Employee Burnout Prediction

Employee burnout is a state of physical, emotional and mental exhaustion caused by excessive and prolonged stress. It can have serious consequences on an individual's well-being and can lead to decreased productivity and job performance. In today's fast-paced and constantly connected world, it is increasingly important to recognize and address the signs of burnout in order to maintain the health and well-being of employees. we will be exploring the use of regression techniques to predict employee burnout. By analyzing a dataset containing various factors that may contribute to burnout such as workload, mental fatigue job and work-life balance, we can develop a model to identify individuals who may be at risk of burnout. By proactively addressing these risk factors, organizations can help prevent burnout and promote the well-being of their employees.

Dataset: Are Your Employees Burning Out?

This dataset consists of 9 columns as follows

• **Employee ID:** The unique ID allocated for each employee (example: fffe390032003000)

. **Date of Joining:** The date-time when the employee has joined the organization (example: 2008-12-30)

• **Gender:** The gender of the employee (Male/Female)

• **Company Type:** The type of company where the employee is working (Service/Product)

• **FH Setup Available:** Is the work from home facility available for the employee (Yes/No)

• **Designation:** The designation of the employee of work in the organization. Iin the range of [0.0, 5.0] bigger is higher designation.

• **Resource Allocation:** The amount of resource allocated to the employee to work, ie. number of working hours. In the range of [1.0, 10.0] (higher means more resource)

• **Mental Fatigue Score:** The level of fatigue mentally the employee is facing. In the range of [0.0, 10.0] where 0.0 means no fatigue and 10.0 means completely fatigue,

• **Burn Rate :**The value we need to predict for each employee telling the rate of Burn out while working. In the range of [0.0, 1.0| where the higher the value is more is the burn out.

```
# Importing neccesary liabries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import pickle as pickle
import os
```

LOADING DATASET

```
data = pd.read_excel("/content/employee_burnout_analysis-AI.xlsx")
```

DATA OVERVIEW

```
data.head()
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
0	fffe32003000360033003200	2008-09-30	Female	Service	No	2	3.0	3.8	0.16
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1	2.0	5.0	0.36
2	fffe31003300320037003900	2008-03-10	Female	Product	Yes	2	NaN	5.8	0.49
3	fffe32003400380032003900	2008-11-03	Male	Service	Yes	1	1.0	2.6	0.20
4	fffe31003900340031003600	2008-07-24	Female	Service	No	3	7.0	6.9	0.52

```
data.tail()
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
22745	fffe31003500370039003100	2008-12-30	Female	Service	No	1	3.0	NaN	0.41
22746	fffe33003000350031003800	2008-01-19	Female	Product	Yes	3	6.0	6.7	0.59
22747	fffe390032003000	2008-11-05	Male	Service	Yes	3	7.0	NaN	0.72
		2008-01-							

```
data.describe()
```

	Date of Joining	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
count	22750	22750.000000	21369.000000	20633.000000	21626.000000
mean	2008-07-01 09:28:05.274725120	2.178725	4.481398	5.728188	0.452005
min	2008-01-01 00:00:00	0.000000	1.000000	0.000000	0.000000
25%	2008-04-01 00:00:00	1.000000	3.000000	4.600000	0.310000
50%	2008-07-02 00:00:00	2.000000	4.000000	5.900000	0.450000
75%	2008-09-30 00:00:00	3.000000	6.000000	7.100000	0.590000
max	2008-12-31 00:00:00	5.000000	10.000000	10.000000	1.000000
std	NaN	1.135145	2.047211	1.920839	0.198226

```
data.columns.tolist()
```

```
['Employee ID',
 'Date of Joining',
 'Gender',
 'Company Type',
 'WFH Setup Available',
 'Designation',
 'Resource Allocation',
 'Mental Fatigue Score',
 'Burn Rate']
```

```
data.nunique()
```

```
Employee ID            22750
Date of Joining          366
Gender                     2
Company Type               2
WFH Setup Available        2
Designation                6
```

```
Resource Allocation        10
Mental Fatigue Score      101
Burn Rate                 101
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22750 entries, 0 to 22749
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Employee ID           22750 non-null  object
 1   Date of Joining       22750 non-null  datetime64[ns]
 2   Gender                22750 non-null  object
 3   Company Type          22750 non-null  object
 4   WFH Setup Available   22750 non-null  object
 5   Designation           22750 non-null  int64
 6   Resource Allocation   21369 non-null  float64
 7   Mental Fatigue Score  20633 non-null  float64
 8   Burn Rate             21626 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(4)
memory usage: 1.6+ MB
```

```
data.isnull().sum()
```

```
Employee ID               0
Date of Joining           0
Gender                    0
Company Type              0
WFH Setup Available       0
Designation               0
Resource Allocation    1381
Mental Fatigue Score   2117
Burn Rate              1124
dtype: int64
```

```
data.isnull().sum().values.sum()
```

```
4622
```

Exploratory Data Analysis

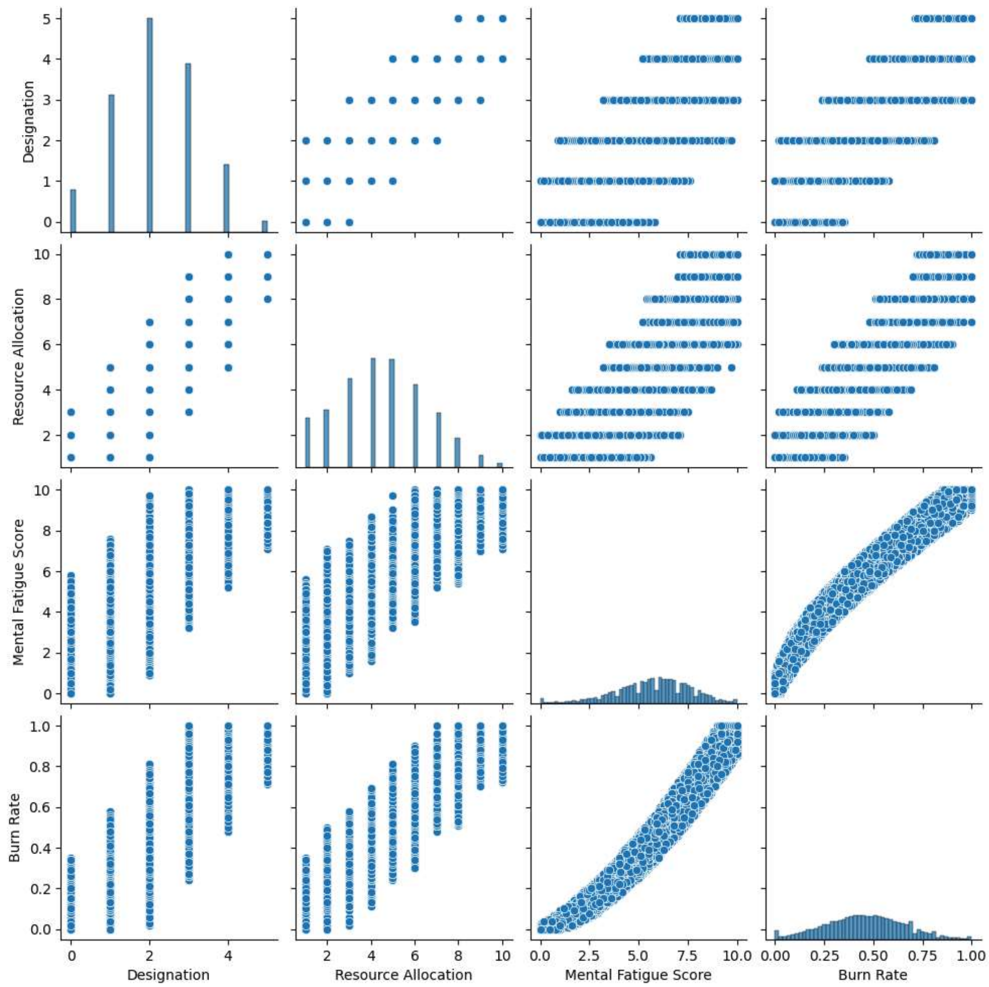
There are NaN values on our target ("Burn Rate") and also in Resource Allocation and Mental Fatigue Score columns. As we are going to perform supervised linear regression, our target variable is needed to do so. Therefore, this 1124 rows with NaN values must be dropped off of our dataframe.

```
data.corr(numeric_only=True)['Burn Rate'][:-1]
```

```
Designation            0.737556
Resource Allocation    0.856278
Mental Fatigue Score   0.944546
Name: Burn Rate, dtype: float64
```

These two variables are strongly correlated with target variable, therefore , important to estimate it.

```
sns.pairplot(data)
plt.show()
```



Drop off all observations with NaN values of our dataframe.

```
data = data.dropna()
```

```
data.shape
```

```
(18590, 9)
```

Analyzing what type of data is each variable

```
data.dtypes
```

```
Employee ID                       object
Date of Joining           datetime64[ns]
Gender                            object
Company Type                      object
WFH Setup Available               object
Designation                        int64
Resource Allocation              float64
Mental Fatigue Score             float64
Burn Rate                        float64
dtype: object
```

The values that each variable contains.

The employees ID doesn't provide any useful information and, therefore, they must be dropped.

```
data = data.drop('Employee ID', axis = 1)
```

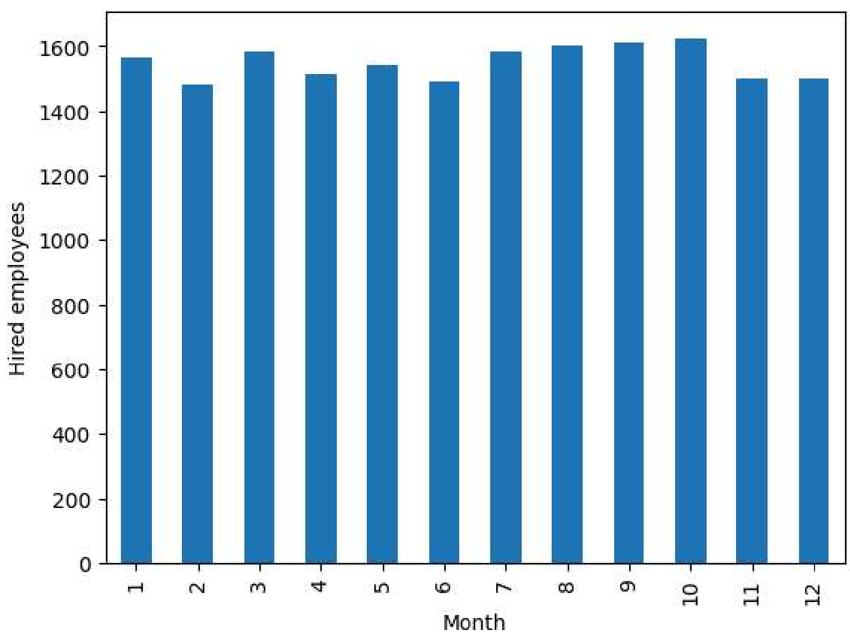
Unsupported Cell Type. Double-Click to inspect/edit the content.

Checking the correlation of Date of Joining with Target variable

```
print(f"Min date {data['Date of Joining'].min()}")
print(f"Max date {data['Date of Joining'].max()}")
data_month = data.copy()

data_month["Date of Joining"] = data_month['Date of Joining'].astype("datetime64[ns]")  # Specify
data_month["Date of Joining"].groupby(data_month['Date of Joining'].dt.month).count().plot(kind="
```

```
Min date 2008-01-01 00:00:00
Max date 2008-12-31 00:00:00
<Axes: xlabel='Month', ylabel='Hired employees'>
```



The date of joining is uniform distributed with values between 2008-01-01 and 2008-12-31. So in order to create a new feature which represents the labor seniority, we could create a variable with de days worked

```
data_2008 = pd.to_datetime(["2008-01-01"]*len(data))
# Specify time unit as nanoseconds when converting to datetime64
data["Days"] = data['Date of Joining'].astype("datetime64[ns]").sub(data_2008).dt.days
data.Days
```

```
0        273
1        334
3        307
4        205
5        330
        ...
22743    349
22744    147
22746     18
22748      9
22749      5
Name: Days, Length: 18590, dtype: int64
```

```
# Select only numeric columns before calculating correlation
numeric_data = data.select_dtypes(include=['number'])
correlation = numeric_data.corr()['Burn Rate']
print(correlation)
```

```
Designation             0.736412
Resource Allocation     0.855005
Mental Fatigue Score    0.944389
Burn Rate               1.000000
Days                    0.000309
Name: Burn Rate, dtype: float64
```

```
data.corr(numeric_only=True)['Burn Rate'][:]
```

```
Designation             0.736412
Resource Allocation     0.855005
Mental Fatigue Score    0.944389
Burn Rate               1.000000
Days                    0.000309
Name: Burn Rate, dtype: float64
```

We observed that there is no strong correlation between Date of Joining and Burn Rate.So, we are dropping the column Date of Joining.

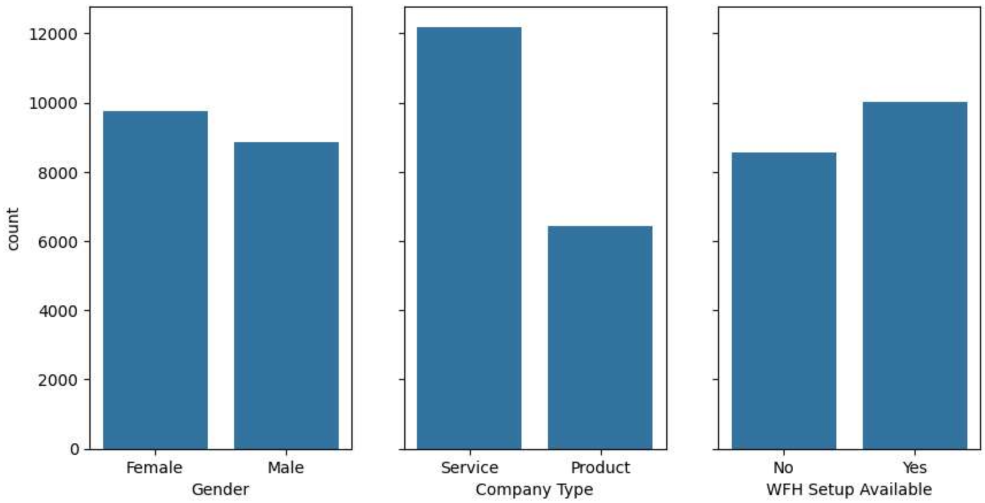
```
data = data.drop(['Date of Joining','Days'], axis = 1)
```

```
data.head()
```

	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
0	Female	Service	No	2	3.0	3.8	0.16
1	Male	Service	Yes	1	2.0	5.0	0.36
3	Male	Service	Yes	1	1.0	2.6	0.20
4	Female	Service	No	3	7.0	6.9	0.52

Now analysing the categorical variables

```
cat_columns = data.select_dtypes(object).columns
fig, ax = plt.subplots(nrows=1, ncols=len(cat_columns), sharey=True, figsize=(10, 5))
for i, c in enumerate(cat_columns):
    sns.countplot(x=c, data=data, ax=ax[i])
plt.show()
```



The number of observations of each category on each variable is equally distributed, except to the Company_Type where the number of service jobs its almost twice that of product ones.

One-Hot Encoding for categorical features

```
# Check if the columns exist before applying get_dummies
if all(col in data.columns for col in ['Company Type', 'WFH Setup Available', 'Gender']):
    data = pd.get_dummies(data, columns=['Company Type', 'WFH Setup Available','Gender'], drop_fi
    data.head()
    encoded_columns = data.columns
else:
    print("Error: One or more of the specified columns are not present in the DataFrame.")
    # Add debugging steps here to investigate why the columns are missing.
    # For example, print the existing columns:
    print(data.columns)
```

Preprocessing

```
# Split df into X and y
y = data['Burn Rate']
X = data.drop('Burn Rate', axis=1)
```

```
# Train-test split
from sklearn.model_selection import train_test_split # Import the required module
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, shuffle=True, random_st

# Scale X
from sklearn.preprocessing import StandardScaler # Import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
X_train = pd.DataFrame(scaler.transform(X_train), index=X_train.index, columns=X_train.columns)
X_test = pd.DataFrame(scaler.transform(X_test), index=X_test.index, columns=X_test.columns )


import os
import pickle

scaler_filename = '../models/scaler.pkl'

# Create the 'models' directory if it doesn't exist
os.makedirs(os.path.dirname(scaler_filename), exist_ok=True)

# Use pickle to save the scaler to the file
with open(scaler_filename, 'wb') as scaler_file:
    pickle.dump(scaler, scaler_file)


X_train
```

	Designation	Resource Allocation	Mental Fatigue Score	Company Type_Service	WFH Setup Available_Yes	Gender_Male
8977	0.723327	0.250185	-0.061773	0.724706	-1.082297	1.051505
14115	-0.159330	0.250185	-0.941481	0.724706	-1.082297	-0.951018
8797	0.723327	0.250185	0.973179	0.724706	-1.082297	-0.951018
1173	-1.041987	-1.214568	-0.579248	-1.379869	-1.082297	-0.951018
1941	-0.159330	0.738436	1.180169	-1.379869	0.923961	1.051505
...	...	...	...	...	...	...
13453	0.723327	1.226687	1.645897	-1.379869	0.923961	-0.951018
21179	0.723327	0.250185	-1.044976	0.724706	0.923961	1.051505
6327	0.723327	0.250185	0.093470	0.724706	-1.082297	1.051505
14933	-0.159330	0.250185	0.714441	0.724706	-1.082297	1.051505
288	-0.159330	0.250185	1.076674	-1.379869	-1.082297	-0.951018

```
y_train
```

```
8977     0.41
14115    0.34
8797     0.61
1173     0.35
1941     0.61
         ...
13453    0.78
21179    0.30
6327     0.42
14933    0.54
288      0.57
Name: Burn Rate, Length: 13013, dtype: float64
```

```
import os
import pickle

#saving the processed data
path = '../data/processed/'

# Create the directory if it doesn't exist
os.makedirs(path, exist_ok=True)

X_train.to_csv(path + 'X_train_processed.csv', index=False)
y_train.to_csv(path + 'y_train_processed.csv', index=False)
```

Model Building

Linear Regression

```
#from sklearn.linear_model import LinearRegression

# Create an instance of the LinearRegression class
linear_regression_model = LinearRegression()

# Train the model
linear_regression_model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
#Linear Regressing Model Performance Metrics

print("Linear Regression Model Performance Metrics:\n")
# Make predictions on the test set
y_pred = linear_regression_model.predict(X_test)

# Calculate mean squared error
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)

# Calculate root mean squared error
rmse = mean_squared_error(y_test, y_pred, squared=False)
print("Root Mean Squared Error:", rmse)

# Calculate mean absolute error
mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error:", mae)

# Calculate R-squared score
r2 = r2_score(y_test, y_pred)
print("R-squared Score:", r2)
```

```
Linear Regression Model Performance Metrics:

Mean Squared Error: 0.0031569779113610717
Root Mean Squared Error: 0.0561869905882231
```

```
Mean Absolute Error: 0.04595032032644773
R-squared Score: 0.918822674247248
```

Based on the evaluation metrics, the Linear Regression model appears to be the best model for predicting burnout analysis.

It has the lowest mean squared error, root mean squared error, and mean absolute error, indicating better accuracy and precision in its predictions. Additionally, it has the highest R-squared score, indicating a good fit to the data and explaining a higher proportion of the variance in the target variable.

So we are choosing this model for deployment