EMPLOYEE ATTRITION PREDICTION ALGORITHM

Three methods to predict who's gonna quit their job!

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Context

McCurr Health Consultancy is an MNC that has thousands of employees spread across the globe. The company believes in hiring the best talent available and retaining them for as long as possible. A huge amount of resources is spent on retaining existing employees through various initiatives. The Head of People Operations wants to bring down the cost of retaining employees. For this, he proposes limiting the incentives to only those employees who are at risk of attrition.

Dataset Description

The data contains information on employees' demographic details, work-related metrics, and attrition flag.

EmployeeNumber - Unique Employee Identifier

Attrition - Did the employee attrite or not?

Age - Age of the employee

BusinessTravel - Travel commitments for the job

DailyRate - Data description not available

Department - Employee's Department

DistanceFromHome - Distance from work to home (in KM)

Education - Employee's Education. 1-Below College, 2-College, 3-Bachelor, 4-Master, 5-Doctor

EducationField - Field of Education

EnvironmentSatisfaction - 1-Low, 2-Medium, 3-High, 4-Very High

Gender - Employee's gender

HourlyRate - Data description not available

JobInvolvement - 1-Low, 2-Medium, 3-High, 4-Very High

JobLevel - Level of job (1 to 5)

JobRole - Job Roles

JobSatisfaction - 1-Low, 2-Medium, 3-High, 4-Very High

MaritalStatus - Marital Status

MonthlyIncome - Monthly Salary

MonthlyRate - Data description not available

NumCompaniesWorked - Number of companies worked at

Over18 - Whether the employee is over 18 years of age?

OverTime - Whether the employee is doing overtime?

PercentSalaryHike - The percentage increase in the salary last year

PerformanceRating - 1-Low, 2-Good, 3-Excellent, 4-Outstanding

RelationshipSatisfaction - 1-Low, 2-Medium, 3-High, 4-Very High

StandardHours - Standard Hours

StockOptionLevel - Stock Option Level

TotalWorkingYears - Total years worked

TrainingTimesLastYear - Number of training attended last year

WorkLifeBalance - 1-Low, 2-Good, 3-Excellent, 4-Outstanding

YearsAtCompany - Years at Company

YearsInCurrentRole - Years in the current role

YearsSinceLastPromotion - Years since the last promotion

YearsWithCurrManager - Years with the current manager

IMPORTS

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# To scale the data using z-score
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Algorithms I will use
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# Metrics to evaluate the model
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report,recall_score,preci

# For tuning the model
from sklearn.model_selection import GridSearchCV

# To ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
df = pd.read_excel('D:/HR_Employee_Attrition_Dataset.xlsx')
df.head()
```

Out[3]:

	EmployeeNumber	Attrition	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	E
0	1	Yes	41	Travel_Rarely	1102	Sales	1	
1	2	No	49	Travel_Frequently	279	Research & Development	8	
2	3	Yes	37	Travel_Rarely	1373	Research & Development	2	
3	4	No	33	Travel_Frequently	1392	Research & Development	3	
4	5	No	27	Travel_Rarely	591	Research & Development	2	

5 rows × 34 columns

SOME QUICK EDA

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2940 entries, 0 to 2939
Data columns (total 34 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   EmployeeNumber            2940 non-null   int64 
 1   Attrition                 2940 non-null   object
 2   Age                       2940 non-null   int64 
 3   BusinessTravel            2940 non-null   object
 4   DailyRate                 2940 non-null   int64 
 5   Department                2940 non-null   object
 6   DistanceFromHome          2940 non-null   int64 
 7   Education                 2940 non-null   int64 
 8   EducationField            2940 non-null   object
 9   EnvironmentSatisfaction   2940 non-null   int64 
 10  Gender                    2940 non-null   object
 11  HourlyRate                2940 non-null   int64 
 12  JobInvolvement            2940 non-null   int64 
 13  JobLevel                  2940 non-null   int64 
 14  JobRole                   2940 non-null   object
 15  JobSatisfaction           2940 non-null   int64 
 16  MaritalStatus             2940 non-null   object
 17  MonthlyIncome             2940 non-null   int64 
 18  MonthlyRate               2940 non-null   int64 
 19  NumCompaniesWorked        2940 non-null   int64 
 20  Over18                    2940 non-null   object
 21  OverTime                  2940 non-null   object
 22  PercentSalaryHike         2940 non-null   int64 
 23  PerformanceRating         2940 non-null   int64 
 24  RelationshipSatisfaction  2940 non-null   int64 
 25  StandardHours             2940 non-null   int64 
 26  StockOptionLevel          2940 non-null   int64 
 27  TotalWorkingYears         2940 non-null   int64 
 28  TrainingTimesLastYear     2940 non-null   int64 
 29  WorkLifeBalance           2940 non-null   int64 
 30  YearsAtCompany            2940 non-null   int64 
 31  YearsInCurrentRole        2940 non-null   int64 
 32  YearsSinceLastPromotion   2940 non-null   int64 
 33  YearsWithCurrManager      2940 non-null   int64 
dtypes: int64(25), object(9)
memory usage: 781.1+ KB
```

In [5]:
```
df.nunique()
```

Out[5]:
```
EmployeeNumber              2940
Attrition                      2
Age                           43
BusinessTravel                 3
DailyRate                    886
Department                     3
DistanceFromHome              29
Education                      5
EducationField                 6
EnvironmentSatisfaction        4
Gender                         2
HourlyRate                    71
JobInvolvement                 4
JobLevel                       5
JobRole                        9
JobSatisfaction                4
MaritalStatus                  3
MonthlyIncome               1349
MonthlyRate                 1427
NumCompaniesWorked            10
Over18                         1
OverTime                       2
PercentSalaryHike             15
PerformanceRating              2
RelationshipSatisfaction       4
StandardHours                  1
StockOptionLevel               4
TotalWorkingYears             40
TrainingTimesLastYear          7
WorkLifeBalance                4
YearsAtCompany                37
YearsInCurrentRole            19
YearsSinceLastPromotion       16
YearsWithCurrManager          18
dtype: int64
```

Observations:

Employee number is an identifier which is unique for each employee and we can drop this column as it would not add any value to our analysis.

Over18 and StandardHours have only 1 unique value. These columns will not add any value to our model hence we can drop them.

Over18 and StandardHours have only 1 unique value. We can drop these columns as they will not add any value to our analysis.

On the basis of number of unique values in each column and the data description, we can identify the continuous and categorical columns in the data.

I will now drop the columns mentioned above and define lists for numerical and categorical columns to explore them separately.

In [6]:
```
df = df.drop(['EmployeeNumber', 'Over18', 'StandardHours'] , axis = 1)
```

In [7]:
```
# Creating numerical columns
num_cols = ['DailyRate', 'Age', 'DistanceFromHome', 'MonthlyIncome', 'MonthlyRate', 'P
            'YearsAtCompany', 'NumCompaniesWorked', 'HourlyRate', 'YearsInCurrentRole'
            'YearsWithCurrManager', 'TrainingTimesLastYear']

# Creating categorical variables
cat_cols = ['Attrition', 'OverTime', 'BusinessTravel', 'Department', 'Education', 'Edu
            'WorkLifeBalance', 'StockOptionLevel', 'Gender', 'PerformanceRating', 'Job
```

Univariate Analysis - Numerical Data

In [8]:
```
df[num_cols].describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
DailyRate	2940.0	802.485714	403.440447	102.0	465.0	802.0	1157.0	1499.0
Age	2940.0	36.923810	9.133819	18.0	30.0	36.0	43.0	60.0
DistanceFromHome	2940.0	9.192517	8.105485	1.0	2.0	7.0	14.0	29.0
MonthlyIncome	2940.0	6502.931293	4707.155770	1009.0	2911.0	4919.0	8380.0	19999.0
MonthlyRate	2940.0	14313.103401	7116.575021	2094.0	8045.0	14235.5	20462.0	26999.0
PercentSalaryHike	2940.0	15.209524	3.659315	11.0	12.0	14.0	18.0	25.0
TotalWorkingYears	2940.0	11.279592	7.779458	0.0	6.0	10.0	15.0	40.0
YearsAtCompany	2940.0	7.008163	6.125483	0.0	3.0	5.0	9.0	40.0
NumCompaniesWorked	2940.0	2.693197	2.497584	0.0	1.0	2.0	4.0	9.0
HourlyRate	2940.0	65.891156	20.325969	30.0	48.0	66.0	84.0	100.0
YearsInCurrentRole	2940.0	4.229252	3.622521	0.0	2.0	3.0	7.0	18.0
YearsSinceLastPromotion	2940.0	2.187755	3.221882	0.0	0.0	1.0	3.0	15.0
YearsWithCurrManager	2940.0	4.123129	3.567529	0.0	2.0	3.0	7.0	17.0
TrainingTimesLastYear	2940.0	2.799320	1.289051	0.0	2.0	3.0	3.0	6.0

Observations:

Average employee age is around 37 years. It has a high range, from 18 years to 60, indicating good age diversity in the organization.

At least 50% of the employees live within a 7 KM radius of the organization. However, there are some extreme values, given that the maximum value is 29 km.

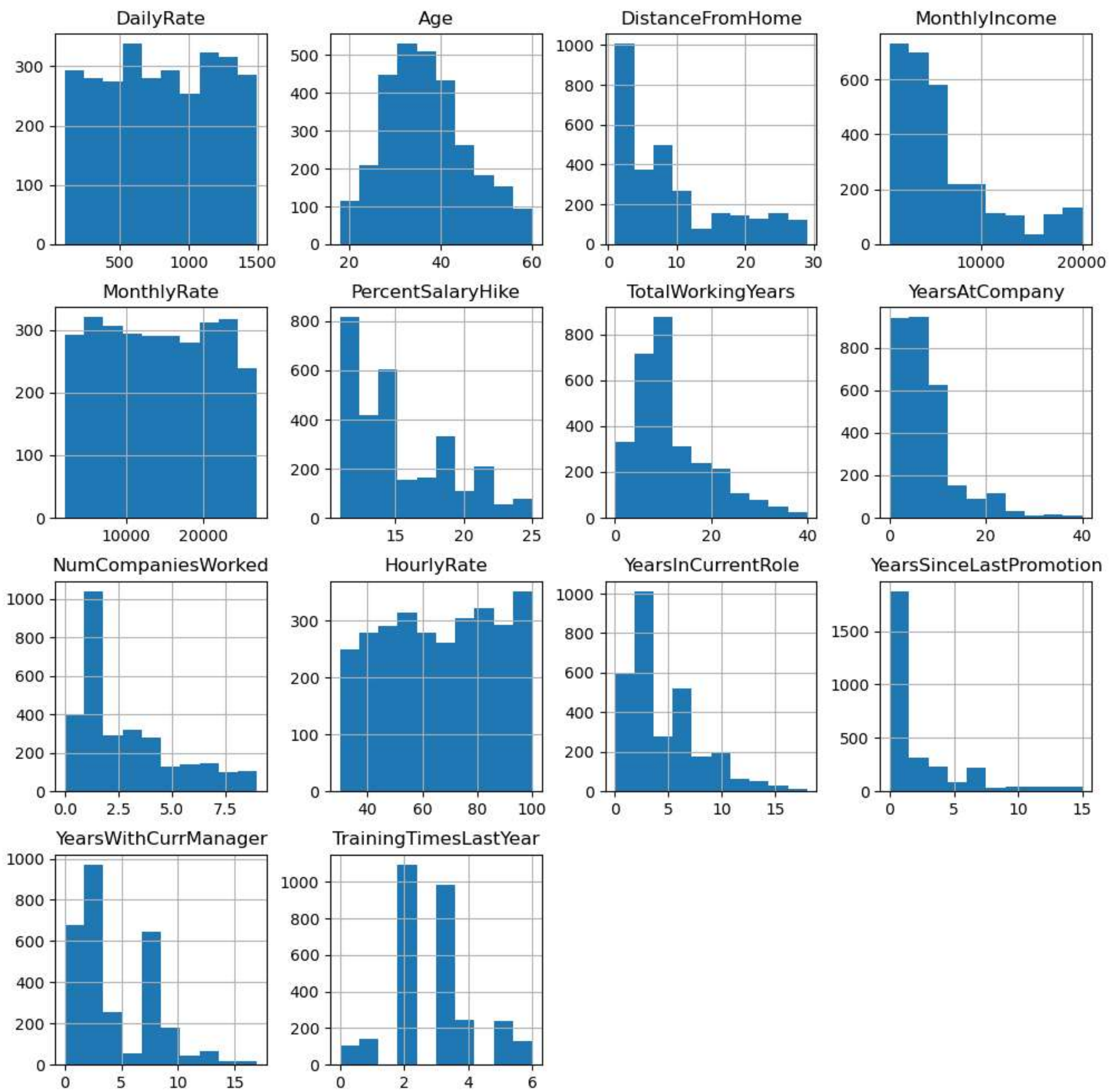
The average monthly income of an employee is USD 6500. It has a high range of values from 1K-20K USD, which is to be expected for any organization's income distribution. There is a big difference between the 3rd quartile value (around USD 8400) and the maximum value (nearly USD 20000), showing that the company's highest earners have a disproportionately large income in comparison to the rest of the employees. Again, this is fairly common in most organizations.

The average salary hike of an employee is around 15%. At least 50% of employees got a salary hike of 14% or less, with the maximum salary hike being 25%.

The average number of years an employee is associated with the company is 7. On average, the number of years since an employee got a promotion is ~2.19. The majority of employees have been promoted since the last year.

In [9]:
```
df[num_cols].hist(figsize = (12, 12))

plt.show()
```



Observations:

The age distribution is close to a normal distribution, with the majority of employees between the ages of 25 and 50. DistanceFromHome also has a right-skewed distribution, meaning most employees live close to work but there are a few that live further away.

MonthlyIncome and TotalWorkingYears are skewed to the right, indicating that the majority of workers are in entry / mid-level positions in the organization.

The percentage salary hike is skewed to the right, which means employees are mostly getting lower percentage salary increaseS.

The YearsAtCompany variable distribution shows a good proportion of workers with 10+ years, indicating a significant number of loyal employees at the organization.

The YearsInCurrentRole distribution has three peaks at 0, 2, and 7. There are a few employees that have even stayed in the same role for 15 years and more.

The YearsSinceLastPromotion variable distribution indicates that some employees have not received a promotion in 10-15 years and are still working in the organization. These employees are assumed to be high work-experience employees in upper-management roles, such as co-founders, C-suite employees, etc.

The distributions of DailyRate, HourlyRate, and MonthlyRate appear to be uniform and do not provide much information. It could be that the daily rate refers to the income earned per extra day worked while the hourly rate could refer to the same concept applied for extra hours worked per day. Since these rates tend to be broadly similar for multiple employees in the same department, that explains the uniform distribution they show.

Univariate Analysis - Categorical Data

In [10]:
```
for i in cat_cols:
    print(df[i].value_counts(normalize = True))
    print('*' * 40)
```

```
No     0.838776
Yes    0.161224
Name: Attrition, dtype: float64
****************************************
No     0.717007
Yes    0.282993
Name: OverTime, dtype: float64
****************************************
Travel_Rarely        0.709524
Travel_Frequently    0.188435
Non-Travel           0.102041
Name: BusinessTravel, dtype: float64
****************************************
Research & Development    0.653741
Sales                     0.303401
Human Resources           0.042857
Name: Department, dtype: float64
****************************************
3    0.389116
4    0.270748
2    0.191837
1    0.115646
5    0.032653
Name: Education, dtype: float64
****************************************
Life Sciences       0.412245
Medical             0.315646
Marketing           0.108163
Technical Degree    0.089796
Other               0.055782
Human Resources     0.018367
Name: EducationField, dtype: float64
****************************************
4    0.312245
3    0.300680
1    0.196599
2    0.190476
Name: JobSatisfaction, dtype: float64
****************************************
3    0.308163
4    0.303401
2    0.195238
1    0.193197
Name: EnvironmentSatisfaction, dtype: float64
****************************************
3    0.607483
2    0.234014
4    0.104082
1    0.054422
Name: WorkLifeBalance, dtype: float64
****************************************
0    0.429252
1    0.405442
2    0.107483
3    0.057823
Name: StockOptionLevel, dtype: float64
****************************************
Male      0.6
Female    0.4
Name: Gender, dtype: float64
```

```
****************************************
3    0.846259
4    0.153741
Name: PerformanceRating, dtype: float64
****************************************
3    0.590476
2    0.255102
4    0.097959
1    0.056463
Name: JobInvolvement, dtype: float64
****************************************
1    0.369388
2    0.363265
3    0.148299
4    0.072109
5    0.046939
Name: JobLevel, dtype: float64
****************************************
Sales Executive              0.221769
Research Scientist           0.198639
Laboratory Technician        0.176190
Manufacturing Director       0.098639
Healthcare Representative    0.089116
Manager                      0.069388
Sales Representative         0.056463
Research Director            0.054422
Human Resources              0.035374
Name: JobRole, dtype: float64
****************************************
Married     0.457823
Single      0.319728
Divorced    0.222449
Name: MaritalStatus, dtype: float64
****************************************
3    0.312245
4    0.293878
2    0.206122
1    0.187755
Name: RelationshipSatisfaction, dtype: float64
****************************************
```

Observations:

The employee attrition rate is ~16%.

Around 28% of the employees are working overtime. This number appears to be on the higher side and might indicate a stressed employee work-life.

71% of the employees have traveled rarely, while around 19% have to travel frequently.

Around 73% of the employees come from an educational background in the Life Sciences and Medical fields.

Over 65% of employees work in the Research & Development department of the organization.

Nearly 40% of the employees have low (1) or medium-low (2) job satisfaction and environment satisfaction in the organization, indicating that the morale of the company appears to be somewhat low.

Over 30% of the employees show low (1) to medium-low (2) job involvement.

Over 80% of the employees either have none or very few stock options.

In terms of performance ratings, none of the employees have rated lower than 3 (excellent). About 85% of employees have a performance rating equal to 3 (excellent), while the remaining have a rating of 4 (outstanding). This could either mean that the majority of employees are top performers, or the more likely scenario is that the organization could be highly lenient with its performance appraisal process.

MODEL BUILDING

In [11]:
```
# Creating a list of columns for which we will create dummy variables
to_get_dummies_for = ['BusinessTravel', 'Department', 'EducationField', 'Gender', 'Mar

# Creating dummy variables
df = pd.get_dummies(data = df, columns = to_get_dummies_for, drop_first = True)

# Mapping overtime and attrition
dict_OverTime = {'Yes': 1, 'No': 0}
dict_attrition = {'Yes': 1, 'No': 0}

df['OverTime'] = df.OverTime.map(dict_OverTime)
df['Attrition'] = df.Attrition.map(dict_attrition)
```

In [12]:
```
# Separating the target variable and other variables
Y = df.Attrition
X = df.drop(['Attrition'], axis = 1)
```

In [13]:
```
# Splitting the data
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3, random_stat
```

Model Evaluation Criteria:

The model can make two types of wrong predictions:

Predicting an employee will attrite when the employee doesn't attrite

Predicting an employee will not attrite when the employee actually attrites

Which case is more important?

Predicting that the employee will not attrite but the employee attrites, i.e., losing out on a valuable employee or asset. This would be considered a major miss for any employee attrition predictor and is hence the more important case of wrong predictions. How to reduce this loss i.e the need to reduce False Negatives?

The company would want the Recall to be maximized, the greater the Recall, the higher the chances of minimizing false negatives. Hence, the focus should be on increasing the Recall (minimizing the false negatives) or, in other words, identifying the true positives (i.e. Class 1) very well, so that the company can provide incentives to control the attrition rate especially, for top-performers. This would help in optimizing the overall project cost towards retaining the best talent.

I will now create a function to calculate and print the classification report and confusion matrix so that we don't have to rewrite the same code repeatedly for each model.

In [14]:
```
def metrics_score(actual, predicted):
    print(classification_report(actual, predicted))

    cm = confusion_matrix(actual, predicted)
    plt.figure(figsize = (8, 5))
    sns.heatmap(cm, annot = True, fmt = '.2f', xticklabels = ['Not Attriate', 'Attriat
    plt.ylabel('Actual')
    plt.xlabel('Predicted')

    plt.show()
```

In [15]:
```
def model_performance_classification(model, predictors, target):
    """
    Function to compute different metrics to check classification model performance

    model: classifier

    predictors: independent variables

    target: dependent variable
    """

    # Predicting using the independent variables
    pred = model.predict(predictors)
    recall = recall_score(target, pred,average = 'macro')                 # To compute
    precision = precision_score(target, pred, average = 'macro')              # To com
    acc = accuracy_score(target, pred)                                  # To compute ac

    # Creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {
            "Precision":  precision,
            "Recall":  recall,
            "Accuracy": acc,
        },

        index = [0],
    )

    return df_perf
```

Decision Tree Model

If the frequency of class A is 17% and the frequency of class B is 83%, then class B will become the dominant class and the decision tree will become biased toward the dominant class.

class_weight is a hyperparameter for the decision tree classifier, and in this case, we can pass a dictionary {0:0.17, 1:0.83} to the model to specify the weight of each class and the decision tree will give more weightage to class 1.

In [16]:
```
dt = DecisionTreeClassifier(class_weight = {0: 0.17, 1: 0.83}, random_state = 1)
dt.fit(x_train, y_train)
```

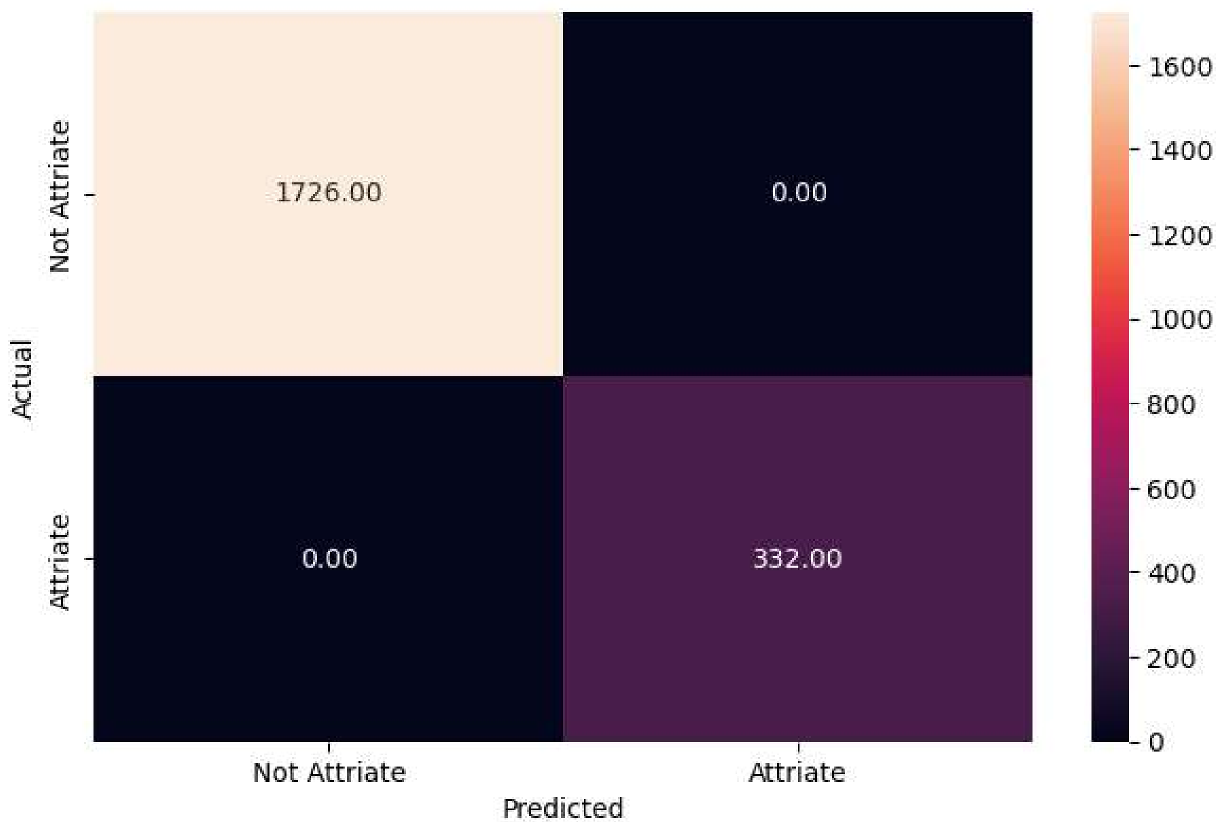
Out[16]:
```
DecisionTreeClassifier(class_weight={0: 0.17, 1: 0.83}, random_state=1)
```

In [17]:
```
# Checking performance on the training dataset
y_train_pred_dt = dt.predict(x_train)
metrics_score(y_train, y_train_pred_dt)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1726
           1       1.00      1.00      1.00       332

    accuracy                           1.00      2058
   macro avg       1.00      1.00      1.00      2058
weighted avg       1.00      1.00      1.00      2058
```



Observation:

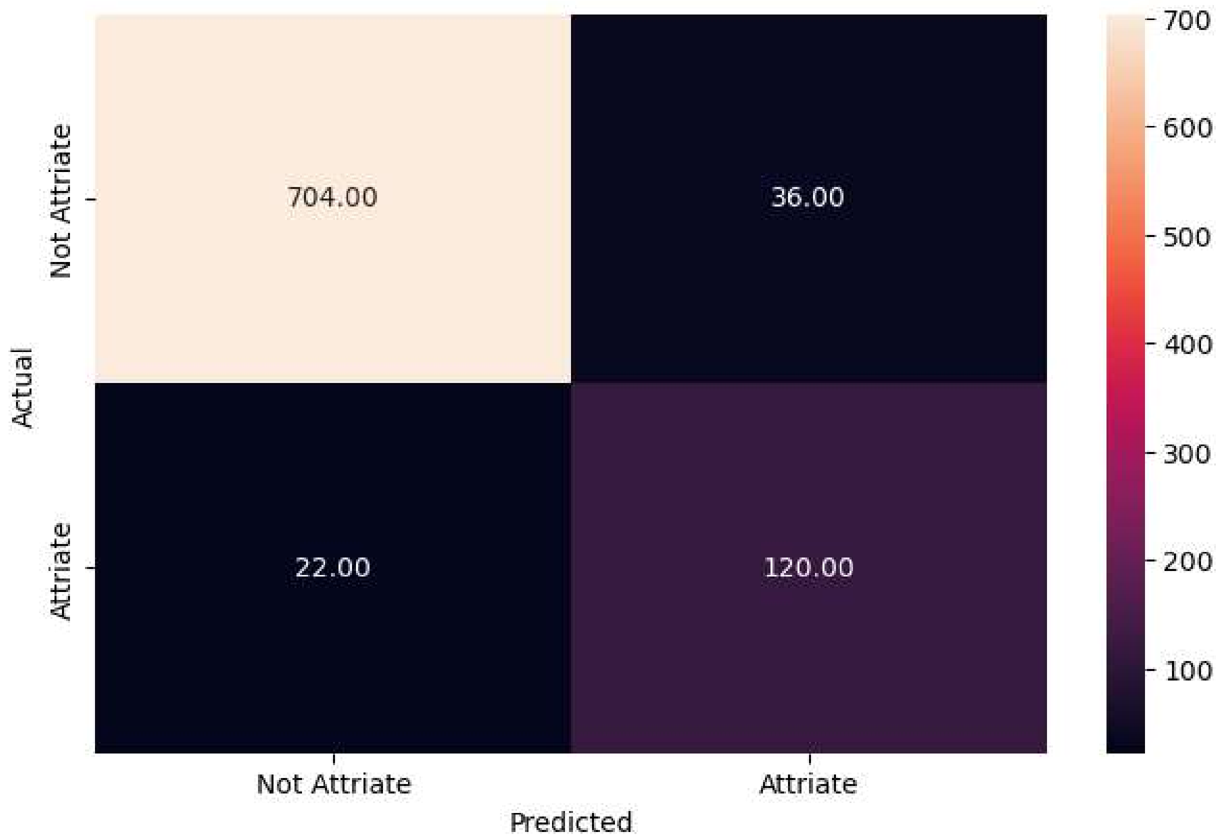
The Decision tree is giving a 100% score for all metrics on the training dataset.

In [18]:
```
# Checking performance on the test dataset
y_test_pred_dt = dt.predict(x_test)
metrics_score(y_test, y_test_pred_dt)
```

```
              precision    recall  f1-score   support

           0       0.97      0.95      0.96       740
           1       0.77      0.85      0.81       142

    accuracy                           0.93       882
   macro avg       0.87      0.90      0.88       882
weighted avg       0.94      0.93      0.94       882
```



In [19]:
```
dtree_test = model_performance_classification(dt,x_test,y_test)
dtree_test
```

Out[19]:

	Precision	Recall	Accuracy
0	0.869464	0.898211	0.93424

Observations:

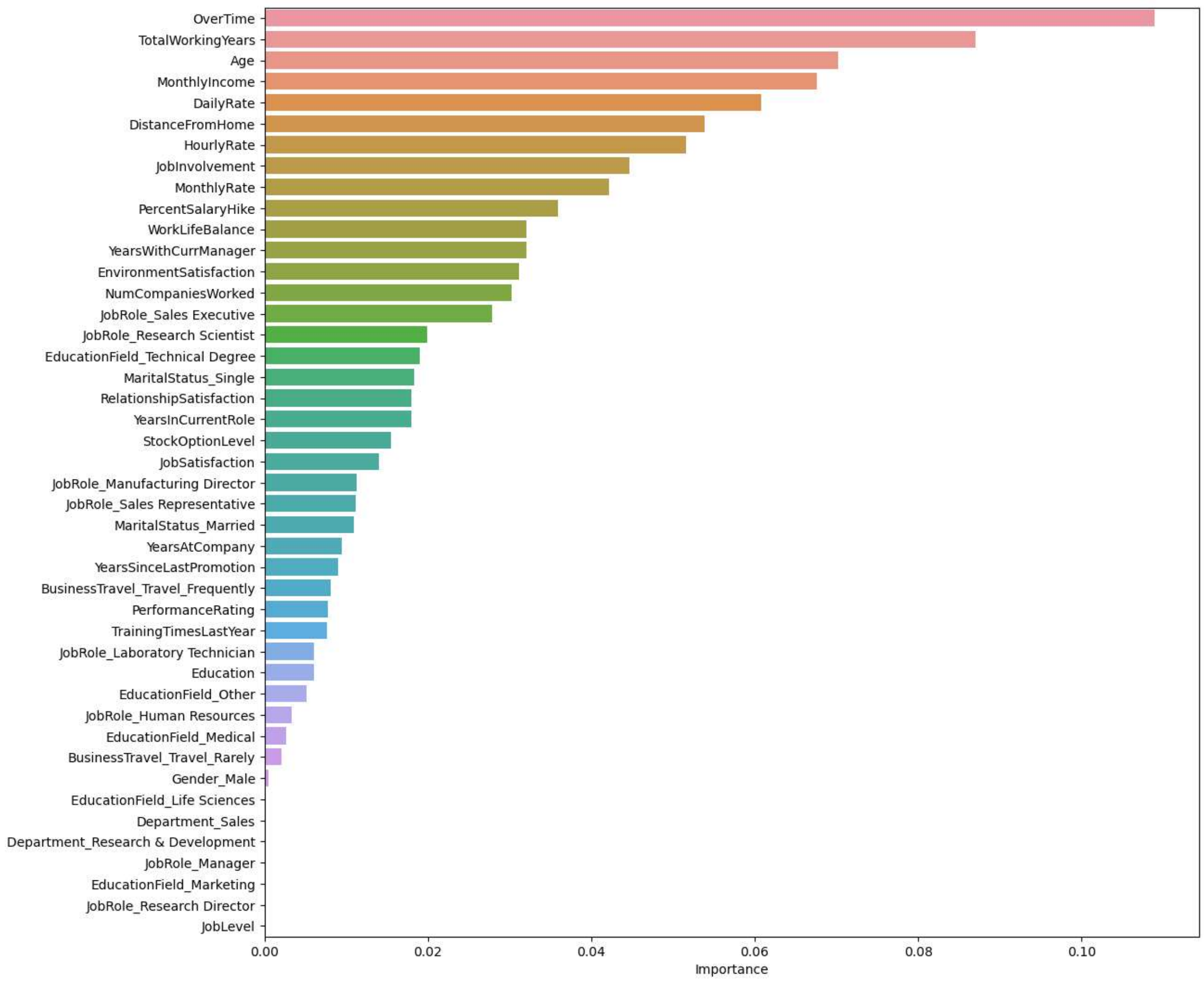
The Decision Tree works well on the training data but not so well on the test data as the recall is 0.83 in comparison to 1 for the training dataset, i.e., the Decision Tree is overfitting the training data.

The precision on the test data suggests that there's a 25% (1 - 0.75) chance that the model will predict that a person is going to leave even though he/she would not, and the company may waste their time and energy on these employees who are not at risk of attrition.

In [20]:
```
# Plot the feature importance

importances = dt.feature_importances_
columns = X.columns
importance_df = pd.DataFrame(importances, index = columns, columns = ['Importance']).s
plt.figure(figsize = (13, 13))
sns.barplot(importance_df.Importance,importance_df.index)
```

Out[20]: <AxesSubplot:xlabel='Importance'>



Observations:

According to the Decision Tree, Overtime is the most important feature, followed by Age, total working years, and Monthly income.

This might signify that people who are at risk of attrition have low income, are doing overtime and have less experience.

The other important features are DailyRate, DistanceFromHome, JobInvolvement, and PercentSalaryHike.

TUNING THE MODEL

Note: Grid Search will take all night to run

Hyperparameter tuning is tricky in the sense that there is no direct way to calculate how a change in the hyperparameter value will reduce the loss of your model, so we usually resort to experimentation. We'll use Grid search to perform hyperparameter tuning.

Grid search is a tuning technique that attempts to compute the optimum values of hyperparameters. It is an exhaustive search that is performed on the specific parameter values of a model. The parameters of the estimator/model used to apply these methods are optimized by cross-validated grid-search over a parameter grid.

Criterion{“gini”, “entropy”}

The function is to measure the quality of a split. Supported criteria are “gini” for the Gini impurity and “entropy” for the information gain.

max_depth

The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.

min_samples_leaf

The minimum number of samples is required to be at a leaf node. A split point at any depth will only be considered if it leaves at least min_samples_leaf training samples in each of the left and right branches. This may have the effect of smoothing the model, especially in regression.

In [21]:
```
# Choose the type of classifier
dtree_estimator = DecisionTreeClassifier(class_weight = {0: 0.17, 1: 0.83}, random_sta

# Grid of parameters to choose from
parameters = {'max_depth': np.arange(2, 7),
              'criterion': ['gini', 'entropy'],
              'min_samples_leaf': [5, 10, 20, 25]
             }

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(recall_score, pos_label = 1)

# Run the grid search
gridCV = GridSearchCV(dtree_estimator, parameters, scoring = scorer, cv = 10)

# Fitting the grid search on the train data
gridCV = gridCV.fit(x_train, y_train)

# Set the classifier to the best combination of parameters
dtree_estimator = gridCV.best_estimator_

# Fit the best estimator to the data
dtree_estimator.fit(x_train, y_train)
```

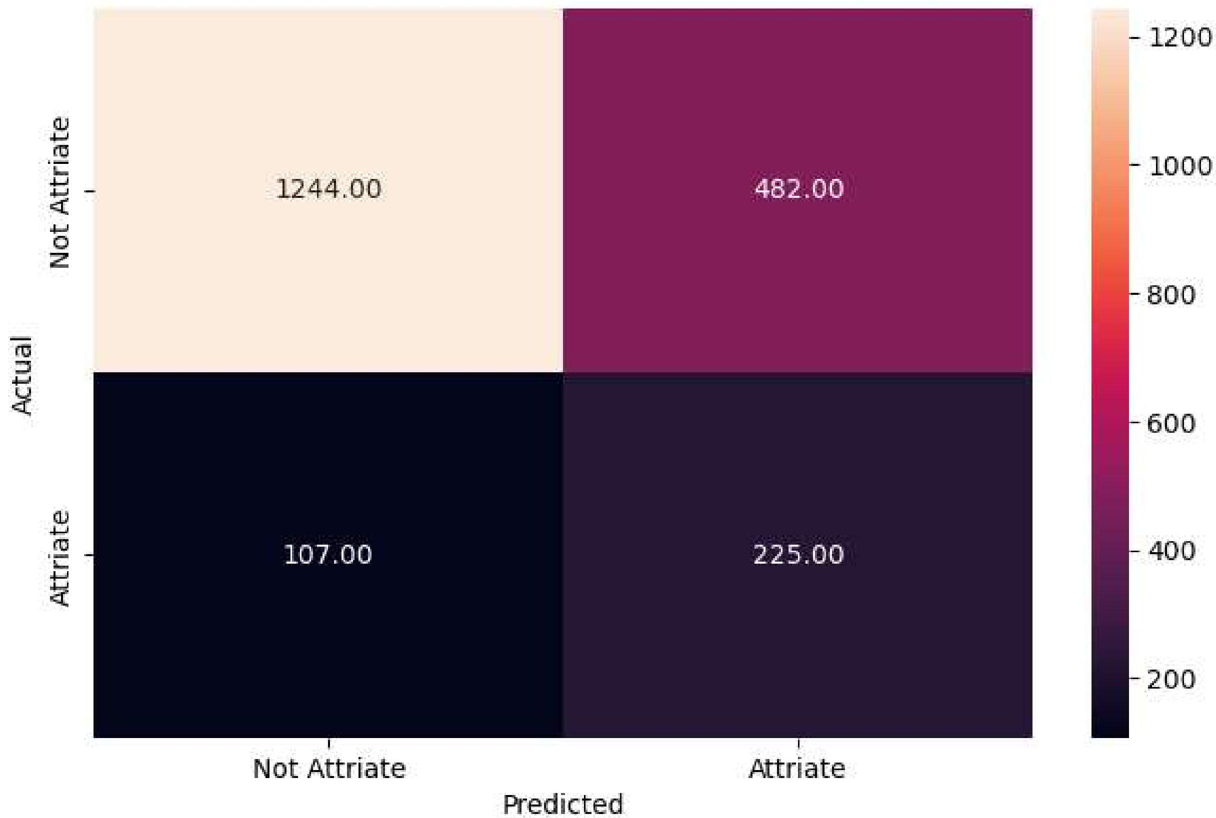
Out[21]:
```
DecisionTreeClassifier(class_weight={0: 0.17, 1: 0.83}, max_depth=2,
                       min_samples_leaf=5, random_state=1)
```

In [22]:
```
# Checking performance on the training dataset
y_train_pred_dt = dtree_estimator.predict(x_train)
metrics_score(y_train, y_train_pred_dt)
```

```
              precision    recall  f1-score   support

           0       0.92      0.72      0.81      1726
           1       0.32      0.68      0.43       332

    accuracy                           0.71      2058
   macro avg       0.62      0.70      0.62      2058
weighted avg       0.82      0.71      0.75      2058
```



Observation:

In comparison to the model with default values of hyperparameters, the performance on the training set has gone down significantly. This makes sense because we are trying to reduce overfitting.

In [23]:
```
# Checking performance on the test dataset
y_test_pred_dt = dtree_estimator.predict(x_test)
metrics_score(y_test, y_test_pred_dt)
```

```
              precision    recall  f1-score   support

           0       0.91      0.71      0.80       740
           1       0.29      0.61      0.39       142

    accuracy                           0.70       882
   macro avg       0.60      0.66      0.59       882
weighted avg       0.81      0.70      0.73       882
```

In [24]:
```
dtree_tuned_test = model_performance_classification(dtree_estimator,x_test,y_test)
dtree_tuned_test
```

Out[24]:

	Precision	Recall	Accuracy
0	0.597186	0.661743	0.695011

Observations:

The tuned model is not performing well in comparison to the model with default values of hyperparameters.

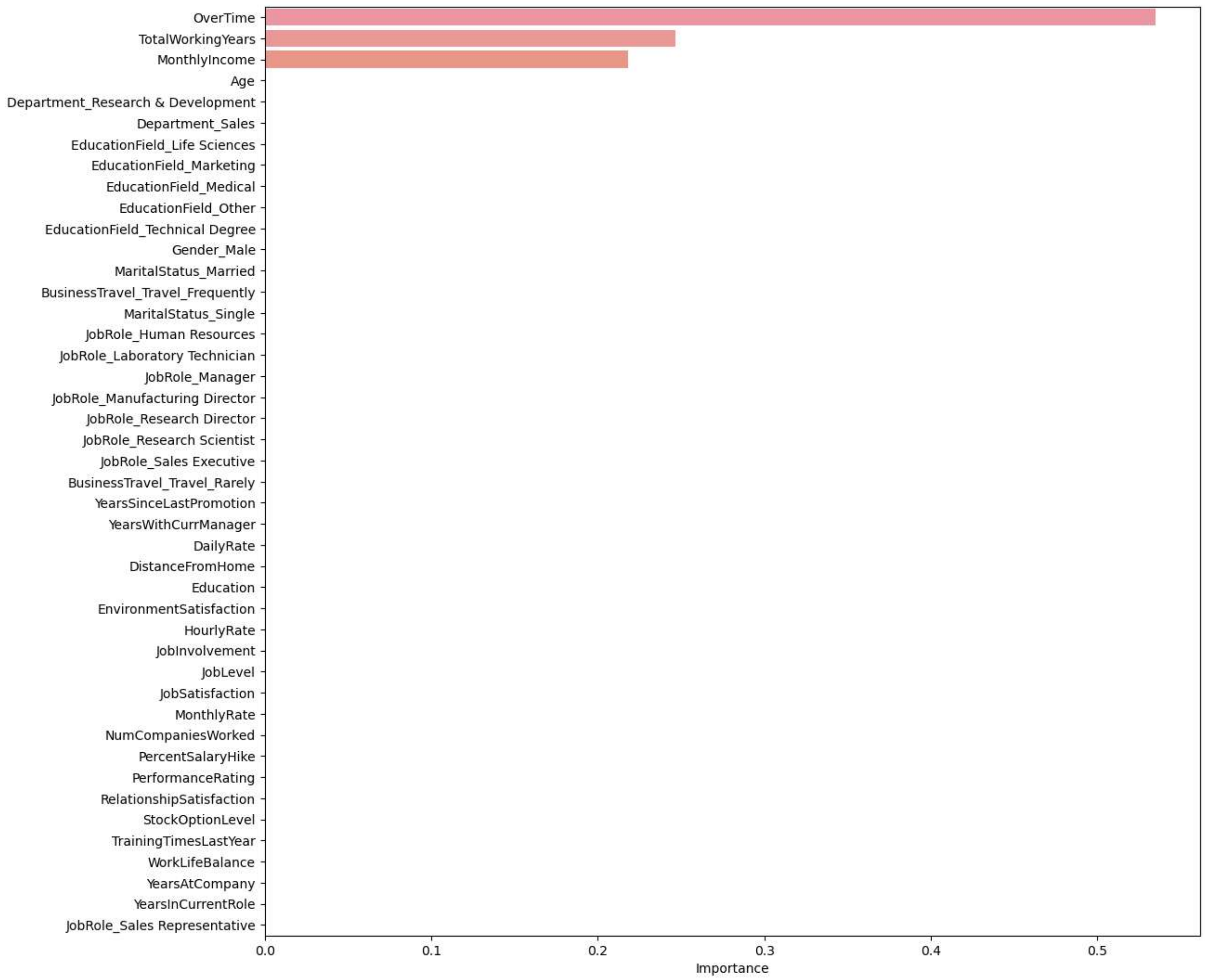
This model is not overfitting the training data and giving approximately the same result on the test and train datasets.

Precision has gone down significantly from .75 to .29 in comparison to the previous model which means the tuned model will give a high number of false positives, i.e., this model will predict the employee is going to leave even if they won't, and this will cost time and effort to the company.

I will now look at the feature importance of this model and try to analyze why this is happening.

In [25]:
```
importances = dtree_estimator.feature_importances_
columns = X.columns
importance_df = pd.DataFrame(importances, index = columns, columns = ['Importance']).s
plt.figure(figsize = (13, 13))
sns.barplot(importance_df.Importance, importance_df.index)
```

Out[25]: <AxesSubplot:xlabel='Importance'>



Observations:

After tuning the model we are getting that only 3 features are important. It seems like the model is having high bias, as it has over-simplified the problem and is not capturing the patterns associated with other variables.

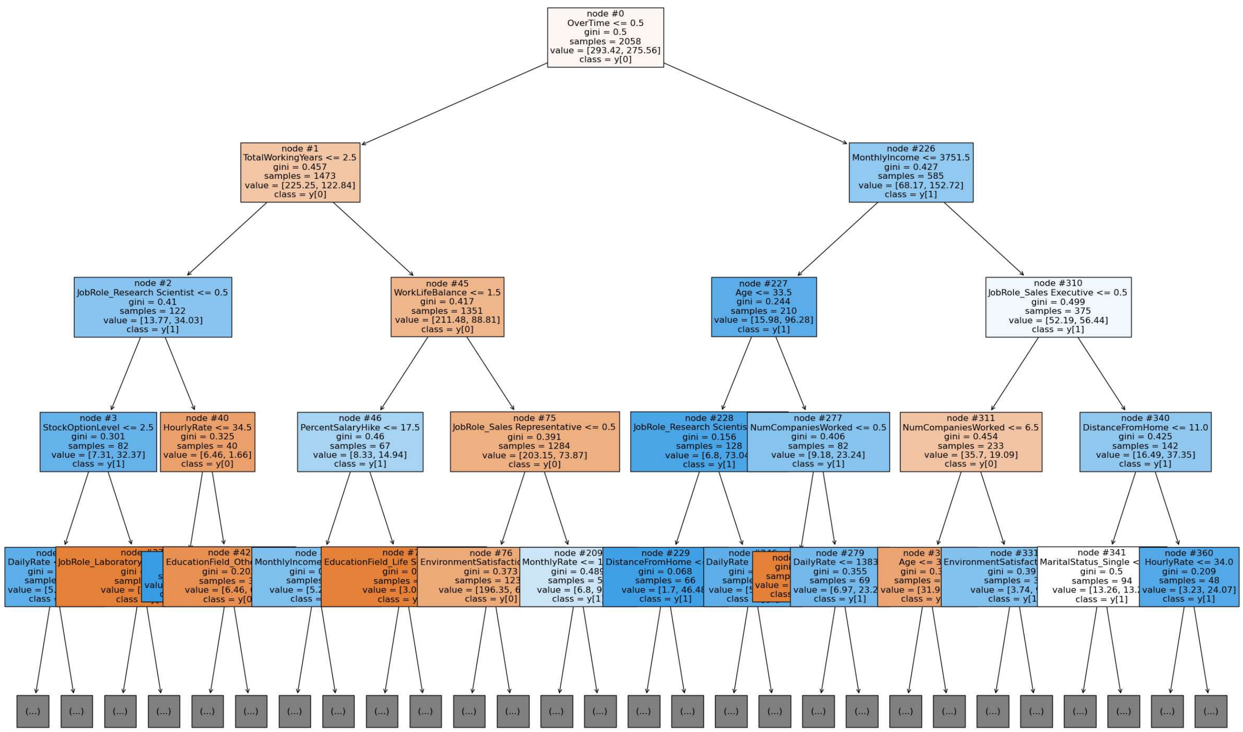
According to this model too, OverTime, TotalWorkingYears, and MonthlyIncome are the 3 most important features that describe why an employee is leaving the organization, which might imply that employees doing overtime may feel that their remuneration is not enough for their efforts.

Let's plot the tree and check if the assumptions about overtime income.

As we know the decision tree keeps growing until the nodes are homogeneous, i.e., it has only one class, and the dataset here has a lot of features, it would be hard to visualize the whole tree with so many features. Therefore, we are only visualizing the tree up to max_depth = 4.

In [26]:
```
features = list(X.columns)
plt.figure(figsize = (30, 20))
tree.plot_tree(dt, max_depth = 4, feature_names = features, filled = True, fontsize =

plt.show()
```



Note:

Blue leaves represent the attrition, i.e., y[1] and the orange leaves represent the non-attrition, i.e., y[0]. Also, the more the number of observations in a leaf, the darker its color gets.

Observations:

Employees who are doing overtime with low salaries and low age have a chance of leaving the company, as they might feel overworked and underpaid and might be looking for better opportunities.

Employees who are doing overtime with low salaries and are not research scientists have a high chance of attriting.

Employees, even if they have an income over 3751.5 units but working as sales executives and living far from home have a high chance of attriting.

Another segment of people are who are doing overtime, with ages younger than 33.5 and not working as research scientists, have a greater chance of attrition. This implies that the model suggests except for the research scientist role, everyone who is young has a high tendency to attrite.

Employees who have over 2.5 years of work experience but low work-life balance and low percentage hike also tend to attrite, probably as they are seeking a more balanced life.

Employees who are not doing overtime, have low experience and are working as research scientists have a smaller chance of attriting. These employees are comfortable or loyal to the organization.

Numcompaniesworked also seems to be an important variable in predicting if an employee's likely to attrite.

Random Forest Classifier

Random Forest is a bagging algorithm where the base models are Decision Trees. Samples are taken from the training data and on each sample, a decision tree makes a prediction.

The results from all the decision trees are combined and the final prediction is made using voting (for classification problems) or averaging (for regression problems).

In [27]:
```
rf_estimator = RandomForestClassifier(class_weight = {0: 0.17, 1: 0.83}, random_state
rf_estimator.fit(x_train, y_train)
```

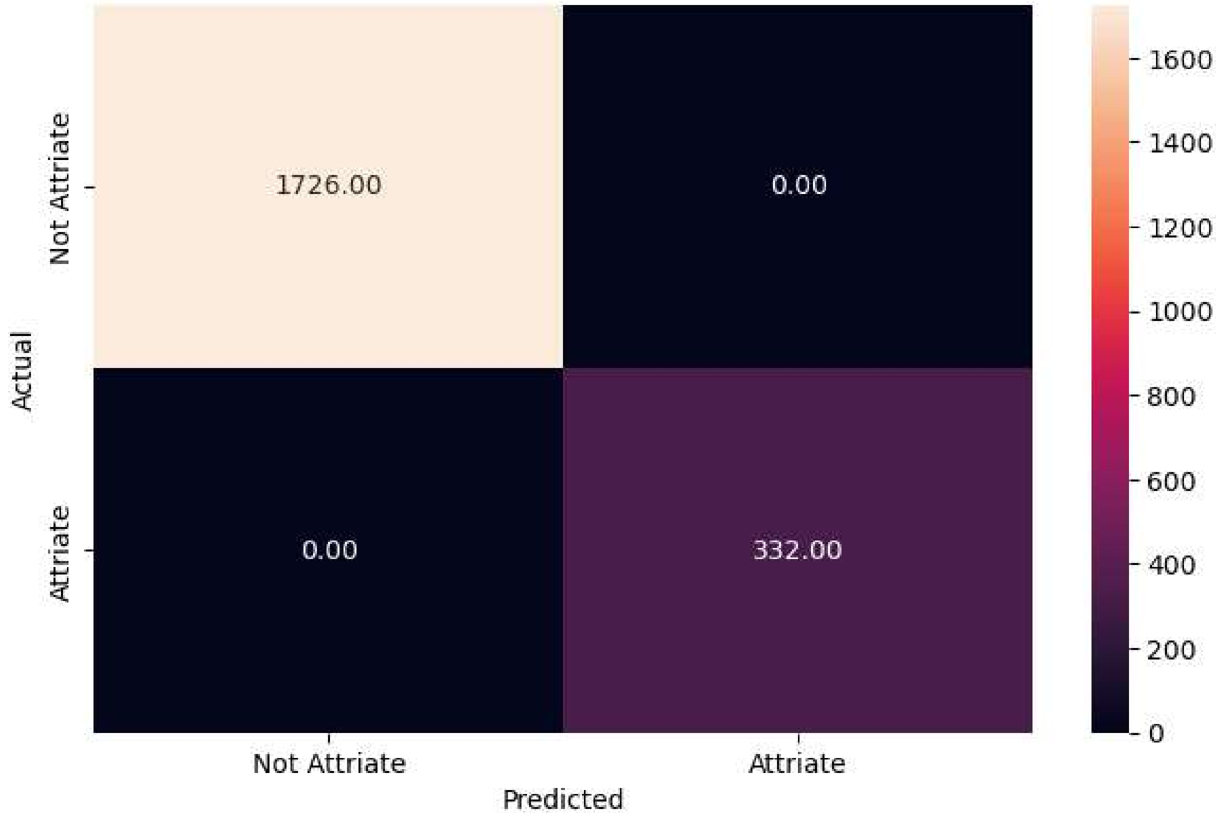
Out[27]:
```
RandomForestClassifier(class_weight={0: 0.17, 1: 0.83}, random_state=1)
```

In [28]:
```
y_pred_train_rf = rf_estimator.predict(x_train)
metrics_score(y_train, y_pred_train_rf)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1726
           1       1.00      1.00      1.00       332

    accuracy                           1.00      2058
   macro avg       1.00      1.00      1.00      2058
weighted avg       1.00      1.00      1.00      2058
```



Observation:

The Random Forest is giving a 100% score for all metrics on the training dataset.

In [29]:
```
y_pred_test_rf = rf_estimator.predict(x_test)
metrics_score(y_test, y_pred_test_rf)
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.98       740
           1       0.97      0.79      0.87       142

    accuracy                           0.96       882
   macro avg       0.96      0.89      0.92       882
weighted avg       0.96      0.96      0.96       882
```

In [30]:
```
rf_estimator_test = model_performance_classification(rf_estimator,x_test,y_test)
rf_estimator_test
```

Out[30]:

	Precision	Recall	Accuracy
0	0.963176	0.891663	0.961451

Observations:

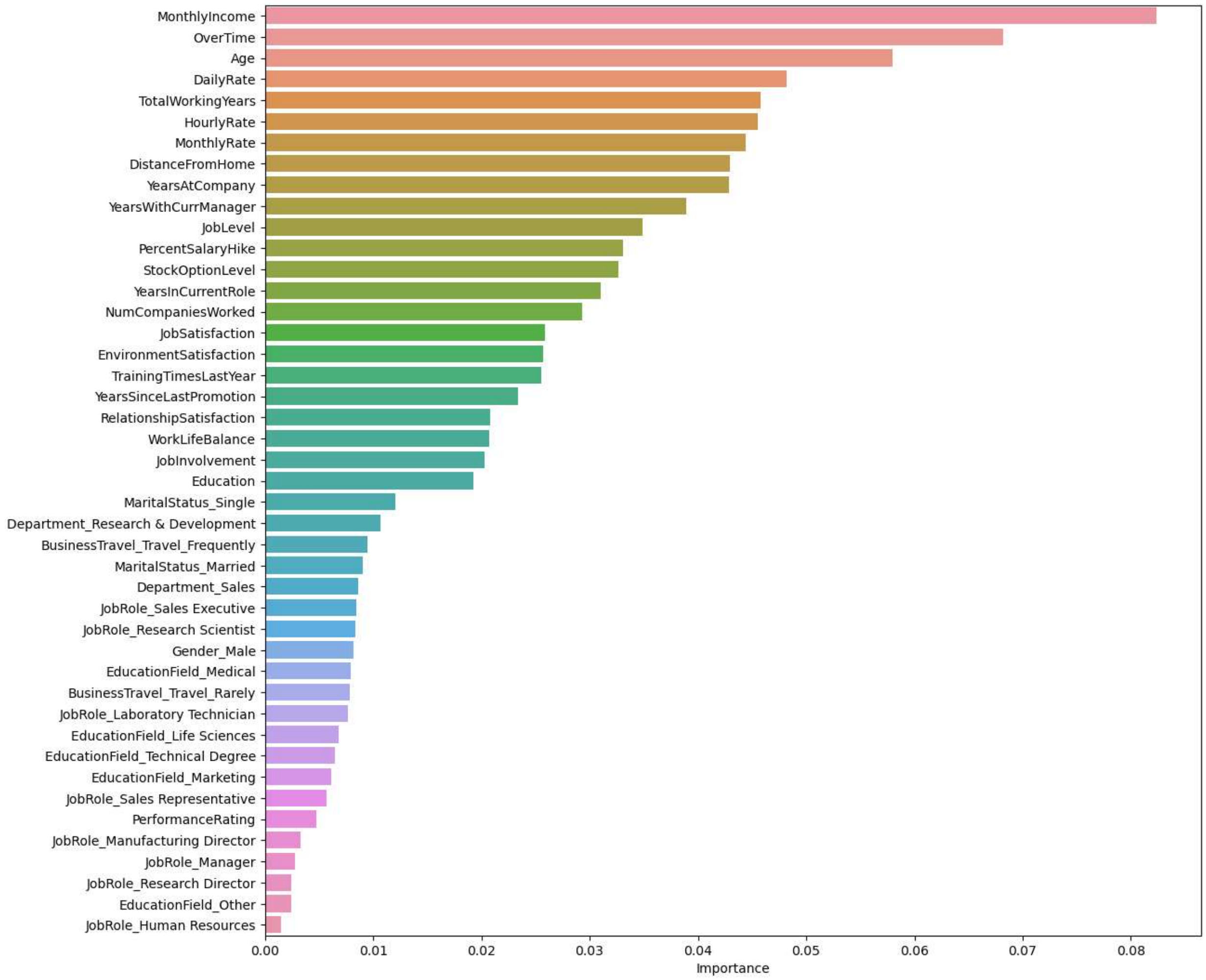
The Random Forest classifier seems to be overfitting the training data. The recall on the training data is 1, while the recall on the test data is only ~ 0.80 for class 1.

Precision is high for the test data as well.

Checking Feature Importance

In [31]:
```
importances = rf_estimator.feature_importances_
columns = X.columns
importance_df = pd.DataFrame(importances, index = columns, columns = ['Importance']).s
plt.figure(figsize = (13, 13))
sns.barplot(importance_df.Importance, importance_df.index)
```

Out[31]: <AxesSubplot:xlabel='Importance'>



Observations:

The Random Forest further verifies the results from the decision tree that the most important features are MonthlyIncome, Age, OverTime.

We can say that the people appear to be leaving the organization because of the overtime they are doing andh s because they are not paid accordingly. These might be mostly junior-level and mid-level employees with less experience.

Distance from home is also a key feature, probably as employees living far from the office have to travel a lot, making their schedules hectic.

Not having stock options is also a driver for attrition - this feature seems to have good importance in both the decision tree and random forest models. This could be related to the junior level employees and their lack of stock options - with the additional burden of a lower salary and working overtime, those without stock options could also be attriting more.

Other features like, number of companies worked and percent salary hike also seem to be intuitive in explaining attrition likelihood, as people who have worked in a large number of companies are probably not going to stay loyal to the current organization and may have a high risk of attrition, while if an employee is not getting enough of a salary hike, that might demotivate them and lead to a higher likelihood of attriting as well.

Other features such as job satisfaction, environment satisfaction and their job level also play a crucial role in knowing whether an employee will attrite or not.

TUNING THE RANDOM FOREST MODEL

REMEMBER: Grid Search can take a long time to run!

In [32]:
```
# Choose the type of classifier
rf_estimator_tuned = RandomForestClassifier(class_weight = {0: 0.17, 1: 0.83}, random_

# Grid of parameters to choose from
params_rf = {
        "n_estimators": [100, 250, 500],
        "min_samples_leaf": np.arange(1, 4, 1),
        "max_features": [0.7, 0.9, 'auto'],
}


# Type of scoring used to compare parameter combinations - recall score for class 1
scorer = metrics.make_scorer(recall_score, pos_label = 1)

# Run the grid search
grid_obj = GridSearchCV(rf_estimator_tuned, params_rf, scoring = scorer, cv = 5)

grid_obj = grid_obj.fit(x_train, y_train)

# Set the classifier to the best combination of parameters
rf_estimator_tuned = grid_obj.best_estimator_
```

In [33]:
```
rf_estimator_tuned.fit(x_train, y_train)
```

Out[33]:
```
RandomForestClassifier(class_weight={0: 0.17, 1: 0.83}, max_features=0.9,
                       min_samples_leaf=3, n_estimators=250, random_state=1)
```

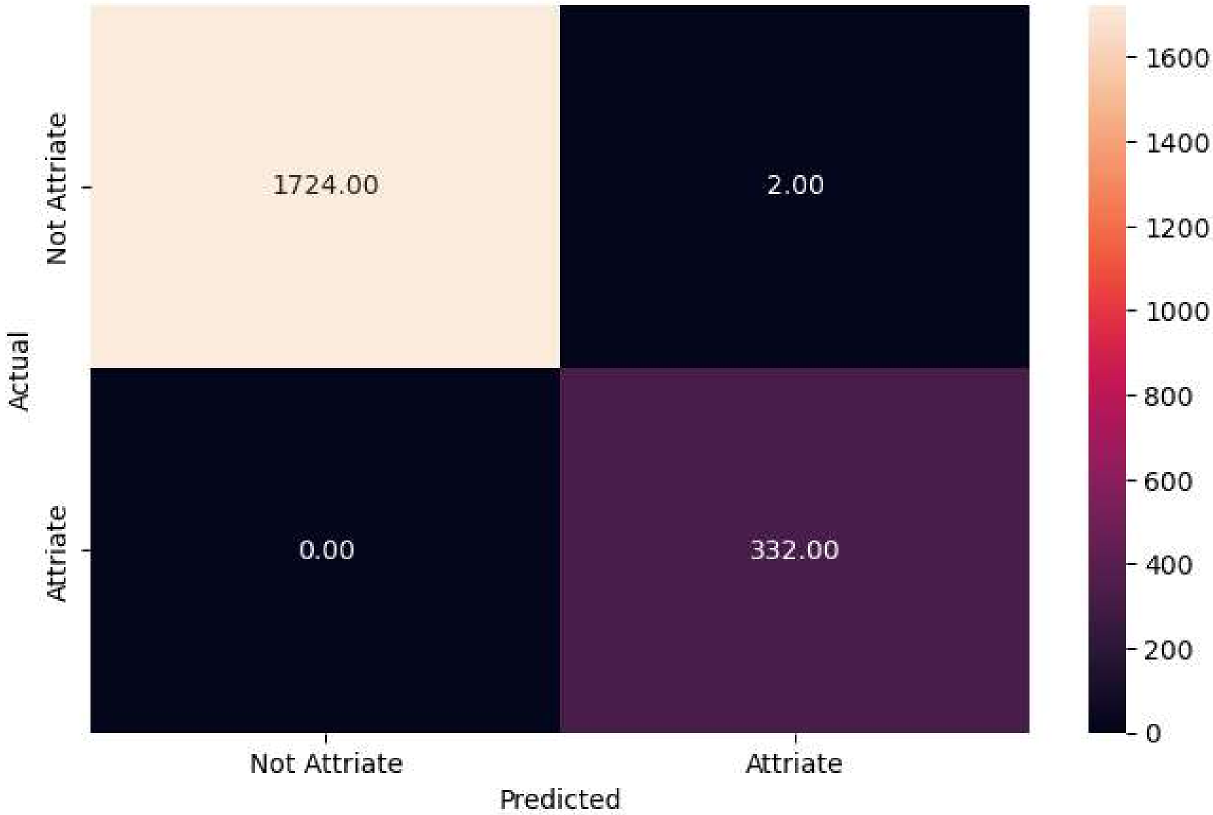
In [34]:
```
# Checking performance on the training data
y_pred_train_rf_tuned = rf_estimator_tuned.predict(x_train)

metrics_score(y_train, y_pred_train_rf_tuned)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1726
           1       0.99      1.00      1.00       332

    accuracy                           1.00      2058
   macro avg       1.00      1.00      1.00      2058
weighted avg       1.00      1.00      1.00      2058
```



In [35]:
```python
# Checking performance on the test data
y_pred_test_rf_tuned = rf_estimator_tuned.predict(x_test)

metrics_score(y_test, y_pred_test_rf_tuned)
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.97       740
           1       0.88      0.83      0.86       142

    accuracy                           0.95       882
   macro avg       0.92      0.90      0.91       882
weighted avg       0.95      0.95      0.95       882
```

In [36]:
```
rf_estimator_tuned_test = model_performance_classification(rf_estimator_tuned, x_test,
rf_estimator_tuned_test
```

Out[36]:

	Precision	Recall	Accuracy
0	0.924256	0.904682	0.954649

Observations:

The tuned model is also slightly overfitting the training dataset, but it shows a good performance on the test dataset.

The recall for class 1 has improved with a small decrease in precision.

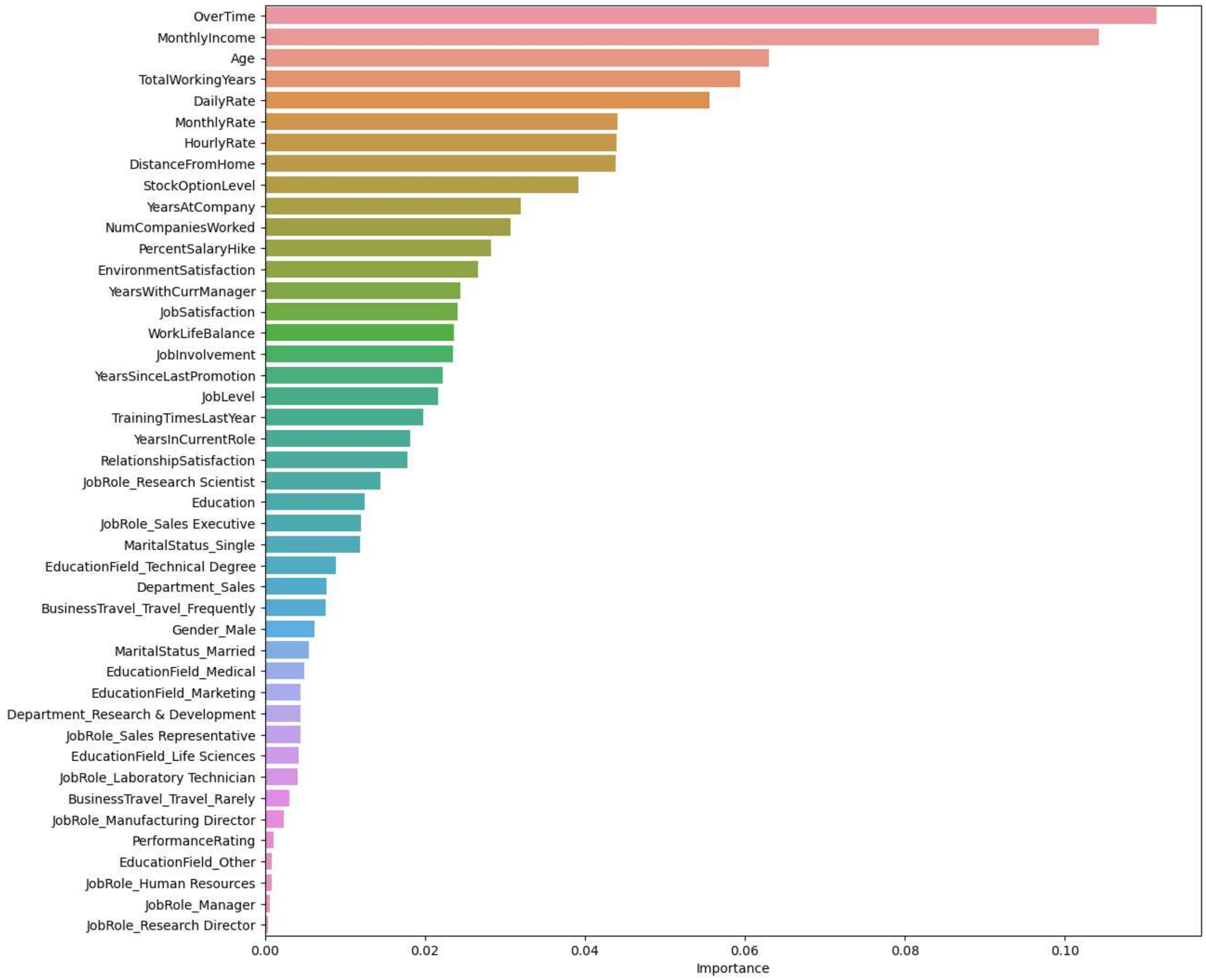
This model is the best-performing of all the models so far,

and is giving us good precision and recall scores on the test dataset.

In [37]:
```
# Plotting feature importance
importances = rf_estimator_tuned.feature_importances_
columns = X.columns
importance_df = pd.DataFrame(importances, index = columns, columns = ['Importance']).s
plt.figure(figsize = (13, 13))

sns.barplot(importance_df.Importance, importance_df.index)
```

Out[37]: <AxesSubplot:xlabel='Importance'>



Observations:

The feature importance plot for the base model and tuned model are quite similar. The model seems to suggest that OverTime, MonthlyIncome, Age,TotalWorkingYears, and DailyRate are the most important features.

Other important features are DistanceFromHome, StockOptionLevel, YearsAt Company, and NumCompaniesWorked.

XG Boost Classifier

In [38]:
```
#This is a brand new computer so I must now

!pip install xgboost
```

```
Collecting xgboost
  Downloading xgboost-1.7.5-py3-none-win_amd64.whl (70.9 MB)
     --------------------------------------- 70.9/70.9 MB 17.2 MB/s eta 0:00:00
Requirement already satisfied: scipy in c:\users\trade\anaconda3\lib\site-packages (f
rom xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\users\trade\anaconda3\lib\site-packages (f
rom xgboost) (1.21.5)
Installing collected packages: xgboost
Successfully installed xgboost-1.7.5
```

In [39]:

```
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
```

In [40]:

```
adaboost_model = AdaBoostClassifier(random_state = 1)

# Fitting the model
adaboost_model.fit(x_train, y_train)

# Model Performance on the test data
adaboost_model_perf_test = model_performance_classification(adaboost_model,x_test,y_te

adaboost_model_perf_test
```

Out[40]:

	Precision	Recall	Accuracy
0	0.814518	0.709136	0.884354

In [41]:

```
# Gradient Boost Classifier
gbc = GradientBoostingClassifier(random_state = 1)

# Fitting the model
gbc.fit(x_train, y_train)

# Model Performance on the test data
gbc_perf_test = model_performance_classification(gbc, x_test, y_test)

gbc_perf_test
```

Out[41]:

	Precision	Recall	Accuracy
0	0.882845	0.728483	0.902494

In [42]:

```
# XGBoost Classifier
xgb = XGBClassifier(random_state = 1, eval_metric = 'logloss')

# Fitting the model
xgb.fit(x_train,y_train)

# Model Performance on the test data
xgb_perf_test = model_performance_classification(xgb,x_test,y_test)

xgb_perf_test
```

Out[42]:

	Precision	Recall	Accuracy
0	0.959975	0.911439	0.965986

Observations:

XG Boost is an even better fit than Random Forests

BUT... I didn't really learn anything new that the previous models didn't show me. I always like to run both in case there is a huge difference in results that could indicate that I need to do further analysis. However, this dataset is pretty straight-forward.

Conclusion

The best model we have got so far is the tuned XG Boost model, but the Random Forest tuned model would have been fine for returning the same results.

The company could use XG Boost to know beforehand which employee is going to attrite and act accordingly. Overtime, MonthlyIncome, DailyRate, number of companies worked, and work experience/age seem to be the most important features.

Recommendations

We saw that working overtime is the most important driver of attrition. The organization should manage their work more efficiently so that employees don't have to work overtime and can manage to have a work-life balance, failing to do this, the company could provide some additional incentives to employees who are working overtime in order to retain them.

A higher monthly income might lower the odds of an employee attriting. The company should make sure that all its employees are compensated at least based on industry standards.

As observed earlier, the organization has a lower percentage salary hike and promotions are given less frequently. The company might be able to focus on giving promotions more frequently or they could increase the annual appraisal hike to incentivize employees to stay.

The organization could come up with a revised CTC plan with stock options for the employees in order to keep them motivated and invested in the company's performance.

The organization should also modify its hiring policy as people who have worked in many companies and have switched a lot, should not be hired very often.

Distance from home is also an important factor for attrition. Employees traveling a larger distance to reach the workplace are the ones attriting. For such employees, the company can provide cab facilities so that the commute of employees gets easier.

The company should also keep track of the hourly rate or the daily rate, so that when the employees need to stay overtime for extra work they are well compensated for that.

The organization should focus on improving the culture and environment at the workplace by coming up with new ideas to make the environment more open and friendly.

Keeping track of the problems which employees with lesser experience face and how the management can help them, will create a healthy environment for the young employees.

The organization should also focus on the employees who are working in sales and marketing, as attrition rate is quite high for these departments. Perhaps the company could look into their incentive schemes and try to come up with new incentive methods to motivate them to stay.

In [ ]: