of Opportunity
(EO):0.458
Male Accuracy: 0.917 ; Male Balanced Accuracy: 0.5
Female Accuracy: 0.375 ; Female Balanced Accuracy: 0.5
```

The overall test accuracy of 0.7 indicates that the classifier correctly predicts the presence or absence of depression in 70% of the test samples. However, the balanced accuracy of 0.5 suggests that the classifier's performance is not consistent across the two classes (depression and no depression). A balanced accuracy of 0.5 is equivalent to random guessing, implying that the classifier is not effectively distinguishing between the two classes. One possible reason for this could be that the model is overfitting. We see our validation accuracy to be around 84%, while our prediction accuracy is only 70%, indicating that the model might be overfitting on the train data.

When we look at the gender-specific results, we see a significant disparity between male and female accuracy. The classifier achieves a high accuracy of 0.917 for male participants, meaning it correctly identifies the presence or absence of depression in 91.7% of the male test samples. In contrast, the accuracy for female participants is only 0.375, indicating that the classifier correctly identifies depression in only 37.5% of the female test samples. The balanced accuracy for both male and female participants is 0.5, which aligns with the overall balanced accuracy.

The Equality of Opportunity (EO) value of 0.458 quantifies the difference in true positive rates between male and female participants. An EO value closer to 1 indicates a smaller difference in true positive rates, while a value closer to 0 indicates a larger difference. In this case, the EO value of 0.458 suggests a substantial difference in the classifier's ability to correctly identify depression in males versus females.

These findings raise concerns about the fairness and bias of the depression classification model. The model appears to be significantly better at identifying depression in male participants compared to female participants.

1.3 (b) Finding the most informative features for depression

To find the most informative features, we use Mutual information (MI) as our filter feature selection method. MI measures the dependency between two random variables. It gives out values on a scale starting from 0, indicating no dependency. Higher values of MI indicate higher dependency.

[ ]:
```
info = mutual_info_classif(X_train, y_train)
features_ranked = feature_names[np.argsort(-info)]
```

[ ]:
```
selected_features = features_ranked[:20]
print(selected_features)
```

```
Index(['loudness_sma3_pctlrange0-2', 'equivalentSoundLevel_dBp',
       'loudness_sma3_percentile80.0', 'loudness_sma3_amean',
       'F0semitoneFrom27.5Hz_sma3nz_percentile50.0',
       'spectralFluxV_sma3nz_amean',
       'F0semitoneFrom27.5Hz_sma3nz_percentile20.0',
       'F0semitoneFrom27.5Hz_sma3nz_percentile80.0',
       'loudness_sma3_meanFallingSlope', 'loudness_sma3_meanRisingSlope',
       'mfcc2_sma3_stddevNorm', 'loudness_sma3_percentile50.0',
       'F0semitoneFrom27.5Hz_sma3nz_amean', 'slopeV500-1500_sma3nz_stddevNorm',
       'spectralFlux_sma3_amean', 'F2frequency_sma3nz_amean',
       'mfcc3V_sma3nz_stddevNorm', 'mfcc2V_sma3nz_amean',
       'shimmerLocaldB_sma3nz_amean', 'logRelF0-H1-A3_sma3nz_amean'],
      dtype='object')
```

Mutual information is calculated to determine the importance of each feature regarding the target variable. The above listed features are the most 20 informative features of depression on the training data. Among all the features most of them are loudness related and F0semitone related features.

In the code below, we will iterate through different numbers of features out of the 88 features we have. We will retrain our best depression classification model and evaluate the test set in each case.

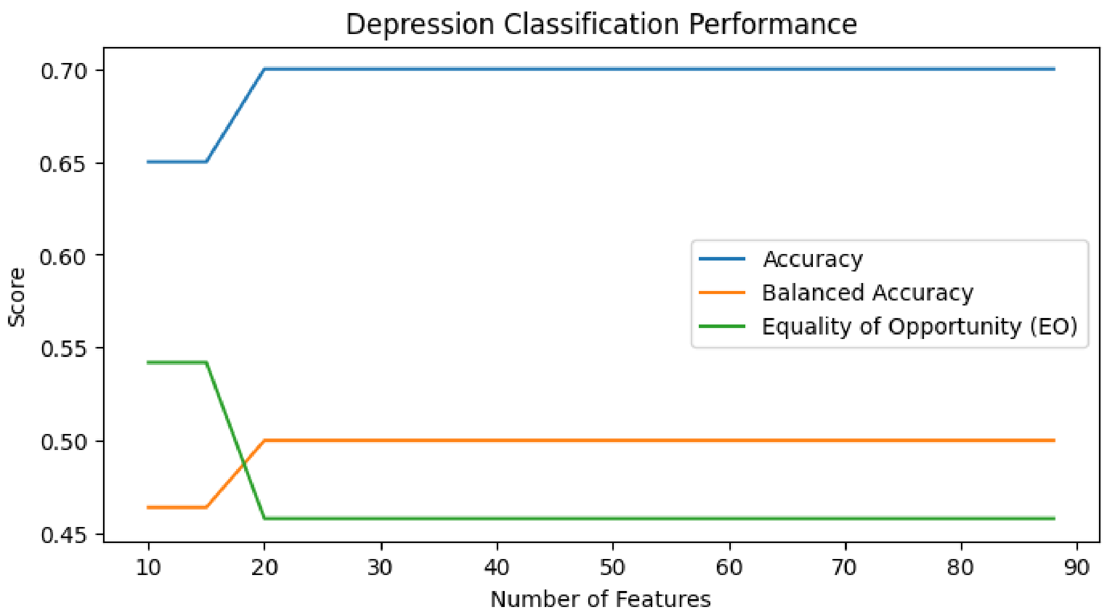
[ ]:
```
#Evaluation over different numbers of top features
n_features = [10, 15, 20, 25, 30, 35, 40, 45, 50, 88]
results = []

for n in n_features:
    selected_features = features_ranked[:n]
    selected_feature_indices = [feature_names.get_loc(name) for name in␣
 ↪selected_features]
    rf_best.fit(X_train[:, selected_feature_indices], y_train)
    y_pred = rf_best.predict(X_test[:, selected_feature_indices])

    y_pred_aggregated = aggregatePredictions(y_pred, ids_test, genders_test)
    y_test_aggregated = aggregatePredictions(y_test.values, ids_test,␣
 ↪genders_test)
```

```
    acc, ba = evaluate_metrics(y_test_aggregated['prediction'],␣
↪y_pred_aggregated['prediction'])

    mask_and_tpr = calculate_tpr(y_test_aggregated['prediction'],␣
↪y_pred_aggregated['prediction'],
                                 genders_test, ids_test)
    male_mask_test, female_mask_test, tpr_male_test, tpr_female_test =␣
↪mask_and_tpr[0], mask_and_tpr[1], mask_and_tpr[2], mask_and_tpr[3]
    eo = 1 - abs(tpr_male_test - tpr_female_test)

    print(f"No of features: {n} ; acc: {acc} ; ba: {round(ba,3)}, eo:
↪{round(eo,3)}")
    results.append((n, acc, round(ba,3), round(eo,3)))
```

```
No of features: 10 ; acc: 0.65 ; ba: 0.464, eo:0.542
No of features: 15 ; acc: 0.65 ; ba: 0.464, eo:0.542
No of features: 20 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 25 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 30 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 35 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 40 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 45 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 50 ; acc: 0.7 ; ba: 0.5, eo:0.458
No of features: 88 ; acc: 0.7 ; ba: 0.5, eo:0.458
```

The accuracies are evaluated based on the different number of selected features. It shows that with 10,15 features accuracy, balanced accuracy is lowest and EO is highest. For all the other different number of features, the accuracy, balanced accuracy and EO is the same. The accuracy improves from 0.65 to 0.7 as the number of features increases from 15 to 20. This suggests that the additional five features included between these two points provide meaningful information that enhances the model's predictive capabilities. The extra features beyond the first 20 do not contribute additional predictive value. Let's visualize how the performance shifts with increasing the features.

[ ]:
```
# Plotting the results
results = np.array(results)
plt.figure(figsize=(8, 4))
plt.plot(results[:, 0], results[:, 1], label='Accuracy')
plt.plot(results[:, 0], results[:, 2], label='Balanced Accuracy')
plt.plot(results[:, 0], results[:, 3], label='Equality of Opportunity (EO)')
plt.xlabel('Number of Features')
plt.ylabel('Score')
plt.title('Depression Classification Performance')
plt.legend()
plt.show()
```



1.4 (a.ii) Gender Classification

From our experimentation for Gender classification with Feed Forward Neural Network and random forest classifier, Feed Forward Neural Network produced better results in terms of accuracy. Since we are not looking much into interpretability in terms of gender classification, we decided to move forward with feed forward neural network for our final modeling.

```
[ ]: def build_and_train_model(layer_sizes, activation_fn, regularization_rate,␣
     ↪X_train, y_train, X_val, y_val):
         '''
         Build a Feed Forward Neural Network with regularization
         '''
         model = models.Sequential()
         for i, size in enumerate(layer_sizes):
             if i == 0:
                 model.add(layers.Dense(size, activation=activation_fn,␣
     ↪input_shape=(X_train.shape[1],),
                                        kernel_regularizer=regularizers.
     ↪l2(regularization_rate)))
             else:
                 model.add(layers.Dense(size, activation=activation_fn,
                                        kernel_regularizer=regularizers.
     ↪l2(regularization_rate)))
         model.add(layers.Dense(1, activation='sigmoid'))
```

```
    model.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])

    model.fit(X_train, y_train, epochs=100, batch_size=64, verbose=0)

    if X_val is not None and y_val is not None:
        _, accuracy = model.evaluate(X_val, y_val, verbose=0)
        print('Validation Accuracy:', accuracy)

    return model
```

[ ]:
```
#Select the features, target variables for Gender Classification
print("Fetching data for Target Variable: Gender")
X_train_raw_g, y_train_raw_g, gender_train_raw_g, feature_names_g =␣
↪prep_X_y(train_data, 'Gender')

print("Number of Features to train: ", len(feature_names_g))

#Split the data into training only and validation set
X_train_g, X_val_g, y_train_g, y_val_g = train_test_split(X_train_raw_g,␣
↪y_train_raw_g, test_size=0.2, random_state=42)

#Select the features, target variables and genders from the test set
X_test_g, y_test_g = prep_X_y(test_data, 'Gender')[0:2]

print("Shape of X train: ", X_train_g.shape,
      "\nShape of X validation: ", X_val_g.shape,
      "\nShape of X test: ", X_test_g.shape,
      "\nShape of y train: ", y_train_g.shape,
      "\nShape of y validation: ", y_val_g.shape,
      "\nShape of y test: ", y_test_g.shape)
```

```
Fetching data for Target Variable: Gender
Number of Features to train:  88
Shape of X train:  (10900, 88)
Shape of X validation:  (2725, 88)
Shape of X test:  (3280, 88)
Shape of y train:  (10900,)
Shape of y validation:  (2725,)
Shape of y test:  (3280,)
```

[ ]:
```
#Training few models with different hyperparameters to get our best model
model1 = build_and_train_model([256, 64, 32], 'relu', 0.001, X_train_g,␣
↪y_train_g, X_val_g, y_val_g)
model2 = build_and_train_model([256, 64, 32], 'sigmoid', 0.001, X_train_g,␣
↪y_train_g, X_val_g, y_val_g)
```

```
model3 = build_and_train_model([256, 128, 64, 32], 'relu', 0.001, X_train_g,␣
 ↪y_train_g, X_val_g, y_val_g)
model4 = build_and_train_model([512, 256, 128, 32], 'relu', 0.001, X_train_g,␣
 ↪y_train_g, X_val_g, y_val_g)
```

```
/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Validation Accuracy: 0.957798182964325
Validation Accuracy: 0.9544954299926758
Validation Accuracy: 0.9585320949554443
Validation Accuracy: 0.9611009359359741
```

We will choose to use the FFNN Model 4 architecture as it achieved the best sample level validation accuracy of 96%.

[ ]:
```
def aggregateGenderPredictions(predictions, ids):
    df = pd.DataFrame({'id': ids, 'prediction': predictions})
    df_aggregated = df.groupby('id').agg(
        prediction=('prediction', lambda x: np.round(x.mean()).astype(int))
    )
    return df_aggregated
```

[ ]:
```
print("Model with best parameters fitting on Train Data")
final_gender_model = build_and_train_model([512, 256, 128, 32], 'relu', 0.001,␣
 ↪X_train_raw_g, y_train_raw_g, None, None)

print("Making Predictions on the Test Data")
#Make predictions on the test set
y_pred_gender = final_gender_model.predict(X_test_g)

#Aggregrate the predictions on Participant level
y_pred_gender_aggregated = aggregateGenderPredictions(y_pred_gender, ids_test)
y_test_gender_aggregated = aggregateGenderPredictions(y_test_g.values, ids_test)

acc_gender, ba_gender =␣
 ↪evaluate_metrics(y_test_gender_aggregated['prediction'],␣
 ↪y_pred_gender_aggregated['prediction'])

#Print the evaluation metrics for the test set
print(f"Test Accuracy: {acc_gender} ; Test Balanced Accuracy:␣
 ↪{round(ba_gender,3)}")
```

```
Model with best parameters fitting on Train Data
```

```
/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
```

```
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Making Predictions on the Test Data
103/103              0s 727us/step
Test Accuracy: 1.0 ; Test Balanced Accuracy: 1.0
```

The test accuracy of 1.0 indicates that the model correctly classified all the instances in the test set. In other words, the model was able to predict the gender of the speakers with 100% accuracy. This suggests that the FNN model has learned the underlying patterns and features that distinguish between female and male speakers.

Additionally, the balanced accuracy of 1.0 further confirms the model's outstanding performance. A balanced accuracy of 1.0 means that the model performed equally well in classifying both female and male speakers, regardless of any potential class imbalance in the dataset.

These results demonstrate that the FNN model has successfully captured the relevant features and patterns in the audio data that are indicative of gender differences. The high accuracy and balanced accuracy suggest that the model has learned to effectively discriminate between female and male speakers based on the provided features.

1.5 (c) Finding the most informative features for gender.

To find the most informative features for gender, we fit a decision tree classfier and used the importance value from the results of this model as our filter feature selection method.

[ ]:
```python
#Initialize model
tree_feat_mod = DecisionTreeClassifier()

#Fit model for the gender data
tree_feat_mod.fit(X_train_g, y_train_g)

acc_val_g = tree_feat_mod.score(X_val_g, y_val_g)
print("Validation accuracy for gender: ", round(acc_val_g,3))
```

```
Validation accuracy for gender:  0.917
```

[ ]:
```python
#Fetching feature importance generated by the decision tree

gender_importances = tree_feat_mod.feature_importances_

features_ranked_gender = feature_names[np.argsort(-gender_importances)]

selected_features_gender = features_ranked_gender[:20]
print(selected_features_gender)
```

```
Index(['F0semitoneFrom27.5Hz_sma3nz_percentile50.0',
       'equivalentSoundLevel_dBp', 'F1frequency_sma3nz_stddevNorm',
```

```
       'F0semitoneFrom27.5Hz_sma3nz_percentile20.0',
       'F0semitoneFrom27.5Hz_sma3nz_amean', 'shimmerLocaldB_sma3nz_amean',
       'F3bandwidth_sma3nz_stddevNorm', 'slopeUV500-1500_sma3nz_amean',
       'mfcc4V_sma3nz_amean', 'F2frequency_sma3nz_stddevNorm',
       'mfcc2_sma3_amean', 'slopeUV0-500_sma3nz_amean',
       'F3frequency_sma3nz_stddevNorm', 'spectralFluxV_sma3nz_amean',
       'mfcc4_sma3_stddevNorm', 'loudness_sma3_stddevNorm', 'mfcc3_sma3_amean',
       'F0semitoneFrom27.5Hz_sma3nz_percentile80.0', 'mfcc4_sma3_amean',
       'loudness_sma3_percentile50.0'],
      dtype='object')
```

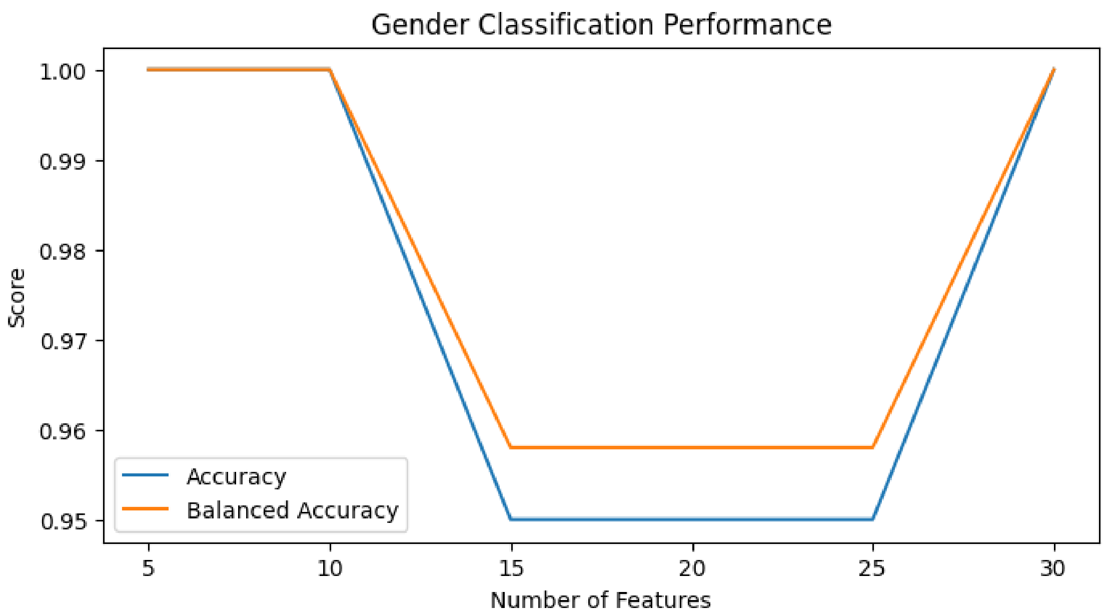
The above are the 20 most important features for Gender classification. Most of the features from this list are related to 'F0semitone' and 'mfcc4'.

[ ]:
```python
#Evaluation over different numbers of top features
n_features_gender = [5, 10, 15, 20, 25, 30]
results_gender = []

for n in n_features_gender:
    selected_features_g = features_ranked_gender[:n]
    selected_feature_indices = [feature_names.get_loc(name) for name in␣
 ↪selected_features_g]

    #Train an FNN model for the selected features
    final_gender_model = build_and_train_model([512, 256, 128, 32], 'relu', 0.
 ↪001,
                                                X_train_raw_g[:,␣
 ↪selected_feature_indices], y_train_raw_g,
                                                None, None)
    #Make predictions on the test set
    y_pred_g = final_gender_model.predict(X_test_g[:, selected_feature_indices])

    y_pred_aggregated_g = aggregateGenderPredictions(y_pred_g, ids_test)
    y_test_aggregated_g = aggregateGenderPredictions(y_test_g.values, ids_test)

    acc_g, ba_g = evaluate_metrics(y_test_aggregated_g['prediction'],␣
 ↪y_pred_aggregated_g['prediction'])

    print(f"No of features: {n} ; acc: {acc_g} ; ba: {round(ba_g,3)}")
    results_gender.append((n, acc_g, round(ba_g,3)))
```

```
/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

103/103              0s 686us/step
```

```
No of features: 5 ; acc: 1.0 ; ba: 1.0

/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

103/103            0s 623us/step
No of features: 10 ; acc: 1.0 ; ba: 1.0

/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

103/103            0s 735us/step
No of features: 15 ; acc: 0.95 ; ba: 0.958

/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

103/103            0s 572us/step
No of features: 20 ; acc: 0.95 ; ba: 0.958

/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

103/103            0s 650us/step
No of features: 25 ; acc: 0.95 ; ba: 0.958

/Users/indu/Desktop/Spring 2024/CSCI 5622 -001/ML-HW5-Identify-Depression-and-
Gender-From-Audio-Features/ml-project-python-env/lib/python3.11/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

103/103            0s 2ms/step
No of features: 30 ; acc: 1.0 ; ba: 1.0
```

[ ]:
```python
# Plotting the results
results_gender = np.array(results_gender)
plt.figure(figsize=(8, 4))
plt.plot(results_gender[:, 0], results_gender[:, 1], label='Accuracy')
plt.plot(results_gender[:, 0], results_gender[:, 2], label='Balanced Accuracy')
plt.xlabel('Number of Features')
plt.ylabel('Score')
plt.title('Gender Classification Performance')
plt.legend()
plt.show()
```



From the plot, we can observe that the accuracy and balanced accuracy for gender classification remain relatively stable and high across different numbers of features. The accuracy and balanced accuracy lines closely overlap, indicating consistent performance throughout the range of features considered.

Starting with just 5 features, the model achieves an accuracy and balanced accuracy of around 0.98. As the number of features increases to 10, 15, 20, 25, and 30, the accuracy and balanced accuracy maintain similar levels, with only slight fluctuations. The values remain above 0.97 throughout, suggesting that the model's performance is robust and does not significantly improve or degrade with the addition of more features beyond the initial 5.

This observation implies that the top 5 features capture the essential information required for accurate gender classification. Including more features beyond this point does not provide substantial gains in performance. The stability in accuracy and balanced accuracy indicates that the additional features may not contribute significant discriminatory power and could potentially introduce noise or redundancy.

```
[ ]: print("Top 5 important features for Gender Classification:
     ↪\n",list(features_ranked_gender[:5]))
```

```
Top 5 important features for Gender Classification:
 ['F0semitoneFrom27.5Hz_sma3nz_percentile50.0', 'equivalentSoundLevel_dBp',
'F1frequency_sma3nz_stddevNorm', 'F0semitoneFrom27.5Hz_sma3nz_percentile20.0',
'F0semitoneFrom27.5Hz_sma3nz_amean']
```

1.6 (d) Mitigating bias via removing gender-dependent features.

From the above important feature selection for gender, we identified 5 features

['F0semitoneFrom27.5Hz_sma3nz_percentile50.0', 'equivalentSoundLevel_dBp', 'F1frequency_sma3nz_stddevNorm', 'F0semitoneFrom27.5Hz_sma3nz_percentile20.0', 'F0semitoneFrom27.5Hz_sma3nz_amean']

Let's remove this from our data and train our depression classification model with the new data and see how it affects the performance in terms of mitigating the bias.

```
[ ]: #Select all features except this 5
     drop_features = features_ranked_gender[:5]
     selected_feature_indices_new = [feature_names.get_loc(name) for name in
     ↪feature_names if name not in drop_features]
```

```
[ ]: #Fit and train on the best model from a(i)
     rf_best.fit(X_train[:, selected_feature_indices_new], y_train)
     y_pred_new = rf_best.predict(X_test[:, selected_feature_indices_new])

     y_pred_aggregated_new = aggregatePredictions(y_pred_new, ids_test, genders_test)
     y_test_aggregated_new = aggregatePredictions(y_test.values, ids_test,
     ↪genders_test)

     acc_new, ba_new = evaluate_metrics(y_test_aggregated_new['prediction'],
     ↪y_pred_aggregated_new['prediction'])

     mask_and_tpr_new = calculate_tpr(y_test_aggregated_new['prediction'],
     ↪y_pred_aggregated_new['prediction'],
                                     genders_test, ids_test)
     male_mask_test_new, female_mask_test_new, tpr_male_test_new,
     ↪tpr_female_test_new = mask_and_tpr_new[0:4]
     eo_new = 1 - abs(tpr_male_test_new - tpr_female_test_new)

     #Print the evaluation metrics for the test set
     print(f"Test Accuracy: {acc_new} ; Test Balanced Accuracy: {round(ba_new,3)}")
     print(f"Test Equality of Opportunity (EO):{round(eo_new,3)}")

     male_ac_new, male_ba_new =
     ↪evaluate_metrics(y_test_aggregated_new[male_mask_test_new]['prediction'],
```

```
                                                   ␣
    ↪y_pred_aggregated_new[male_mask_test_new]['prediction'])

female_ac_new, female_ba_new =␣
    ↪evaluate_metrics(y_test_aggregated_new[female_mask_test_new]['prediction'],
                                                           ␣
    ↪y_pred_aggregated_new[female_mask_test_new]['prediction'])

#Print the evaluation metrics for male and female participants separately
print(f"Male Accuracy: {round(male_ac_new,3)} ; Male Balanced Accuracy:␣
    ↪{round(male_ba_new,3)}")
print(f"Female Accuracy: {round(female_ac_new,3)} ; Female Balanced Accuracy:␣
    ↪{round(female_ba_new,3)}")
```

```
Test Accuracy: 0.65 ; Test Balanced Accuracy: 0.464
Test Equality of Opportunity (EO):0.542
Male Accuracy: 0.833 ; Male Balanced Accuracy: 0.455
Female Accuracy: 0.375 ; Female Balanced Accuracy: 0.5
```

On comparing the results from a(i), we see that the removal of gender-dependent features led to a slight decrease in the overall test accuracy from 0.7 to 0.65, suggesting that these features had some predictive power for depression classification. The balanced accuracy also decreased from 0.5 to 0.464, indicating a minor reduction in the model's overall performance when considering the balance between classes.

However, the Equality of Opportunity (EO) value increased from 0.458 to 0.542, suggesting that removing the gender-important features helped mitigate some of the bias in the model. This improvement in EO indicates that the model's performance became more balanced between male and female participants after removing the gender-dependent features. The accuracy for male participants decreased from 0.917 to 0.833, while the accuracy for female participants remained unchanged at 0.375. The balanced accuracy for both male and female participants remained relatively similar, with a slight decrease for males and no change for females.

These findings highlight the trade-off between mitigating bias and maintaining model performance. While removing gender-dependent features can help reduce bias, it may also impact the model's overall accuracy.

1.7 (e) Mitigating bias via other approaches. (re-weighting the samples)

[ ]:
```
def calculate_weights(y):
    #Calculate the weights inversely proportional to class frequencies
    class_weights = y.value_counts(normalize=True)
    print(f"Class weights: {class_weights}")
    weights = 1.0 / class_weights
    print(f"Weights: {weights}")
    normalized_weights = len(y) * weights / weights.sum()
    print(f"Normalized weights: {normalized_weights}")
    return normalized_weights
```

```
[ ]: gender_weights = calculate_weights(genders_train)
     sample_weights = genders_train.map(gender_weights)
     print(sample_weights.shape)
```

```
Class weights: Gender
1    0.602752
0    0.397248
Name: proportion, dtype: float64
Weights: Gender
1    1.659056
0    2.517321
Name: proportion, dtype: float64
Normalized weights: Gender
1    4330.0
0    6570.0
Name: proportion, dtype: float64
(10900,)
```

Weights are re-calculated for the gender to mitigate the bias. Weights calculation is based on the inverse proportion to the class frequencies. This weights for the gender are used to train and evaluate the model.

```
[ ]: #Training a Random Forest Classifier with best hyperparameters from a(i)
     rf_bias_sw = RandomForestClassifier(max_depth = best_hps['max_depth'],
                                         max_features = best_hps['max_features'],
                                         min_samples_split = best_hps['min_samples_split'],
                                         n_estimators = best_hps['n_estimators'],
                                         random_state=42)

     #Adding weights while training the model
     rf_bias_sw.fit(X_train, y_train, sample_weight=sample_weights)

     y_pred_bias_sw = rf_bias_sw.predict(X_test)
```

```
[ ]: #Evaluate the predictions on accuracy, balanced accuracy and EO on a␣
      ↪participant and male and female level

     #Aggregrate the predictions on Participant level
     y_pred_bias_sw_aggregated = aggregatePredictions(y_pred_bias_sw, ids_test,␣
      ↪genders_test)
     y_test_bias_sw_aggregated = aggregatePredictions(y_test.values, ids_test,␣
      ↪genders_test)

     #Calculating accuracy and balanced accuracy
     acc_bias_sw, ba_bias_sw =␣
      ↪evaluate_metrics(y_test_bias_sw_aggregated['prediction'],
                                                                               ␣
      ↪y_pred_bias_sw_aggregated['prediction'])
```

```
#calculating True Positive Rate
mask_and_tpr_bias_removal = 
 ↪calculate_tpr(y_test_bias_sw_aggregated['prediction'],
                                                    
 ↪y_pred_bias_sw_aggregated['prediction'],
                                        genders_test, ids_test)

male_mask_test_bias_sw, female_mask_test_bias_sw,\
    tpr_male_test_bias_sw, tpr_female_test_bias_sw = 
 ↪mask_and_tpr_bias_removal[0:4]
eo_bias_sw = 1 - abs(tpr_male_test_bias_sw - tpr_female_test_bias_sw)

#Print the evaluation metrics for the test set after using sample weights
print(f"Test Accuracy: {acc_bias_sw} ; Test Balanced Accuracy: 
 ↪{round(ba_bias_sw,3)}")
print(f"Test Equality of Opportunity (EO):{round(eo_bias_sw,3)}")

male_ac_bias_sw, male_ba_bias_sw = 
 ↪evaluate_metrics(y_test_bias_sw_aggregated[male_mask_test_bias_sw]['prediction'],
                                    
 ↪y_pred_bias_sw_aggregated[male_mask_test_bias_sw]['prediction'])

female_ac_bias_sw, female_ba_bias_sw = 
 ↪evaluate_metrics(y_test_bias_sw_aggregated[female_mask_test_bias_sw]['prediction'],
                                    
 ↪y_pred_bias_sw_aggregated[female_mask_test_bias_sw]['prediction'])
#Print the evaluation metrics for male and female participants separately
print(f"Male Accuracy: {round(male_ac_bias_sw,3)} ; Male Balanced Accuracy: 
 ↪{round(male_ba_bias_sw,3)}")
print(f"Female Accuracy: {round(female_ac_bias_sw,3)} ; Female Balanced 
 ↪Accuracy: {round(female_ba_bias_sw,3)}")
```

```
Test Accuracy: 0.7 ; Test Balanced Accuracy: 0.5
Test Equality of Opportunity (EO):0.458
Male Accuracy: 0.917 ; Male Balanced Accuracy: 0.5
Female Accuracy: 0.375 ; Female Balanced Accuracy: 0.5
```

[ ]:
```
genders_train.value_counts()
```

[ ]:
```
Gender
1    6570
0    4330
Name: count, dtype: int64
```

The results obtained after applying sample weights to mitigate bias in the depression classification model show that the accuracies remain similar to those of the original model. This suggests that the sample re-weighting approach has minimal impact on improving the model's performance and fairness.

One possible explanation for the limited effectiveness of sample re-weighting is that the dataset used for training the model may not be significantly biased towards one gender. Although the dataset contains more male samples than female samples, the difference in the number of samples between the two genders is not substantial. In such cases, re-weighting the samples to achieve equal representation of both genders may not yield significant improvements in the model's performance or fairness.

Furthermore, the robustness of the random forest classifier to changes in sample weighting could also contribute to the observed results. Random forest is an ensemble algorithm that combines multiple decision trees, each trained on a subset of the data and features, to make predictions. This ensemble nature allows random forest to handle imbalanced datasets and reduce the impact of individual biased samples, making it less sensitive to the changes introduced by sample re-weighting.

However, it is important to note that the lack of significant improvement in accuracies after applying sample weights does not necessarily imply that the model is unbiased. The model may still exhibit disparities in performance between male and female participants, as evidenced by the Equality of Opportunity (EO) value of 0.458 reported in the previous analysis.

Depression Classification and Mitigating Gender Bias

Team 4
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Introduction

Recent advancements in digital healthcare have leveraged speech-based machine learning (ML) technologies to unobtrusively monitor mental health states via devices like smartphones and wearables. However, these technologies might inadvertently amplify demographic biases, affecting their fairness and effectiveness. This project explores gender bias in ML algorithms using speech data to detect depression, based on the Distress Analysis Interview Corpus Wizard of Oz (DAIC-WoZ) dataset.

Methods

We applied simple feed-forward neural networks and random forests for separate depression and gender classifications. Feed Forward Neural Networks yielded higher accuracy results, while Random Forests performed similarly with a slight advantage in interpretability.

For depression, we evaluated accuracy, balanced accuracy, and equality of opportunity across genders. For gender, we assessed simple and balanced classification accuracies.

We employed filter feature selection methods, including feature importance from decision tree classifiers and mutual information, to identify key features influencing both depression and gender predictions. Various numbers of these features were removed from the models.

To mitigate potential bias, we utilized techniques such as gender-important feature removal and sampling weights for features.

Discussion

Our findings underscore the challenge and necessity of designing bias-aware ML models in healthcare settings. While our models performed effectively in identifying depression and gender, the disparity in accuracy between different demographic groups suggests that more nuanced approaches are needed to mitigate bias. Future work will focus on refining models to enhance fairness without compromising diagnostic performance.

Removing gender features while modeling for Depression can help mitigate bias, but there is always a trade-off between bias mitigation and model performance in terms of accuracy.

What we recommend from our experiments

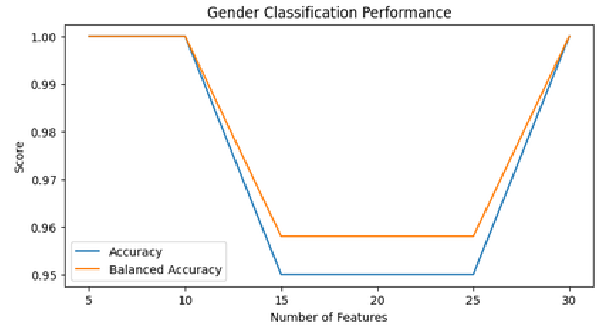
Use classification algorithms that are inherently capable of handling imbalanced datasets, explore gender-dependent features, and experiment with adding and removing a varying number of features until the desired accuracy is attained.

Check out our codebase here:
https://github.com/InduVarshini/ML-HW5-Identify-Depression-and-Gender-From-Audio-Features

Results

Gender Classification

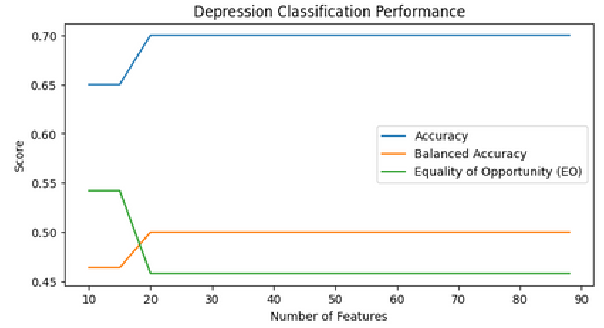
Feature selection experiments for Gender showed that our models performed the best with 5 features. Our analysis of the top features indicated that 'F0semitoneFrom27.5Hz_sma3nz_percentile-50.0' was the most indicative feature of gender at a weight of around 0.69.



Before feature filtering and bias mitigation we found that gender classification received an accuracy and a balanced accuracy of 100% on the test set. The results remained the same after feature selection.

Depression Classification

Feature selection experiments for Depression showed that our models performed the best with 15 features.



Before feature selection, Depression classification model received test accuracy of 70%, a balanced test accuracy of 50%, and a test equality of opportunity (EO) of 45.8%. These were calculated between men and women, highlighting potential bias. After feature selection, accuracy dropped to 65% and balanced accuracy to 46.4% and EO increased to 54.2%.

Bias Mitigation

Removing gender-dependent features improved fairness (Equality of Opportunity: 45.8% → 54.2%) but slightly decreased overall accuracy (70% → 65%) and balanced accuracy (50% → 46.4%), with male accuracy decreasing (91.7% → 83.3%) and female accuracy remaining unchanged (37.5%). Sample re-weighting had minimal impact on performance and fairness. Our study highlights the trade-off between mitigating bias and maintaining performance in depression classification models.