Samsung Electronics Reviews

Navigating Samsung Electronics: Employee Reviews (People Insights)

The dataset serves as a valuable repository of insights gleaned from employee reviews of Samsung India Electronics, a renowned Consumer Electronics & Appliances company. This dataset provides a unique window into the experiences, sentiments, and perspectives of individuals who have worked at Samsung India Electronics. It was curated by web scraping employee reviews from Ambition Box, a platform where employees share their experiences and opinions about their workplaces. The data encompasses reviews covering various topics, including work-life balance, career growth, company culture, and more.

In this project, I leveraged this dataset for sentiment analysis. I employed various machine learning models, including Decision Tree, Random Forest, Support Vector Machine, and XGBoost, with the aim of predicting the key factors influencing positive, neutral, or negative sentiments in the given reviews. Through this analysis, my goal is to delve into the essence of employee reviews and identify key elements that can impact their perceptions of the work experience at the company.

In [1]:
```
# Import the necessary libraries

import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import random
import shap

from tqdm import tqdm
import re
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download("vader_lexicon")
from bs4 import BeautifulSoup
from nltk.tag import pos_tag
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from nltk.corpus import wordnet

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score,
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
import xgboost as xgb

from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
```

```
from sklearn.metrics import roc_auc_score

from plotly import __version__
import cufflinks as cf
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
from plotly.subplots import make_subplots
import plotly.graph_objects as go

init_notebook_mode(connected=True)
cf.go_offline()
cf.set_config_file(theme='space', sharing='public', offline=True)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ACER\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Data Preparation

In [117…

```
# Read the data using pandas

df = pd.read_csv('Samsung_India_Electronics_Employee_Reviews_from_AmbitionBox.csv')
df.head()
```

Out[117…

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_develo
0	Professional Logistics	Chennai	Full Time	SCM & Logistics Department	5 Sep 2023	3.0	3.0	
1	Supervisor Instructor	Noida	Full Time	Production & Manufacturing Department	1 Sep 2023	5.0	5.0	
2	Quality Inspector	Noida	Full Time	Quality Assurance and Testing Department	3 Aug 2023	4.0	4.0	
3	Lead Engineer	Noida	Full Time	Software Development Department	6 Aug 2023	4.0	3.0	
4	Zonal Sales Manager	Chennai	Full Time	Retail & B2C Sales Department	1 Aug 2023	4.0	2.0	

Columns Additional Information:

- Title: The job title or role of the employee providing the review.
- Place: The geographical location or city where the employee works.
- Job Type: The employment status of the reviewer (e.g., Full Time).
- Department: The specific department or functional area within the organization.
- Date: The date when the review was submitted.
- Overall Rating: A numerical rating given by the employee for their overall job satisfaction.

- Work Life Balance: Rating indicating the work-life balance experienced by the employee.
- Skill Development: Rating reflecting the opportunities for skill enhancement and growth.
- Salary and Benefits: Rating assessing the satisfaction with compensation and benefits.
- Job Security: Rating expressing the employee's sense of job security.
- Career Growth: Rating indicating the perceived career advancement opportunities.
- Work Satisfaction: Rating showcasing the employee's contentment with their work.
- Likes: Positive aspects and pros highlighted by the employee in their review.
- Dislikes: Negative aspects and cons mentioned by the employee in their review.

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1211 entries, 0 to 1210
Data columns (total 14 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Title                1125 non-null   object 
 1   Place                1057 non-null   object 
 2   Job_type             373 non-null    object 
 3   Department           946 non-null    object 
 4   Date                 1125 non-null   object 
 5   Overall_rating       1123 non-null   float64
 6   work_life_balance    1210 non-null   float64
 7   skill_development    1210 non-null   float64
 8   salary_and_benefits  1209 non-null   float64
 9   job_security         1208 non-null   float64
 10  career_growth        1207 non-null   float64
 11  work_satisfaction    1205 non-null   float64
 12  Likes                1004 non-null   object 
 13  Dislikes             959 non-null    object 
dtypes: float64(7), object(7)
memory usage: 132.6+ KB
```

In [118…
```
# Combine 'Likes' and 'Dislikes' columns into a new 'review' column
df['review'] = df['Likes'].astype(str) + ' ' + df['Dislikes'].astype(str)
df.head()
```

Out[118…

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_develo
0	Professional Logistics	Chennai	Full Time	SCM & Logistics Department	5 Sep 2023	3.0	3.0	
1	Supervisor Instructor	Noida	Full Time	Production & Manufacturing Department	1 Sep 2023	5.0	5.0	
2	Quality Inspector	Noida	Full Time	Quality Assurance and Testing Department	3 Aug 2023	4.0	4.0	
3	Lead Engineer	Noida	Full Time	Software Development Department	6 Aug 2023	4.0	3.0	

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_develo
4	Zonal Sales Manager	Chennai	Full Time	Retail & B2C Sales Department	1 Aug 2023	4.0	2.0	

In [119…

```
# Replaces contracted words in a given phrase with their expanded forms
def decontracted(phrase):
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase

nltk.download('stopwords')
eng_stopwords = set(stopwords.words('english'))

# Performs various text cleaning operations on the 'review' column of the DataFrame.
# This includes removing URLs, HTML tags, contracted words, non-alphabetic character
def cleaning(data):
  preprocessed_reviews = []
  for sentance in tqdm(df['review'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in eng_
    preprocessed_reviews.append(sentance.strip())
  df['review']=preprocessed_reviews
  return data
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\ACER\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [120…

```
df_clean_review = cleaning(df)
```

```
100%|██████████████████████████████████████| 1
211/1211 [00:01<00:00, 1004.03it/s]
```

In [7]:

```
pd.set_option('display.max_colwidth', None)
print(df_clean_review['review'].iloc[0])
pd.reset_option('display.max_colwidth')
```

```
company provide free cost transportation good medical insurance policies including p
arents montonous work manager assign responsibility others team culture depends kore
an e expat learning less ppl top level years new ideas r welcomed
```

In [121…

```
# Perform sentiment analysis using SentimentIntensityAnalyzer
sentiment = SentimentIntensityAnalyzer()

# Calculate positive, negative, neutral, and compound scores for each review
df_clean_review["positive"] = [sentiment.polarity_scores(i)["pos"] for i in df_clean
df_clean_review["negative"] = [sentiment.polarity_scores(i)["neg"] for i in df_clean
df_clean_review["neutral"] = [sentiment.polarity_scores(i)["neu"] for i in df_clean_
```

```
df_clean_review['compound'] = [sentiment.polarity_scores(i)["compound"] for i in df_
df_clean_review.head()
```

Out[121…

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_develo
0	Professional Logistics	Chennai	Full Time	SCM & Logistics Department	5 Sep 2023	3.0	3.0	
1	Supervisor Instructor	Noida	Full Time	Production & Manufacturing Department	1 Sep 2023	5.0	5.0	
2	Quality Inspector	Noida	Full Time	Quality Assurance and Testing Department	3 Aug 2023	4.0	4.0	
3	Lead Engineer	Noida	Full Time	Software Development Department	6 Aug 2023	4.0	3.0	
4	Zonal Sales Manager	Chennai	Full Time	Retail & B2C Sales Department	1 Aug 2023	4.0	2.0	

In [122…

```
# Define a function to categorize sentiment based on compound score
def get_sentiment(score):
    return 'positive' if score >= 0.05 else ('negative' if score <= -0.05 else 'neut

df_clean_review['sentiment'] = df_clean_review['compound'].apply(get_sentiment)
df_clean_review.head()
```

Out[122…

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_develo
0	Professional Logistics	Chennai	Full Time	SCM & Logistics Department	5 Sep 2023	3.0	3.0	
1	Supervisor Instructor	Noida	Full Time	Production & Manufacturing Department	1 Sep 2023	5.0	5.0	
2	Quality Inspector	Noida	Full Time	Quality Assurance and Testing Department	3 Aug 2023	4.0	4.0	
3	Lead Engineer	Noida	Full Time	Software Development Department	6 Aug 2023	4.0	3.0	

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_develo
4	Zonal Sales Manager	Chennai	Full Time	Retail & B2C Sales Department	1 Aug 2023	4.0	2.0	

In [10]:
```
df_clean_review["sentiment"].value_counts()
```

Out[10]:
```
positive    749
neutral     369
negative     93
Name: sentiment, dtype: int64
```

In [123…
```
# drop unused columns
df_clean_review.drop(columns = ['Likes', 'Dislikes', 'positive', 'negative', 'neutra
```

In [12]:
```
df_clean_review.select_dtypes(include='object').nunique()
```

Out[12]:
```
Title         612
Place         304
Job_type        4
Department    224
Date          491
review        983
sentiment       3
dtype: int64
```

In [13]:
```
df_clean_review.Job_type.unique()
```

Out[13]:
```
array(['Full Time', 'Contractual', 'Part Time', 'Intern', nan],
      dtype=object)
```

In [14]:
```
df_clean_review[df_clean_review['Job_type'].isnull()].head()
```

Out[14]:

	Title	Place	Job_type	Department	Date	Overall_rating	work_life_balance	skill_de
89	Apprentice Training (working remotely)	NaN	NaN	Operations, Maintenance & Support Department	1 May 2023	5.0	4.0	
129	Area Business Manager	Nagpur, Maharashtra	NaN	BD / Pre Sales Department	4 Nov 2022	4.0	3.0	
139	Production Supervisor	Chennai	NaN	Production Department	2 Mar 2023	5.0	5.0	
157	Production Lead	Chennai, Tamil Nadu	NaN	Operations, Maintenance & Support Department	8 Nov 2022	3.0	3.0	
158	Customer Experience Executive	Gurgaon	NaN	Sales Support & Operations Department	4 Oct 2022	5.0	5.0	

In [124…

```
# # Fill missing values in the 'Job_type' column with the value 'Other'
df_clean_review['Job_type'].fillna('Other', inplace=True)
```

In [16]:

```
df_clean_review.Department.unique()
```

Out[16]:

```
array(['SCM & Logistics Department',
       'Production & Manufacturing Department',
       'Quality Assurance and Testing Department',
       'Software Development Department', 'Retail & B2C Sales Department',
       'Sales Department', 'Enterprise & B2B Sales Department',
       'Service Delivery Department', 'Administration Department',
       'HR Operations Department', 'Marketing Department',
       'Operations, Maintenance & Support Department',
       'Operations Department', 'Engineering Department',
       'Other Department', 'Sales Support & Operations Department',
       'Operations Support Department',
       'After Sales Service & Repair Department',
       'Engineering & Manufacturing Department',
       'Procurement & Purchase Department', 'Telecom Department',
       'Accounting & Taxation Department', 'Customer Success Department',
       'General Insurance Department',
       'Warehouse Manpower supervisor  Department', nan,
       'Back Office Department', 'Quality Department',
       'Corporate Communication Department',
       'Product Management - Technology Department',
       'Employee Relations Department',
       'Stores & Material Management Department', 'Management Department',
       'Strategic Management Department', 'Non Voice Department',
       'Retail Store Operations Department',
       'BFSI, Investments & Trading Department',
       'IT Consulting Department',
       'Customer Success, Service & Operations Department',
       'Other-Project & Program Management Department',
       'Facility Management Department', 'Computer Operating Department',
       'CRM Department', 'BD / Pre Sales Department',
       'Production Department', 'Front Office Department',
       'Store manager and accountant  Department',
       'Top Management Department', 'Digital Marketing Department',
       'Community Health & Safety Department',
       'Customer Service Department', 'Research & Development Department',
       'Admin Department', 'After Sales Department',
       'Business Intelligence & Analytics Department',
       'Paid media campaigns team corporate marketing setup Department',
       'Design Department', 'Supplier Quality Department',
       'Retail Sales Department', 'Sales  Department',
       'Content Management (Print / Online / Electronic) Department',
       'Technology / IT Department', 'Finance Department',
       'SMD Maintenance Department', 'Store Sales Department',
       'Retail sale from stores Department', 'Purchase Department',
       'Quality control production Department', 'Network  Department',
       'eCommerce Operations Department', 'Manufacturing Department',
       'Sales Promotion Department', 'Rso Department',
       'It Infrastructure Department', 'Outsourcing  Department',
       'Administration & Staff Department',
       'Sales & Marketing Department', 'Human Resources Department',
       'RnD Department', 'Banking Operations Department',
       'Electrical Maintenance Department',
       'Pharmaceutical & Biotechnology Department',
       'Out Bound Department', 'CSR & Sustainability Department',
       'Market Research & Insights Department',
       'Voice / Blended Department', 'Corporate Training Department',
       'Production & Quality Department',
       'Construction / Manufacturing Department',
       'Online Marketing Department', 'Warehouse Department',
       'Customer Experience Department', 'Marketing & Sales Department',
       'Logistics Department', 'Consumer Electronics Department',
```

```
'Noida Department', 'HHP material kitting Department',
'Sales & Distribution Department', 'Audit & Control Department',
'Mobile Department', 'SMD Department',
'Corporate Social Responsibility Department',
'New Product Development Department', 'Innovation Department',
'Sales b2b Department', 'Executive Office Department',
'Vd  Department', 'Network Department', 'Operator  Department',
'Hhp Department', 'Maintenance Department',
'IT Infrastructure Services Department', 'SMT Repeyir Department',
'Mechanical Engineering Department', 'Refrigeration Department',
'Construction Engineering Department', 'Quality Check Department',
'Sales and promotion  Department',
'Utility Maintenance Department', 'Selling Department',
'Supervisor Department', 'Anyway Department', 'Mfg Department',
'Outlet Department', 'Jig Maintenance- Technician  Department',
'Quality Assurance Department', 'Product Management Department',
'IT Support Department', 'Production & Maintenance Department',
'Smt Department', 'Samsung experience  Department',
'Store Operations Department',
'Dhanshree mobile pindwara  Department',
'Sale Executive Department', 'Offline kitting Department',
'East Region  Department', 'SOP Department',
'HHP Production Department', 'Main line Department',
'Production Engineering Department', 'Ecommerce Department',
'Mechanical Maintenance Department', 'EHS Department',
'H H P MAIN LINE Department', 'Noida sec 81 Department',
'DBA / Data warehousing Department', 'Import & Export Department',
'HHP Department', 'IT Network Department', 'CE Department',
'Production Control Department', 'Quality Control Department',
'Mobile Application Development Department', 'RF  Department',
'Electronics & Telecommunication Department',
'Mobile Development Department', 'Network Operations Department',
'Infrastructure Management and Utility  Department',
'Mobile plant  Department', 'Service Department',
'networking Department', 'Logistic  Department', 'Hhp  Department',
'Deployment Department', 'OPERATOR  Department',
'DevOps Department', 'Hardware Department',
'Security Officer Department', 'Custo Department',
'Designer Department', 'Manufacturing Engineering Department',
'Maintenance and Automation Department', 'Ce Department',
'Flight & Airport Operations Department', 'Apprentice Department',
'AM Department', 'utility  Department', 'Sale Department',
'Database  Department', 'Telecoms  Department',
'HHP SMD MATERIAL/TECHNICIAN Department', 'SMT Department',
'Sales excutive Department', 'R&D Department',
'Network Development  Department', 'CS Department',
'Area sales manager  Department', 'Branding Department',
'Printing Department', 'Electronic  Department', 'B2B Department',
'Network Businesd Department', 'production Department',
'Quilt visit Department', 'Home Applaince Department',
'Customer Care Department', 'Financial  Department',
'SERVICE Department', 'quality Department', 'It Department',
'Chhattisgarh Department', 'Marketing Operations Department',
'Customer Service  Department', 'Commercial Department',
'Bhubaneswar Department', 'Kitting  Department', 'HA Department',
'Da Department', 'Team Leadership Department',
'HME -CS Department', 'Mobile division Department',
'Utility Department', 'Other Hospital Staff Department',
'Chennai  Department', 'PBA Department', 'Product Department',
'Operation  Department', 'Sales & Marketing  Department',
'warehouse  Department', 'Sub t.r.c Department',
'12500 Department', 'Warehousing Department', 'sales  Department',
'Prodution Department', 'Purchase &PP Department'], dtype=object)
```

In [17]:

```
df_clean_review['Department'].value_counts().head(20)
```

Out[17]:

```
Retail & B2C Sales Department                77
Software Development Department              72
Enterprise & B2B Sales Department            56
```

```
Operations, Maintenance & Support Department    46
BD / Pre Sales Department                       46
Production & Manufacturing Department           27
Marketing Department                            26
Engineering Department                          21
SCM & Logistics Department                      20
Operations Department                           19
Accounting & Taxation Department                19
Quality Assurance and Testing Department        18
Procurement & Purchase Department               18
Sales Support & Operations Department           17
Sales Department                                17
Administration Department                       15
Voice / Blended Department                      14
Technology / IT Department                      14
Engineering & Manufacturing Department          14
Telecom Department                              14
Name: Department, dtype: int64
```

In [125…

```python
# Function to categorize departments into broader segments
def group_department(department):
    if pd.isna(department):
        return 'Other'

    if any(keyword in department for keyword in ['Sales', 'Marketing', 'Retail', 'B2
        return 'Sales and Marketing'
    elif any(keyword in department for keyword in ['Production', 'Manufacturing', 'E
        return 'Production and Manufacturing'
    elif any(keyword in department for keyword in ['Logistics', 'Operations', 'Suppl
        return 'Operation and Logistic'
    elif any(keyword in department for keyword in ['Quality', 'Quality Assurance', '
        return 'Quality Assurance and Testing'
    elif any(keyword in department for keyword in ['Corporate Communication', 'Emplo
        return 'Administration and Support'
    elif any(keyword in department for keyword in ['IT Consulting', 'Technology / IT
        return 'Technology'
    else:
        return 'Other'

# Apply the function to create a new column 'department_segment'
df_clean_review['department_segment'] = df_clean_review['Department'].apply(group_de
```

In [19]:

```python
df_clean_review.Place.unique()
```

Out[19]:

```
array(['Chennai', 'Noida', 'Faridabad, Haryana',
       'Bengaluru/Bangalore, Karnataka', 'Hyderabad/Secunderabad',
       'Guwahati, Assam', 'Gurgaon/Gurugram, Haryana', 'Gurgaon/Gurugram',
       'Mumbai', 'Bangalore Rural, Karnataka', 'Chennai, Tamil Nadu',
       'Patna, Bihar', nan, 'Lucknow, Uttar Pradesh',
       'Tirupati, Andhra Pradesh', 'Varanasi, Uttar Pradesh',
       'Jaipur, Rajasthan', 'Mumbai, Maharashtra',
       'Puranpur, Uttar Pradesh', 'Ludhiana, (Punjab)',
       'Noida, Uttar Pradesh', 'Faridkot, Punjab',
       'Mysuru/Mysore, Karnataka', 'Nizamabad, Telangana',
       'Sriperumbudur, Tamil Nadu', 'Jaipur', 'Jammu, Jammu & Kashmir',
       'Kolkata, West Bengal', 'Bhagalpur, Bihar',
       'Hyderabad/Secunderabad, Telangana', 'Raipur, Chhattisgarh',
       'Bhubaneswar, Odisha', 'Ahmedabad, Gujarat',
       'Kancheepuram, Tamil Nadu', 'Chhutmalpur',
       'Maldah/Malda, West Bengal', 'Bhilwara Rajasthan',
       'Agra, Uttar Pradesh', 'Katwa, West Bengal',
       'Ujjain, Madhya Pradesh', 'Vijayawada, Andhra Pradesh',
       'But I M Working From Non Branch Locations.So Have From Different MDD Point
s',
       'New Delhi, Delhi', 'Sunguvarchathiram', 'Surat, Gujarat',
       'Rudrapur, Uttarakhand', 'Shahdol, Madhya Pradesh',
       'Nagpur, Maharashtra', 'Noida, Uttar Pradesh Sector 85',
```

```
        'Sunguvarchatram,kanchipuram', 'Vizianagaram, Andhra Pradesh',
        'Bhopal, Madhya Pradesh', 'Sunguvarchatram', 'Gaya, Bihar',
        'NARASARAOPET', 'Gurgaon', 'Srikakulam, Andhra Pradesh',
        'Goregaon West', 'Rudrpur Uttarakhand',
        'Allahabad/Prayagraj, Uttar Pradesh', 'Adajan',
        'Ranchi, Jharkhand', 'Gorakhpur, Uttar Pradesh',
        'Multiple Locations', 'Odhav Ahmedabad', 'Kadapa, Andhra Pradesh',
        'Srinagar', 'Warangal', 'Budaun, Uttar Pradesh', 'Sungavactharam',
        'Berhampur, Odisha', 'Begumpet', 'Goregaon',
        'North S K Puri, Boring Road, Near 9 To 9 Supermarket, Patna',
        'Delhi NCR', 'Saharanpur', 'Anand, Gujarat', 'Sriperumbudur',
        'Kolkata', 'Ahmedabad', 'Gurgoan', 'Madurai, Tamil Nadu',
        'Muzaffarpur', 'Pune', 'Trichy', 'Maudaha, Uttar Pradesh',
        'Allahabad/Prayagraj', 'Chandigarh', 'Guwahati', 'Abohar',
        'Bangalore', 'Indore', 'Ballia, Uttar Pradesh', 'Noida Sector 81',
        'Sungavachatram', 'Shamli, Uttar Pradesh', 'Surat', 'Nagpur',
        'Noida Sec 81', 'Kochi/Cochin', 'Goregoan Mumbai', 'New Delhi',
        'Venkatagiri', 'NOIDA', 'Bengaluru/Bangalore',
        'Goregaon, Maharashtra', 'Vashi', 'Sunguvarchathram', 'AHMEDABAD',
        'Noida Sector 135', 'Begumpet, Hyderabad', 'Hyderabad',
        'Sunguvarchatram, Chennai', 'Upleta', 'Sec 126 Noida', 'Lucknow',
        'Kanpur', 'Gautam Buddha Nagar', 'Kolhapur', 'Odisha',
        'Gaya Bihar', 'Jharkhand', 'PUNE HEAD OFFICE', 'Malappuram',
        'RANCHI', 'Kanniyakumari', 'Hubli', 'Andhra Pradesh', 'Patna',
        'Kanchipuram', 'Udaipur', 'Gurugram', 'Madurai',
        'Pune, Maharashtra', 'Wardha', 'Sector 81 Noida', 'Gwalior',
        'Greater Noida', 'Bareilly', 'Badaun', 'Amritsar, Punjab',
        'Jabalpur', 'Mumbai Suburban', 'Indian  Noida',
        'Sunghuvarchathiram', 'Bhubaneswar', 'Noida Uttar Pardesh',
        'Chapra', 'Ranchi', 'Kota', 'Ludhiana', 'Sheohar', 'Kanpur Nagar',
        'Red Building', 'WFH (working remotely)', 'Ghaziabad',
        'Sector 81 ,Noida', 'GGN', 'Puducherry/Pondicherry, Puducherry',
        'Raipur', 'Gorakhpur', 'Udupi', 'GAUTAM BUDDH NAGAR', 'Coimbatore',
        'Varanasi', 'Chenani', 'Bhanvad, Gujarat', 'Mathura', 'Jammu',
        'Sunguvarchatram.', 'Mysuru', 'Tamilnadu', 'Siliguri, Check Post',
        'Kokrajhar', 'Sunguvarchathiram-602106', 'Gaya', 'PUNE OFFICE',
        'Kalyan/Dombivli', 'Jaunpur Up', 'Sunguvarchattram', 'Bengaluru',
        'Nashik', 'Sungava Saththiram', 'Bhopal', 'Bikaner', 'Davanagere',
        'Kerala', 'Bilaspur Chhattisgarh', 'Vadodara', 'Barola', 'Pali',
        'Dhaka ,Bangladesh', 'Pindwara', 'JABALPUR', 'Navi Mumbai',
        'Tirupur', 'Patnagarh', 'Nagaur', 'HYDERABAD',
        'Sector 81 Phase 2 Noida', 'India', 'Sangola', 'Sambalpur',
        'Main Line', 'Bhopalpattnam', 'Saharsa', 'Gauhati', 'Agra',
        'Buxar, Bihar And Varanasi UP', 'Amritsar', 'Jodhpur',
        'Sangli Miraj Kupwad', 'Patna Bihar', 'Shinde Ki Chawani Gwalior',
        'Noida, UP', 'Sarita Vihar New Delhi', 'Kota Rajasthan', 'Asansol',
        'Assam', 'Bangalore Rural', 'Agartala, Tripura', 'Patan', 'Shimla',
        'Noida UP', 'VIJAYAWADA', 'Bagalkot', 'Gurgram Haryana', 'Delhi',
        'Noida Sector-81', 'Hazaribagh', 'Jalandhar', 'Guntur',
        'Sriperumbuthur Chennai',
        'A-25, 26, 27, Pacific Business Park, (Ground Floor) 37/1 Sahibabad Industria
l Area, (Site IV) Ghazia',
        'Jhargram', 'Banglore', 'Jalgaon,nandurbar', 'Vizag',
        'Jalpaiguri, West Bengal', 'Bathinda', 'Karnal', 'SOUTH DELHI',
        'Goa', 'THOOTHUKUDI', 'Vijayawada', 'Hazaribag',
        'Chiplun Maharashtra', 'Mirzapur', 'Dehradun', 'Tiruvuru',
        'Sipcart', 'Mohali', 'Okhla', 'Sumerpur', 'Visakhapatnam',
        'Ananthapur', 'Kochi', 'Jalgaon', 'West Zone', 'Forbesganj',
        'Aurangabad', 'Meeeut', 'Jammu & Kashmir', 'Pondicherry', 'Meerut',
        'Silchar', 'Siliguri', 'Salem', 'HUBLI', 'Suray',
        'Jabalpur Madhya Pradesh', 'Calicut', 'Amravati', 'Ballia',
        'Nabarangapur', 'Hubli-Dharwad', 'Noida Sector 82', 'Shikohabad',
        'Ggn', 'Bhilai Nagar', 'Hyderabad, Kompally', 'Ballari, Karnataka',
        'Thane', 'Anand.', 'Chandrapur', 'Tirunelveli', 'Mumbai / Thane',
        'Godrej Water Side Sector-IV Kolkata', 'Punjab', 'Sriprempudur',
        'DIBRUGARH', 'I Was In Gurgaon', 'Delhi Noida', 'KANCHIPURAM',
        'Ernakulam', 'Kathmandu', 'Cuttack', 'Phase 2 Sec 48',
        'Sunguvasathiram , Chennai', 'Dehtadun', 'Behala',
```

```
       'Patnagarh, Odisha', 'Gurgaon And Bangalore', 'Begumpet Hyderabad',
       'Gurg'], dtype=object)
```

In [126…

```
# Function to categorize places into broader segments
def group_place(place):
    if pd.isna(place):
        return 'Other'

    if any(keyword in place for keyword in ['Jammu & Kashmir', 'Haryana', 'Himachal
        return 'Northern Zone'
    elif any(keyword in place for keyword in ['Uttar Pradesh', 'Chhattisgarh', 'Utta
        return 'Central Zone'
    elif any(keyword in place for keyword in ['Bihar', 'Jharkhand', 'Odhisa', 'Sikki
        return 'Eastern Zone'
    elif any(keyword in place for keyword in ['Goa', 'Gujarat', 'Maharashtra', 'Dama
        return 'Western Zone'
    elif any(keyword in place for keyword in ['Telangana', 'Hyderabad', 'Amaravati',
        return 'Southern Zone'
    else:
        return 'Other'

df_clean_review['place_segment'] = df_clean_review['Place'].apply(group_place)
```

In [21]:

```
df_clean_review['Place'].value_counts().head(20)
```

Out[21]:

```
Noida                          194
Chennai                         86
Gurgaon                         39
Gurgaon/Gurugram                38
Mumbai                          36
Noida, Uttar Pradesh            29
Kolkata                         23
Patna                           18
Delhi NCR                       17
Greater Noida                   17
Gurgaon/Gurugram, Haryana       16
Bangalore                       13
Pune                            12
Jaipur                          11
Lucknow                         11
Indore                          11
Chennai, Tamil Nadu             11
Raipur                          10
Ahmedabad                       10
Bhubaneswar                      9
Name: Place, dtype: int64
```

In [127…

```
df_clean_review.drop(columns = ['Title', 'Place', 'Department', 'Date', 'review'], i
df_clean_review.head()
```

Out[127…

	Job_type	Overall_rating	work_life_balance	skill_development	salary_and_benefits	job_security	ca
0	Full Time	3.0	3.0	1.0	3.0	3.0	
1	Full Time	5.0	5.0	5.0	5.0	5.0	
2	Full Time	4.0	4.0	4.0	4.0	4.0	
3	Full Time	4.0	3.0	4.0	5.0	5.0	
4	Full Time	4.0	2.0	3.0	3.0	3.0	

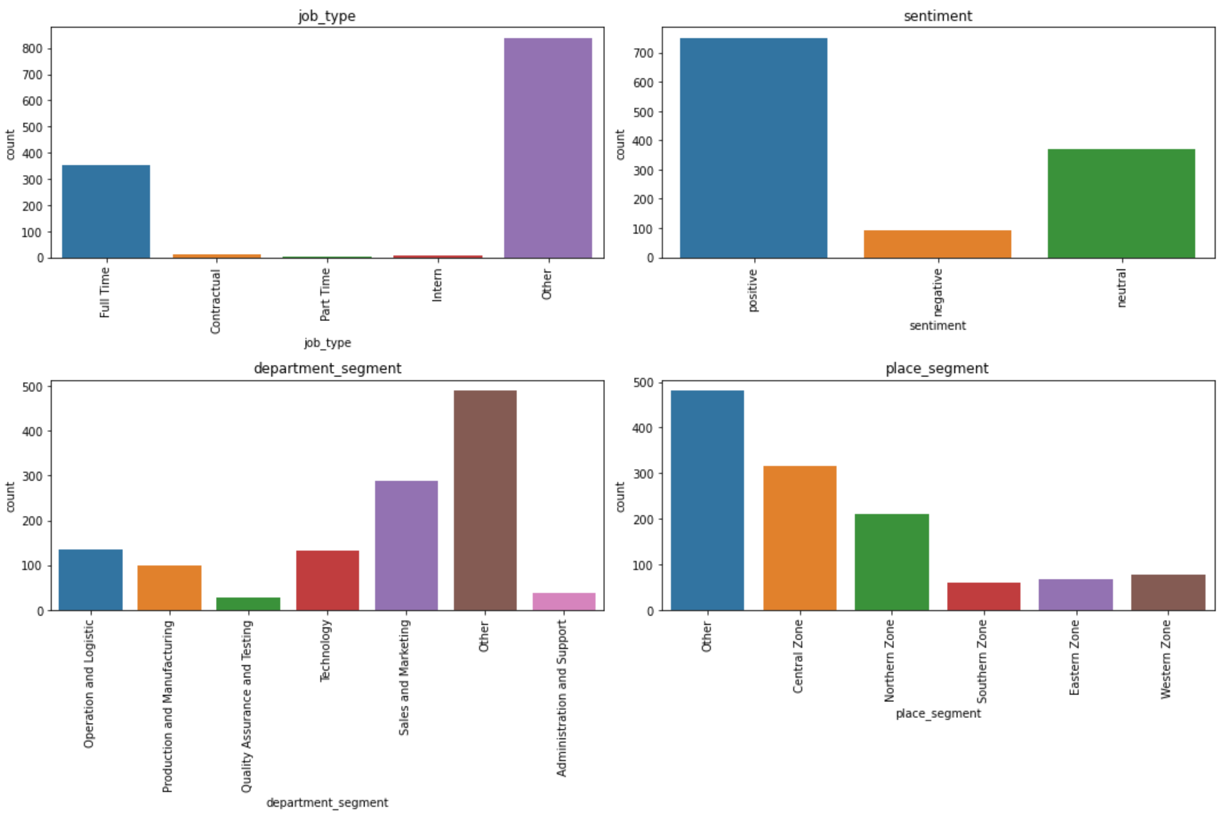
In [128...

```
df_clean_review.rename(columns = {'Job_type':'job_type'}, inplace=True)
```

Exploratory Data Analysis

In [129...

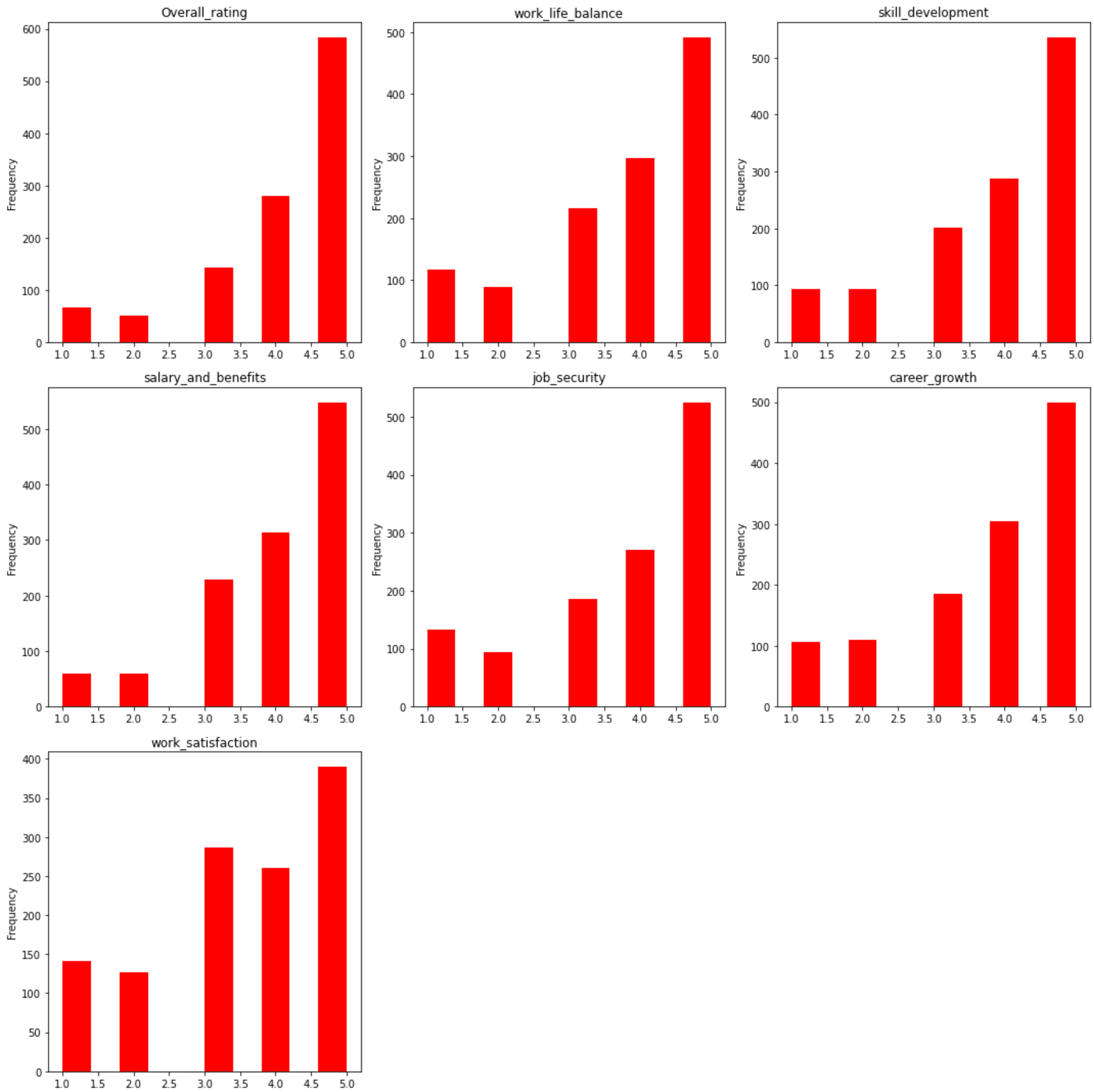
```
# Get categorical variables
cat_vars = df_clean_review.select_dtypes(include='object').columns.tolist()

# Determine subplot layout
num_cols = len(cat_vars)
num_rows = (num_cols + 1) // 2

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=2, figsize=(15, 5*num_rows))

# Plot count for each categorical variable
for i, var in enumerate(cat_vars):
    top_values = df_clean_review[var].value_counts().index
    filtered_df = df_clean_review[df_clean_review[var].isin(top_values)]

    # Plot count using seaborn
    sns.countplot(x=var, data=filtered_df, ax=axs[i // 2, i % 2])

    axs[i // 2, i % 2].set_title(var)
    axs[i // 2, i % 2].set_xticklabels(axs[i // 2, i % 2].get_xticklabels(), rotatio

# Adjust layout
fig.tight_layout()

# Display the plot
plt.show()
```



In [134...

```
# Get numerical variables
num_vars = df_clean_review.select_dtypes(include=['int', 'float']).columns.tolist()

# Determine subplot layout
num_cols = len(num_vars)
```

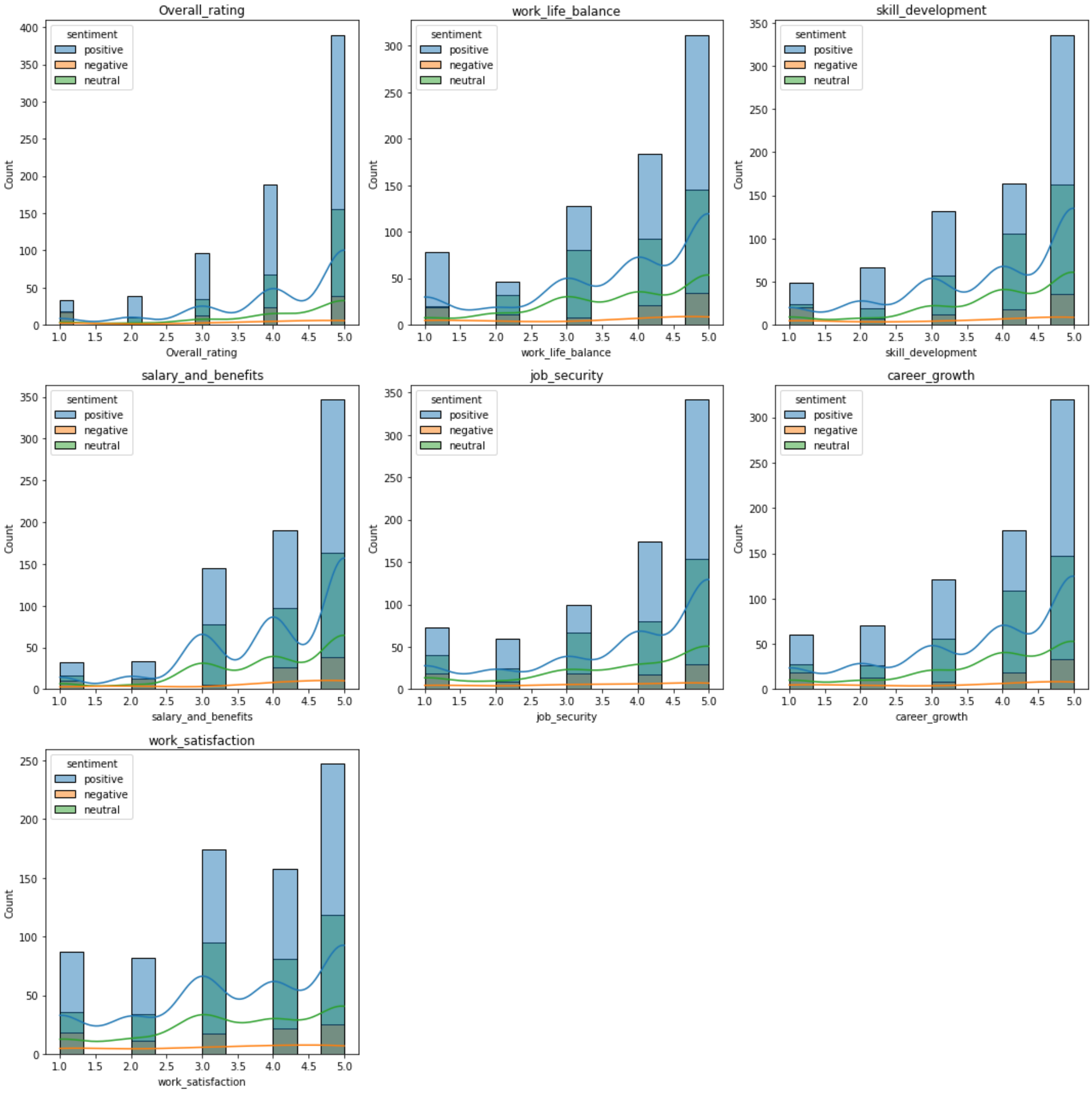
```
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot histogram for each numerical variable
for i, var in enumerate(num_vars):
    df_clean_review[var].plot.hist(ax=axs[i], color='red')
    axs[i].set_title(var)

if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Display the plot
plt.show()
```



In [26]:

```
# Get numerical variable
num_vars = df_clean_review.select_dtypes(include=['int', 'float']).columns.tolist()

# Determine subplot layout
```

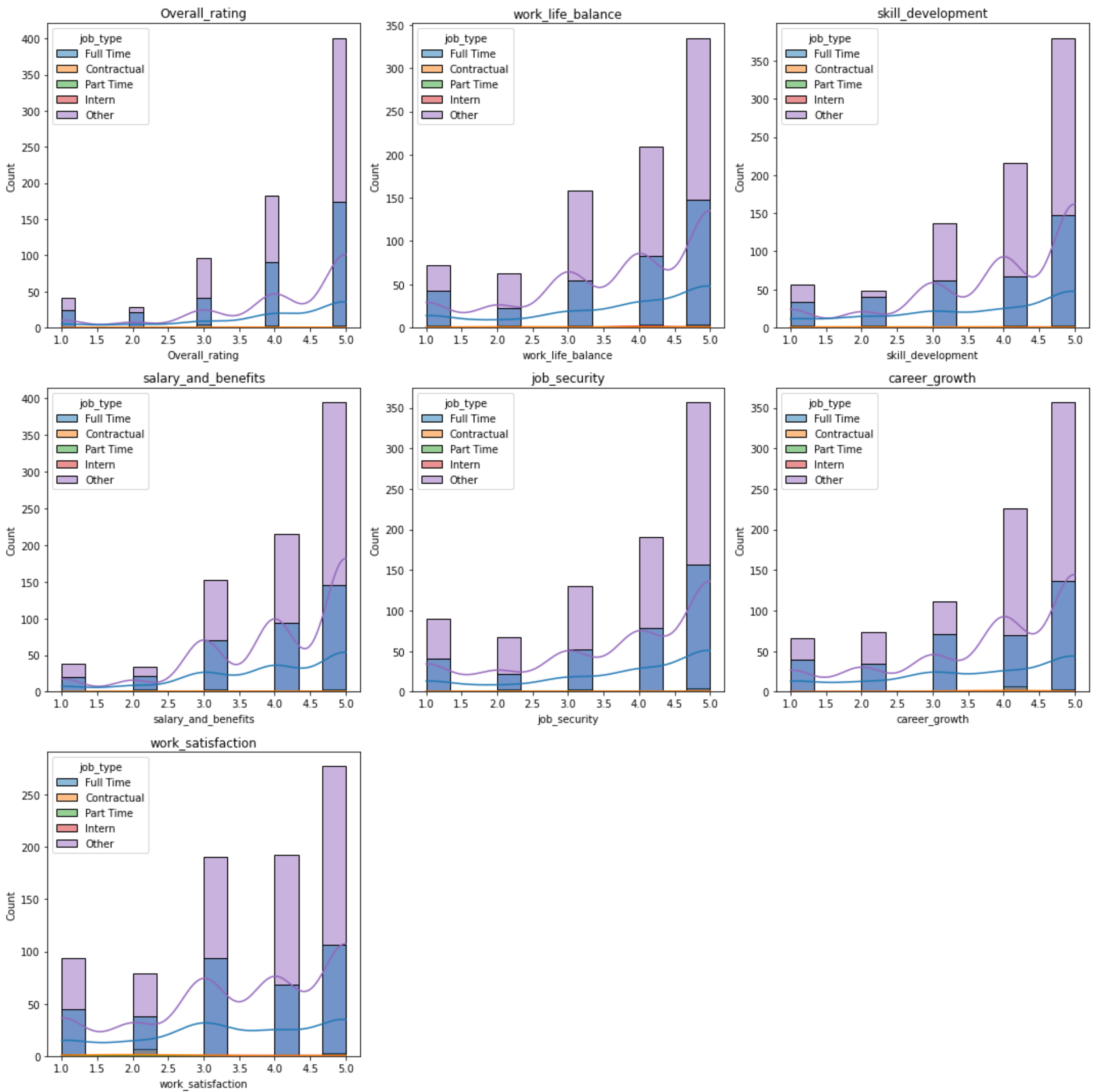
```python
num_cols = len(num_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot histogram for each numerical variable with sentiment color-coding
for i, var in enumerate(num_vars):
    sns.histplot(data=df_clean_review, x=var, hue='sentiment', kde=True, ax=axs[i])
    axs[i].set_title(var)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



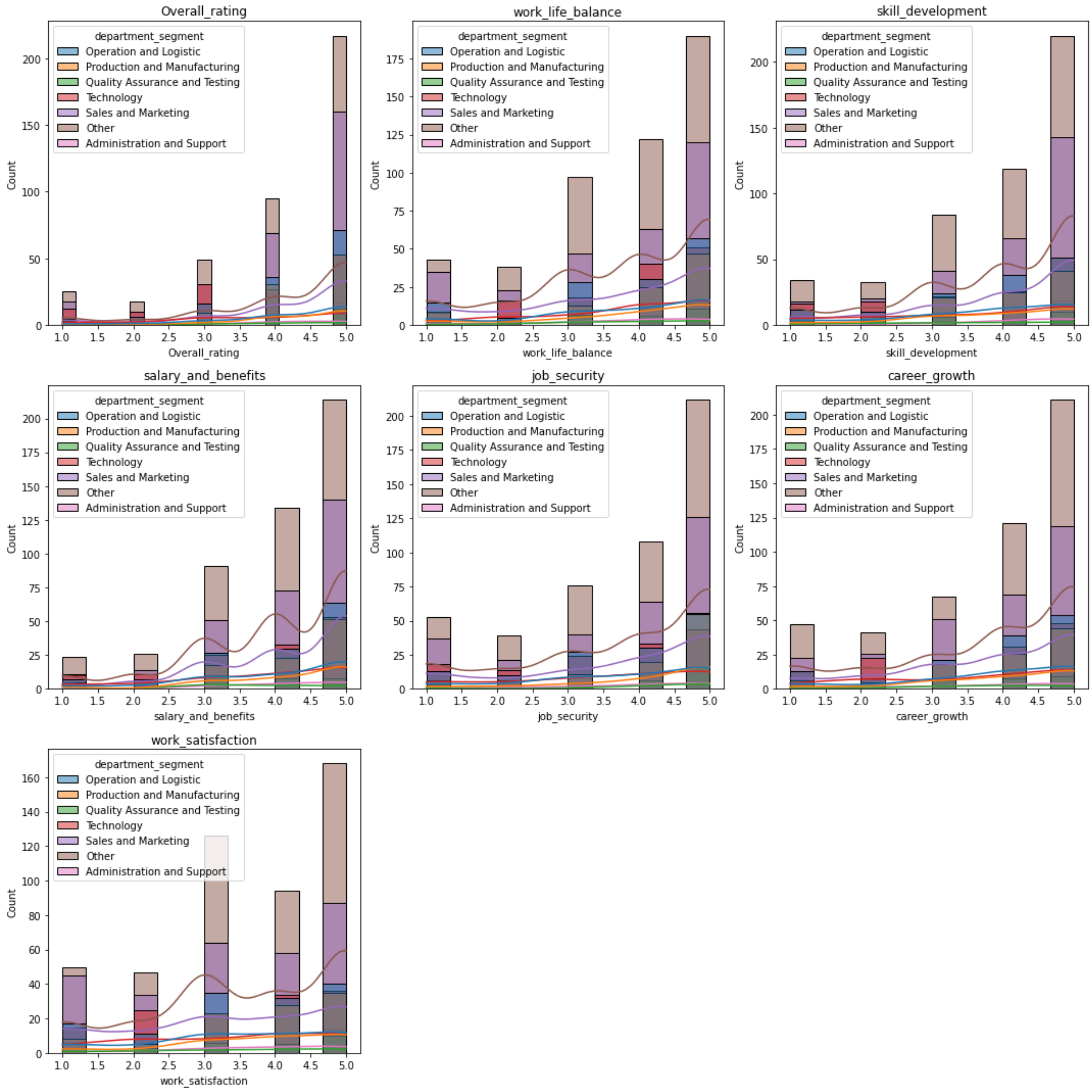
In [27]:

```python
# Get numerical variables
num_vars = df_clean_review.select_dtypes(include=['int', 'float']).columns.tolist()
```

```python
# Determine subplot layout
num_cols = len(num_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot histogram for each numerical variable with job_type color-coding
for i, var in enumerate(num_vars):
    sns.histplot(data=df_clean_review, x=var, hue='job_type', kde=True, ax=axs[i])
    axs[i].set_title(var)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



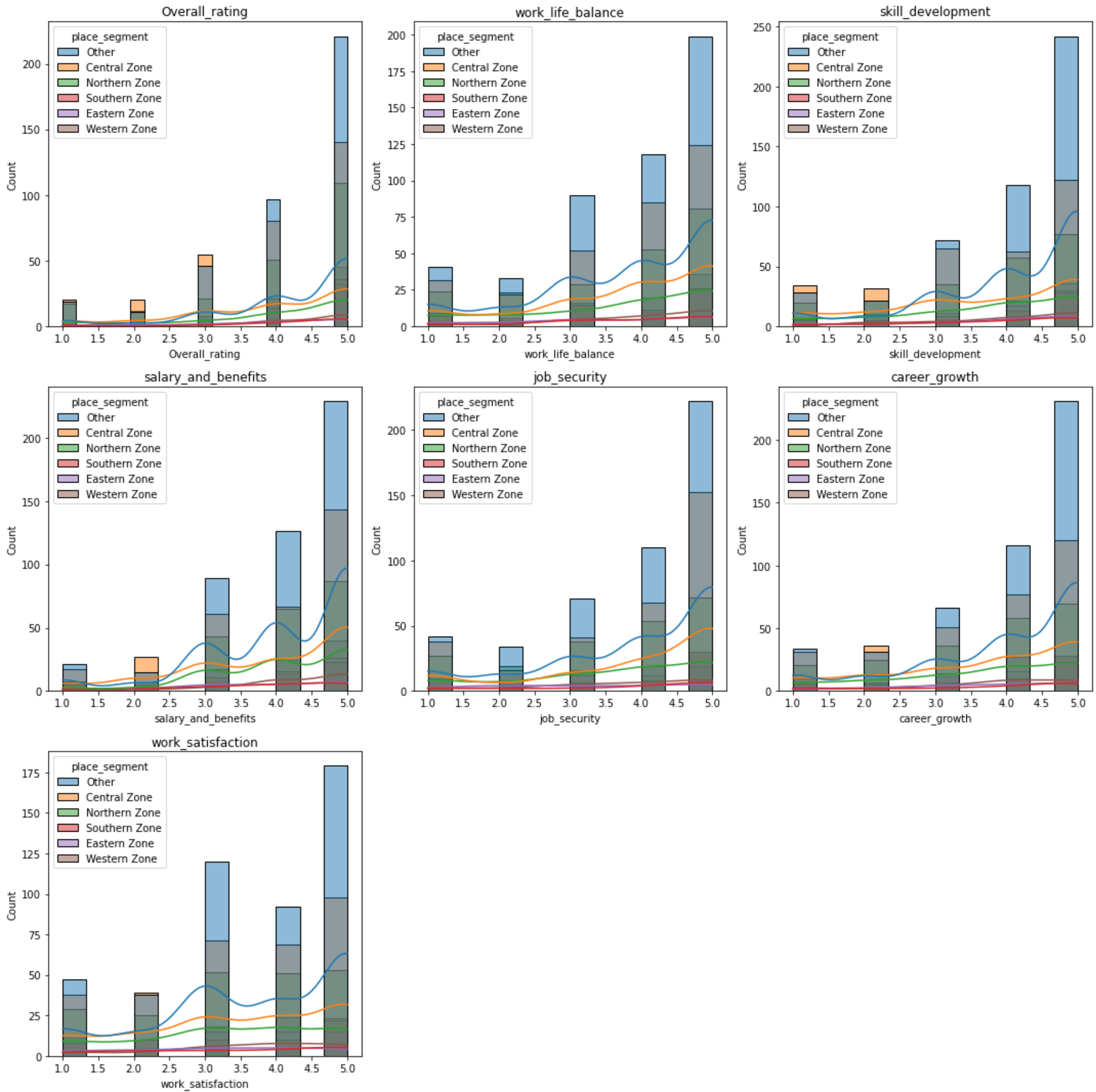
In [28]:
```
# Get numerical variables
num_vars = df_clean_review.select_dtypes(include=['int', 'float']).columns.tolist()

# Determine subplot layout
num_cols = len(num_vars)
num_rows = (num_cols + 2) // 3

# Cretae subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot histogram for each numerical variable with department_segment color-coding
for i, var in enumerate(num_vars):
    sns.histplot(data=df_clean_review, x=var, hue='department_segment', kde=True, ax
    axs[i].set_title(var)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



In [29]:

```
# Get numerical variables
num_vars = df_clean_review.select_dtypes(include=['int', 'float']).columns.tolist()

# Determine subplot layout
num_cols = len(num_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot histogram for each numerical variable with place_segment color-coding
for i, var in enumerate(num_vars):
    sns.histplot(data=df_clean_review, x=var, hue='place_segment', kde=True, ax=axs[
    axs[i].set_title(var)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()
```

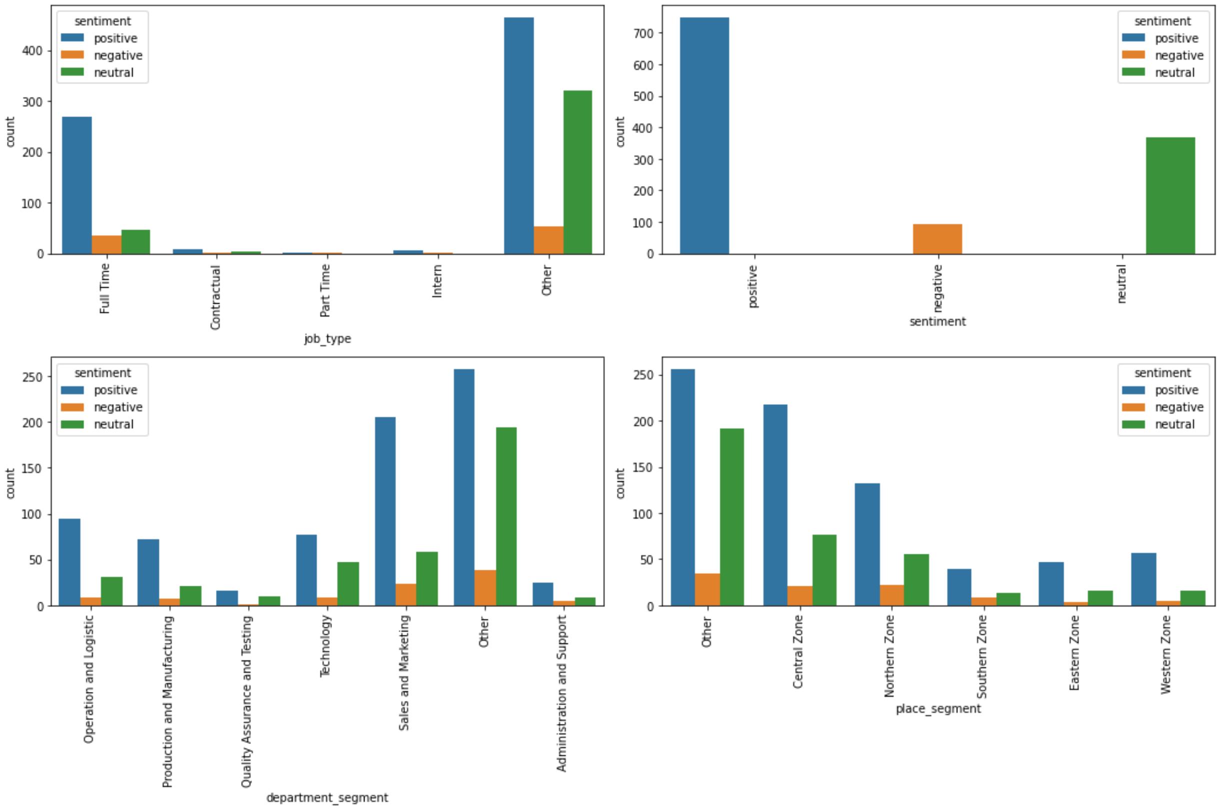
```
# Show the plot
plt.show()
```



In [30]:

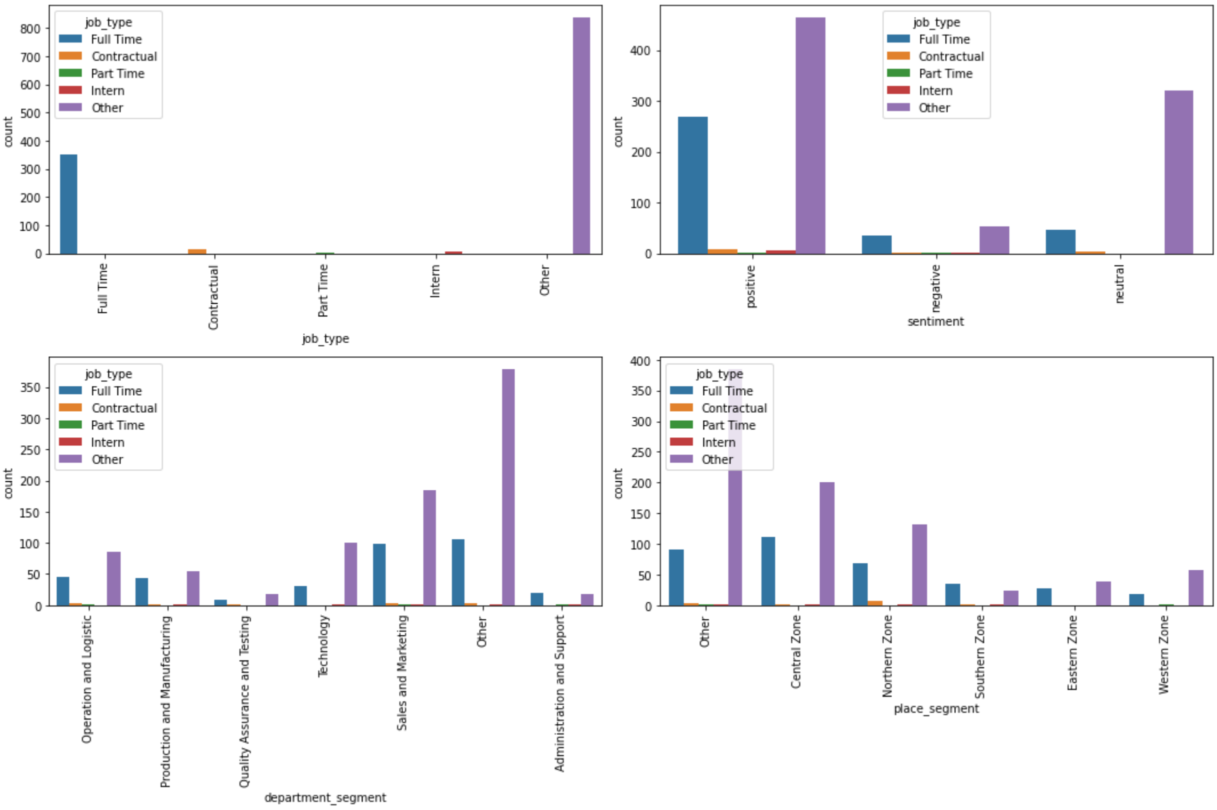
```
# Get categorical variables
cat_vars = df_clean_review.select_dtypes(include=['object']).columns.tolist()

# Determine subplot layout
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=2, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot countplot for each categorical variable with sentiment color-coding
for i, var in enumerate(cat_vars):
    # Exclude rows with NaN values in the variable
    filtered_df = df_clean_review[df_clean_review[var].notnull()]

    sns.countplot(x=var, hue='sentiment', data=filtered_df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# Remove any remaining blank subplots
for i in range(num_cols, len(axs)):
    fig.delaxes(axs[i])
```

```
# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



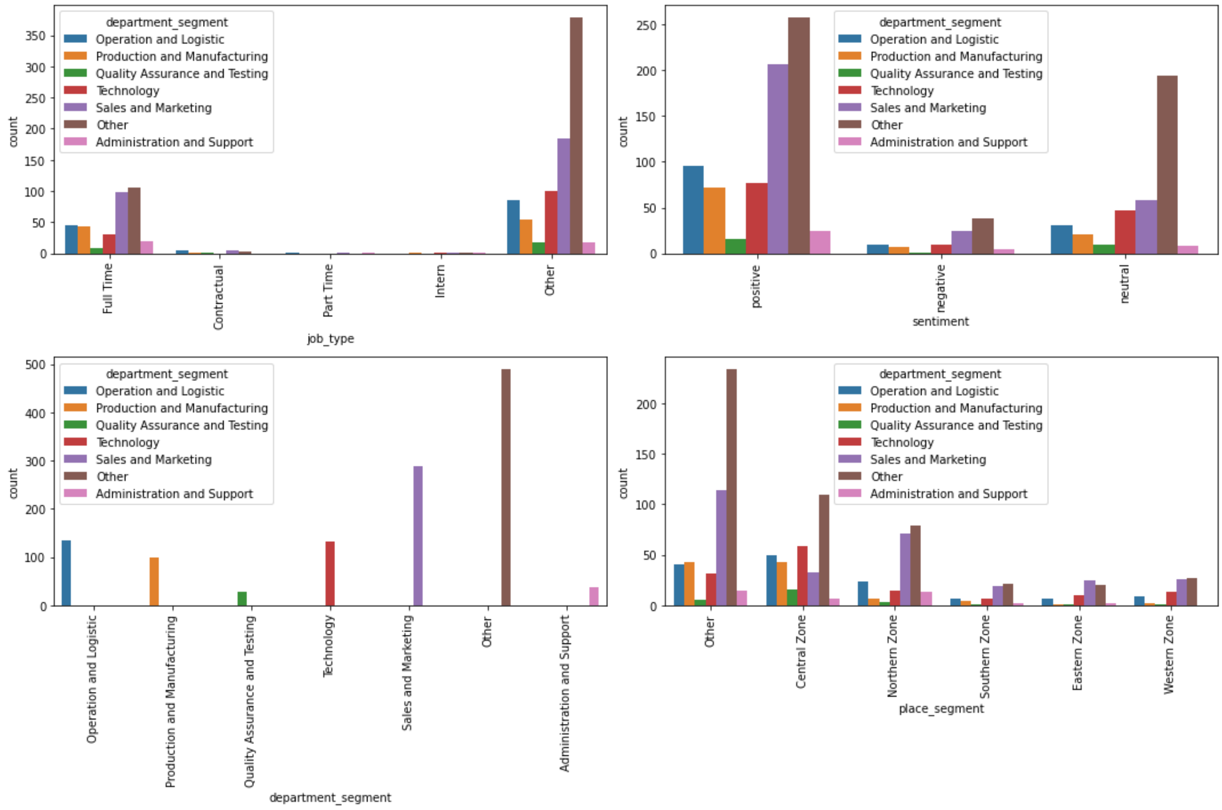
In [31]:

```
# Get categorical variables
cat_vars = df_clean_review.select_dtypes(include=['object']).columns.tolist()

# Determine subplot layout
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=2, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot countplot for each categorical variable with sentiment color-coding
for i, var in enumerate(cat_vars):
    # Exclude rows with NaN values in the variable
    filtered_df = df_clean_review[df_clean_review[var].notnull()]

    sns.countplot(x=var, hue='job_type', data=filtered_df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# Remove any remaining blank subplots
for i in range(num_cols, len(axs)):
    fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



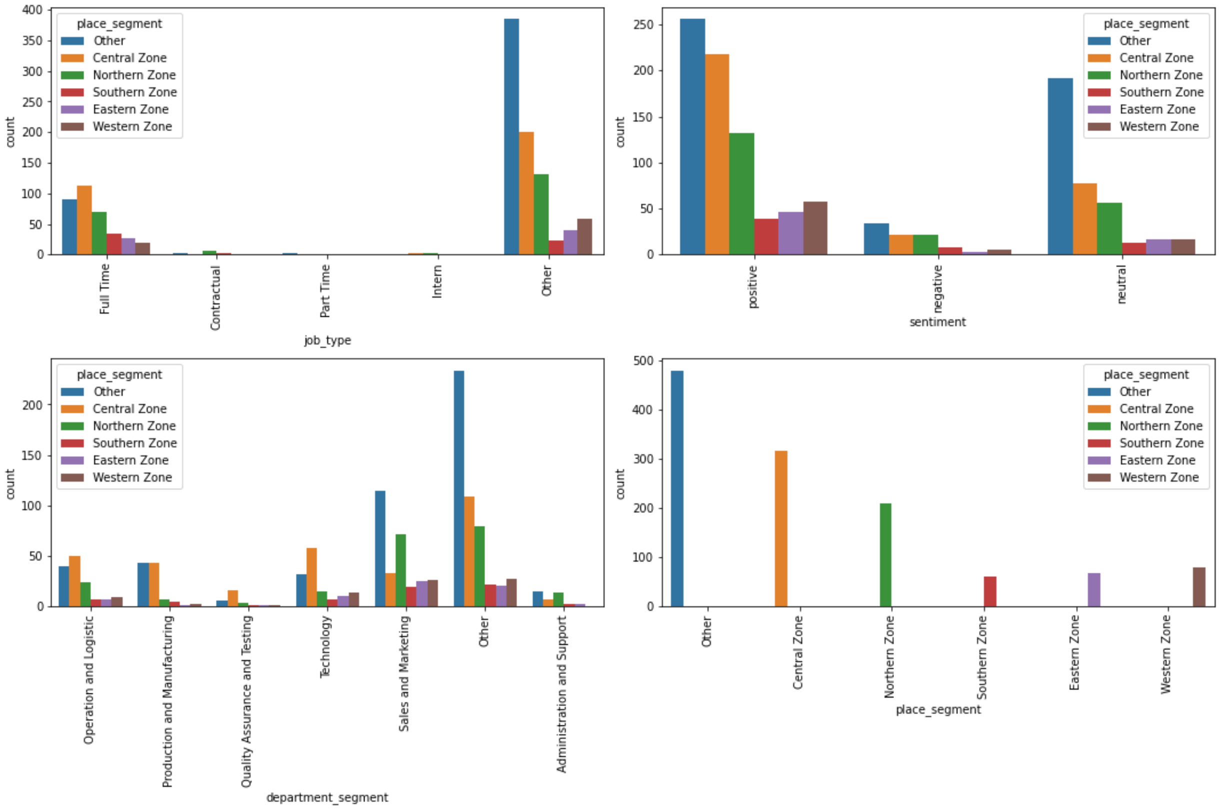
In [32]:

```
# Get categorical variables
cat_vars = df_clean_review.select_dtypes(include=['object']).columns.tolist()

# Determine subplot layout
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=2, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot countplot for each categorical variable with sentiment color-coding
for i, var in enumerate(cat_vars):
    # Exclude rows with NaN values in the variable
    filtered_df = df_clean_review[df_clean_review[var].notnull()]

    sns.countplot(x=var, hue='department_segment', data=filtered_df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# Remove any remaining blank subplots
for i in range(num_cols, len(axs)):
    fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



In [33]:

```python
# Get categorical variables
cat_vars = df_clean_review.select_dtypes(include=['object']).columns.tolist()

# Determine subplot layout
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3

# Create subplot
fig, axs = plt.subplots(nrows=num_rows, ncols=2, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Plot countplot for each categorical variable with sentiment color-coding
for i, var in enumerate(cat_vars):
    # Exclude rows with NaN values in the variable
    filtered_df = df_clean_review[df_clean_review[var].notnull()]

    sns.countplot(x=var, hue='place_segment', data=filtered_df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# Remove any remaining blank subplots
for i in range(num_cols, len(axs)):
    fig.delaxes(axs[i])

# Adjust layout
fig.tight_layout()

# Show the plot
plt.show()
```



Based on exploratory data analysis above it reveals that the majority of object-type categorical attributes have the largest values labeled as 'Other.' Specifically, in the job_type attribute, 'Full Time' dominates as the second-largest value, while 'Part Time' is the smallest. A similar pattern occurs in the department_segment attribute, where 'Sales and Marketing' holds the second-largest value, and in the place_segment attribute, 'Central Zone' ranks second.

Future strategies could involve further exploration of the 'Other' category to understand its composition better. If feasible, considering the consolidation of several categories into larger groups may enhance interpretation. Additionally, focusing on increasing variation in minor values such as 'Part Time' and 'Southern Zone' might provide further insights into trends and patterns within the dataset.

For the sentiment attribute, a deeper understanding of factors influencing negative sentiment could be a focus. Delving into the analysis of this category can help identify specific aspects that may need improvement. Therefore, further actions can be taken to enhance employee experience and workplace atmosphere.

Data Preprocessing

In [34]:
```
df_clean_review.head()
```

Out[34]:

	job_type	Overall_rating	work_life_balance	skill_development	salary_and_benefits	job_security	ca
0	Full Time	3.0	3.0	1.0	3.0	3.0	
1	Full Time	5.0	5.0	5.0	5.0	5.0	
2	Full Time	4.0	4.0	4.0	4.0	4.0	
3	Full Time	4.0	3.0	4.0	5.0	5.0	

	job_type	Overall_rating	work_life_balance	skill_development	salary_and_benefits	job_security	ca
4	Full Time	4.0	2.0	3.0	3.0	3.0	

In [35]:
```
# Calculate and display the percentage of missing values for each column
missing_percentages = (df_clean_review.isnull().mean() * 100).sort_values(ascending=
missing_values = missing_percentages[missing_percentages > 0]
print(missing_values)
```

```
Overall_rating          7.266722
work_satisfaction       0.495458
career_growth           0.330306
job_security            0.247729
salary_and_benefits     0.165153
skill_development       0.082576
work_life_balance       0.082576
dtype: float64
```

Feature Engineering: Label Encoding for Object datatypes

In [36]:
```
for col in df_clean_review.select_dtypes(include='object').columns:
    unique_values = df_clean_review[col].unique()
    print(f"{col}: {unique_values}")
```

```
job_type: ['Full Time' 'Contractual' 'Part Time' 'Intern' 'Other']
sentiment: ['positive' 'negative' 'neutral']
department_segment: ['Operation and Logistic' 'Production and Manufacturing'
 'Quality Assurance and Testing' 'Technology' 'Sales and Marketing'
 'Other' 'Administration and Support']
place_segment: ['Other' 'Central Zone' 'Northern Zone' 'Southern Zone' 'Eastern Zon
e'
 'Western Zone']
```

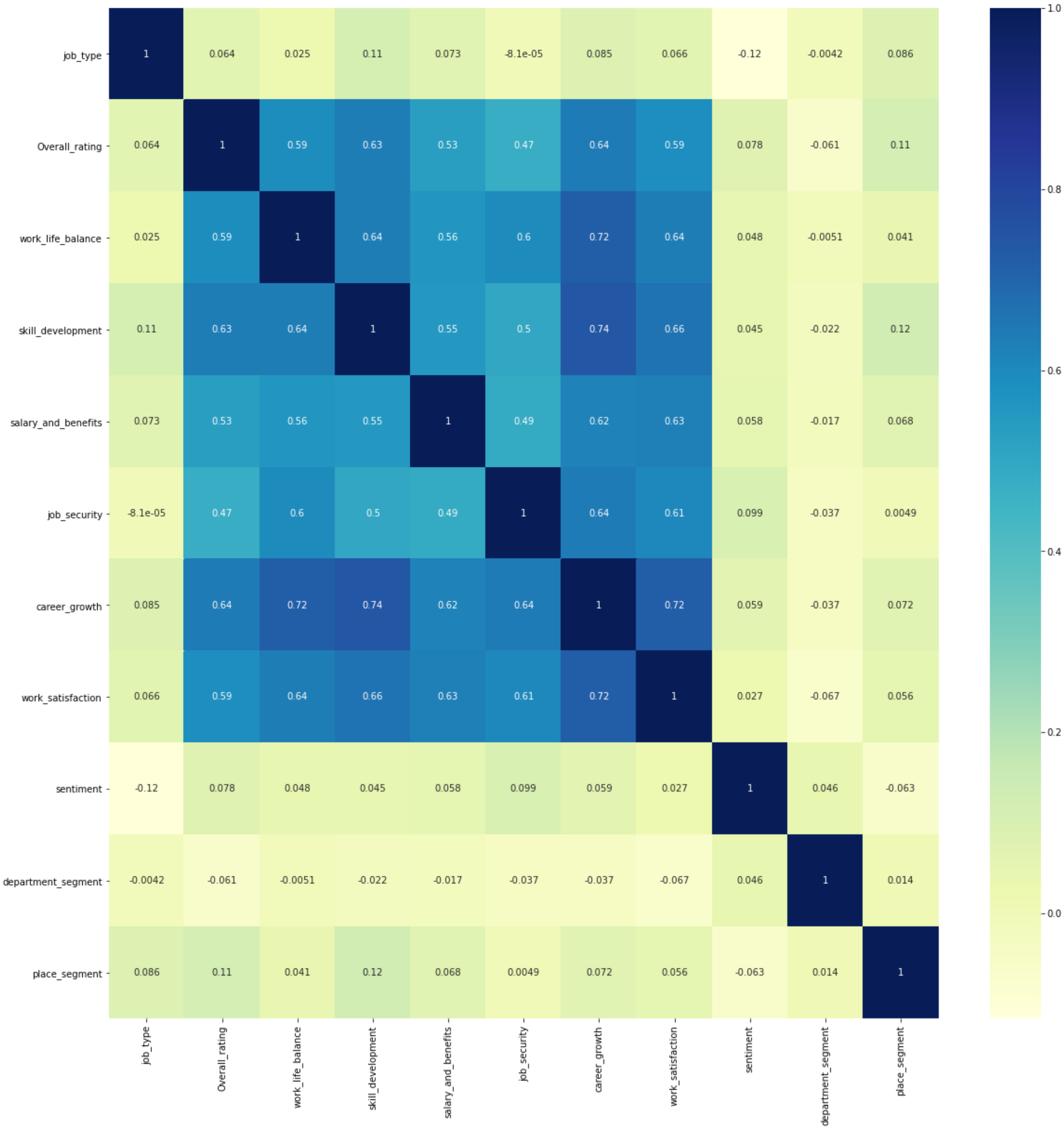
In [37]:
```
label_encoder = LabelEncoder()

# Loop over each column in the DataFrame where dtype is 'object'
for col in df_clean_review.select_dtypes(include=['object']).columns:

    # Use LabelEncoder directly with apply
    df_clean_review[col] = label_encoder.fit_transform(df_clean_review[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df_clean_review[col].unique()}")
```

```
job_type: [1 0 4 2 3]
sentiment: [2 0 1]
department_segment: [1 3 4 6 5 2 0]
place_segment: [3 0 2 4 1 5]
```

Feature Selection: Correlation Matrix with Heatmap

In [39]:
```
plt.figure(figsize=(20, 20))
sns.heatmap(df_clean_review.corr(), cmap="YlGnBu", fmt='.2g', annot=True)
```

Out[39]: <AxesSubplot:>



In [40]:
```python
df_clean_review.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1211 entries, 0 to 1210
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   job_type             1211 non-null   int32  
 1   Overall_rating       1123 non-null   float64
 2   work_life_balance    1210 non-null   float64
 3   skill_development    1210 non-null   float64
 4   salary_and_benefits  1209 non-null   float64
 5   job_security         1208 non-null   float64
 6   career_growth        1207 non-null   float64
 7   work_satisfaction    1205 non-null   float64
 8   sentiment            1211 non-null   int32  
 9   department_segment   1211 non-null   int32  
 10  place_segment        1211 non-null   int32  
dtypes: float64(7), int32(4)
memory usage: 85.3 KB
```

In [41]:
```python
# Handling Missing Values:
# Fill missing values in specific columns with the mean of each column
columns_null = ['Overall_rating', 'work_life_balance', 'skill_development', 'salary_
```

```
for col in columns_null:
    df_clean_review[col].fillna(df_clean_review[col].mean(), inplace=True)
```

In [42]:
```
df_clean_review.head()
```

Out[42]:

	job_type	Overall_rating	work_life_balance	skill_development	salary_and_benefits	job_security	ca
0	1	3.0	3.0	1.0	3.0	3.0	
1	1	5.0	5.0	5.0	5.0	5.0	
2	1	4.0	4.0	4.0	4.0	4.0	
3	1	4.0	3.0	4.0	5.0	5.0	
4	1	4.0	2.0	3.0	3.0	3.0	

In [43]:
```
# Splitting the dataset
x = df_clean_review.drop(columns = ['sentiment', 'Overall_rating'], axis=1)
y = df_clean_review['sentiment']
```

In [44]:
```
# Convert to numpy arrays
x = x.values
y = y.values
```

In [45]:
```
# Shuffle the data to ensure the overall distribution of the data
# before split into train dan test data
z = list(zip(x, y))
random.shuffle(z)
x, y = zip(*z)
x, y = np.array(x), np.array(y)
```

In [46]:
```
# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.3, random_state
```

Imbalanced Data Solutions: SMOTE

In [47]:
```
from imblearn.over_sampling import SMOTE

# Display class distribution before SMOTE
print("Before OverSampling, counts of label '2': {}".format(sum(y_train == 2)))
print("Before OverSampling, counts of label '1': {}".format(sum(y_train == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(y_train == 0)))

# Apply SMOTE to balance the class distribution
sm = SMOTE()
x_train_smote, y_train_smote = sm.fit_resample(x_train, y_train.ravel())

# Display class distribution after SMOTE
print('After OverSampling, the shape of train_X: {}'.format(x_train_smote.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_smote.shape))

print("After OverSampling, counts of label '2': {}".format(sum(y_train_smote == 2)))
print("After OverSampling, counts of label '1': {}".format(sum(y_train_smote == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_smote == 0)))
```

```
Before OverSampling, counts of label '2': 523
Before OverSampling, counts of label '1': 252
Before OverSampling, counts of label '0': 72

After OverSampling, the shape of train_X: (1569, 9)
```

```
After OverSampling, the shape of train_y: (1569,)

After OverSampling, counts of label '2': 523
After OverSampling, counts of label '1': 523
After OverSampling, counts of label '0': 523
```

Training and Testing Model Machine Learning

Decision Tree Classifier

In [48]:

```
# Creating a Decision Tree Classifier
dt_classifier = DecisionTreeClassifier()

# Defining the parameter grid for hyperparameter tuning
param_grid = {
    'max_depth': [None, 1, 2, 3, 4, 5, 6, 7, 8],
    'min_samples_split': [None, 1, 2, 3, 4, 5],
    'min_samples_leaf': [None, 1, 2, 3, 4],
    'random_state': [0, 42]
}

# Performing Grid Search with cross-validation
grid_search = GridSearchCV(dt_classifier, param_grid, cv=5)
grid_search.fit(x_train_smote, y_train_smote)
print(grid_search.best_params_)
```

```
{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'random_state':
0}
```

In [113…

```
# Creating a Decision Tree Classifier with the best hyperparameters
dt_classifier = DecisionTreeClassifier(max_depth=None, min_samples_leaf=1, min_sampl

# Fitting the model on the SMOTE-resampled training data
dt_classifier.fit(x_train_smote, y_train_smote)

# Making predictions on the data test
y_pred = dt_classifier.predict(x_test)

# Displaying the classification report
print('Classification report: \n', classification_report(y_test, y_pred))
```

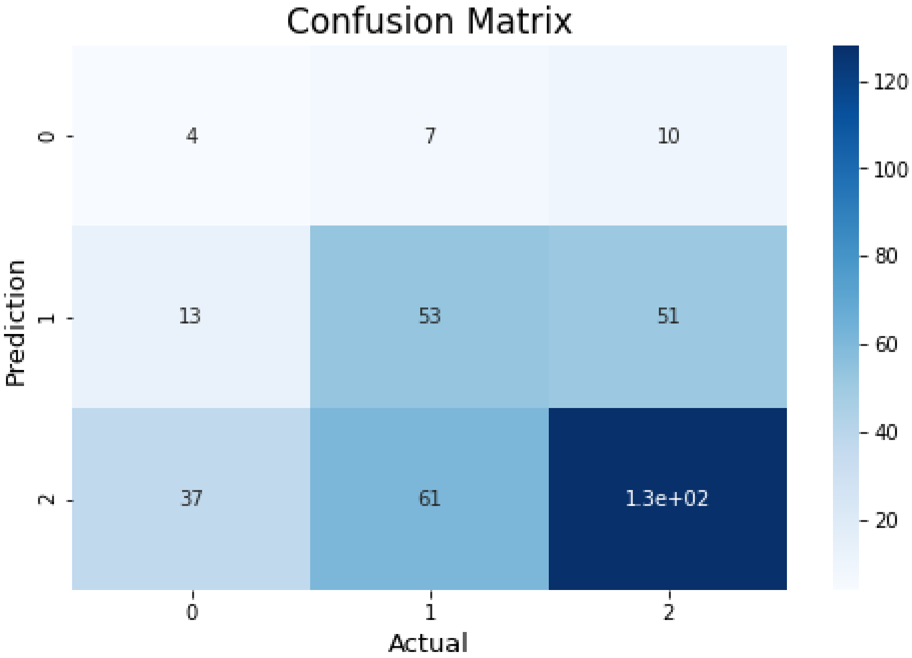
```
Classification report:
              precision    recall  f1-score   support

           0       0.07      0.19      0.11        21
           1       0.44      0.45      0.45       117
           2       0.68      0.57      0.62       226

    accuracy                           0.51       364
   macro avg       0.40      0.40      0.39       364
weighted avg       0.57      0.51      0.53       364
```

In [114…

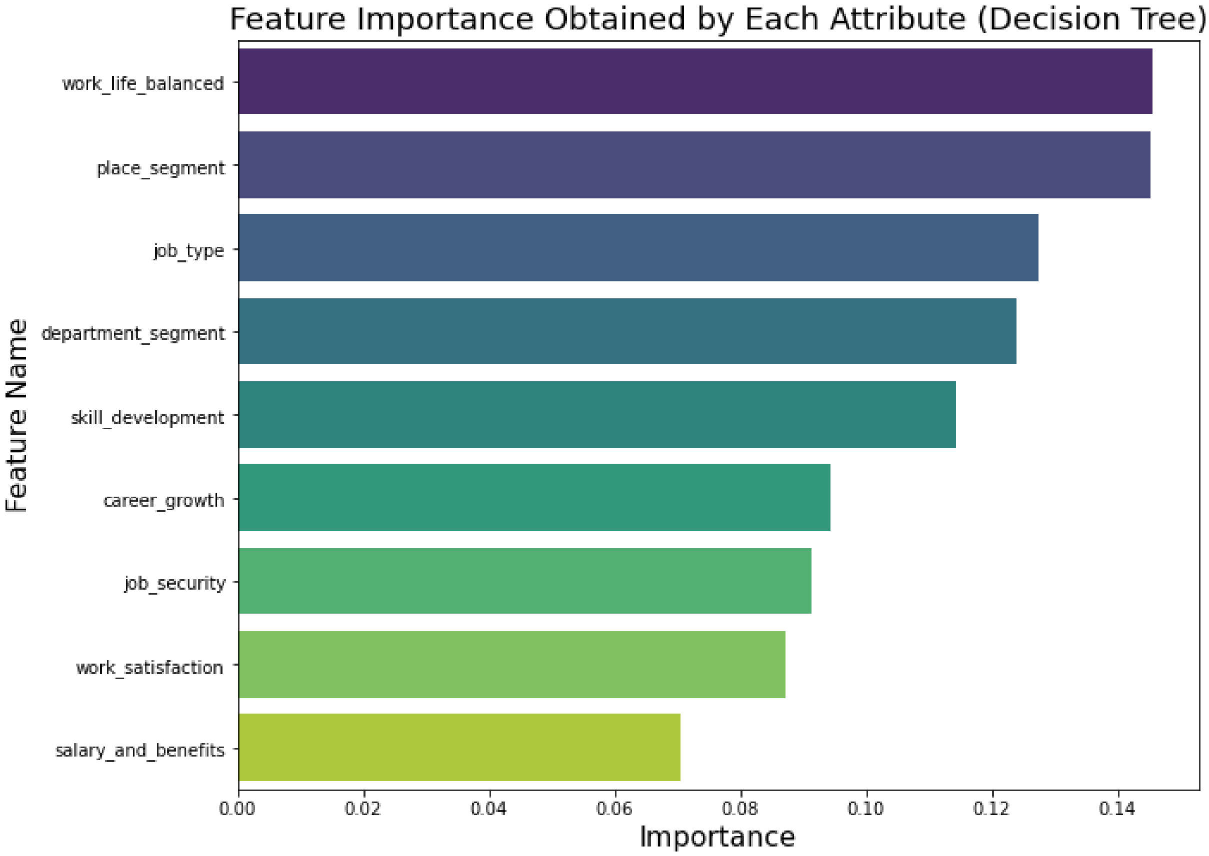
```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,5))
sns.heatmap(cm, annot=True, cmap='Blues')
plt.ylabel('Prediction', fontsize=13)
plt.xlabel('Actual', fontsize=13)
plt.title('Confusion Matrix', fontsize=17)

# Displaying additional performance metrics
print('Accuracy: ', accuracy_score(y_test, y_pred))
print('F-1 Score : ',(f1_score(y_test, y_pred, average='micro')))
```

```
print('Precision Score : ',(precision_score(y_test, y_pred, average='micro')))
print('Recall Score : ',(recall_score(y_test, y_pred, average='micro')))
```

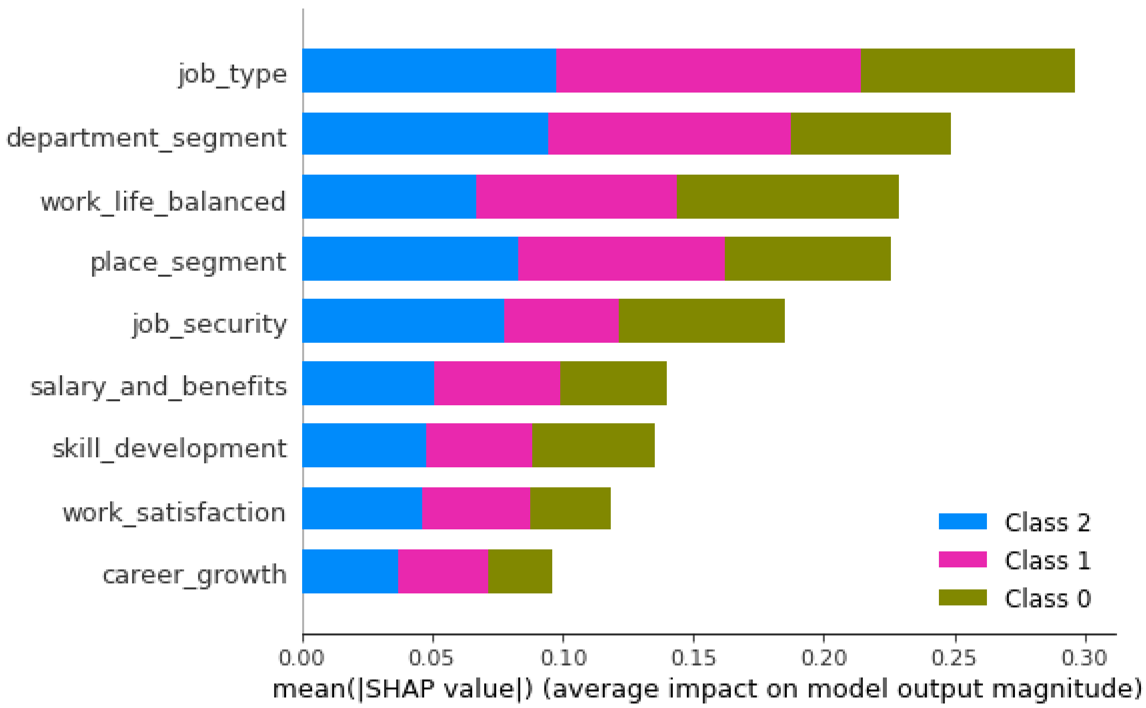
```
Accuracy:  0.5082417582417582
F-1 Score :  0.5082417582417582
Precision Score :  0.5082417582417582
Recall Score :  0.5082417582417582
```



In [83]:
```
# Creating a DataFrame for feature importance
feature_names = ['job_type', 'work_life_balanced', 'skill_development', 'salary_and_
feature_df = pd.DataFrame({
    'Feature Name': feature_names,
    'Importance': dt_classifier.feature_importances_
})
# Sorting features based on importance
feature_imp = feature_df.sort_values(by='Importance', ascending=False)

# Plotting a bar plot for feature importance
plt.figure(figsize=(10,8))
sns.barplot(data=feature_imp, x='Importance', y='Feature Name', palette='viridis')
plt.title('Feature Importance Obtained by Each Attribute (Decision Tree)', fontsize=
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



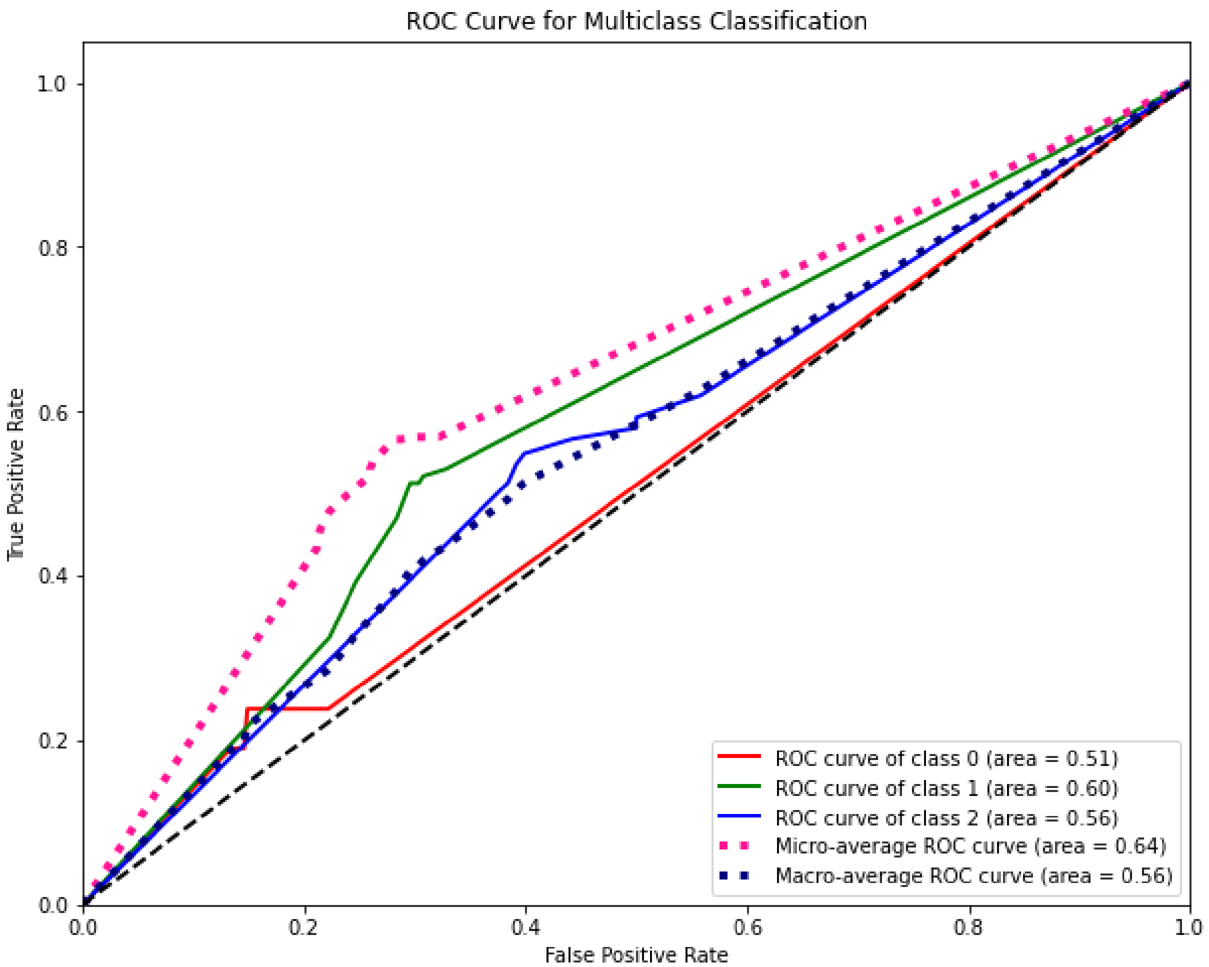
In [84]:
```
# Creating a DataFrame for x_test with feature names as columns
x_test_df = pd.DataFrame(x_test, columns=feature_names)

# Creating a TreeExplainer for the Decision Tree model
explainer = shap.TreeExplainer(dt_classifier)

# Generating SHAP values for x_test
shap_values = explainer.shap_values(x_test)

# Plotting a summary plot for SHAP values
shap.summary_plot(shap_values, x_test_df)
```



In [85]:
```
explainer = shap.TreeExplainer(dt_classifier)
shap_values = explainer.shap_values(x_test)
shap.summary_plot(shap_values[2], x_test_df, feature_names=feature_names)
```

In [86]:
```
# Calculate the number of classes
num_classes = len(np.unique(y_test))

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

# Fit the classifier and obtain predicted probabilities
y_score = dt_classifier.fit(x_train_smote, y_train_smote).predict_proba(x_test)

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), y_score.ravel())
roc_auc_micro = auc(fpr_micro, tpr_micro)

# Compute macro-average ROC curve and ROC area
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(num_classes)]))
mean_tpr = np.zeros_like(all_fpr)
for i in range(num_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

mean_tpr /= num_classes

fpr_macro = all_fpr
tpr_macro = mean_tpr
roc_auc_macro = auc(fpr_macro, tpr_macro)

# Plot the ROC curve
```

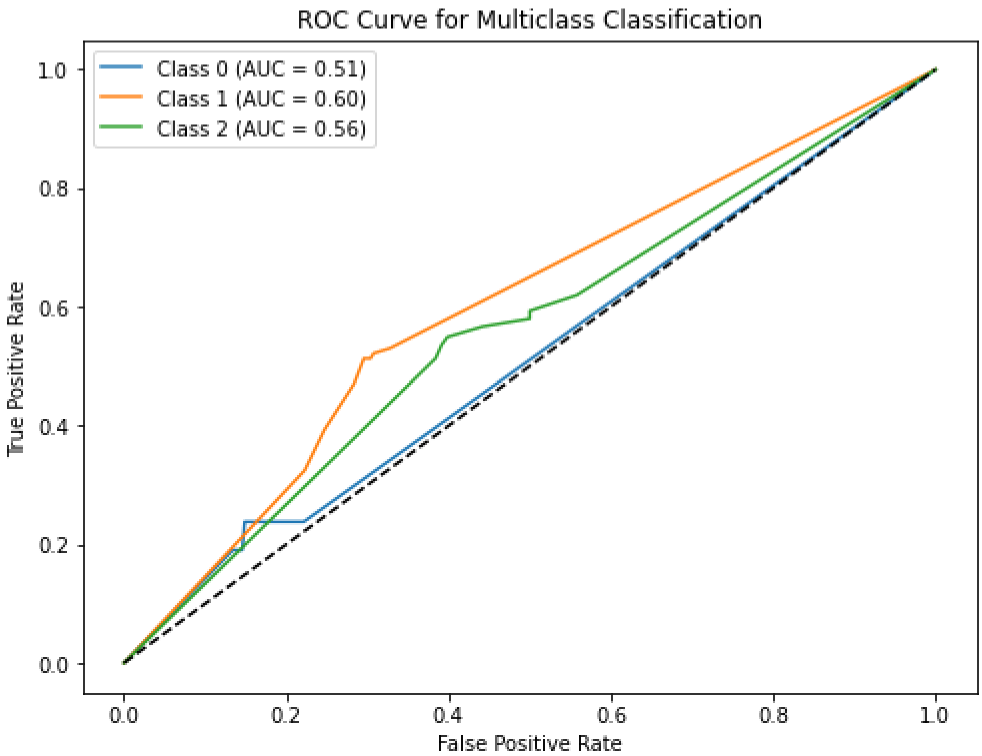
```
plt.figure(figsize=(10, 8))

colors = ['red', 'green', 'blue']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='ROC curve of class {0} (area = {1:0.2f})'
                   ''.format(i, roc_auc[i]))

plt.plot(fpr_micro, tpr_micro, color='deeppink', linestyle=':', linewidth=4,
         label='Micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_micro))

plt.plot(fpr_macro, tpr_macro, color='navy', linestyle=':', linewidth=4,
         label='Macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_macro))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend(loc="lower right")
plt.show()
```



In [87]:
```
# Predicted probabilities for each class
y_pred_proba = dt_classifier.predict_proba(x_test)

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
```

```
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Calculate the average AUC
average_auc = np.mean(list(roc_auc.values()))

# Plot the ROC curve for each class
plt.figure(figsize=(8, 6))
for i in range(num_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Print the average AUC
print(f'Average AUC: {average_auc:.2f}')

# Plot the diagonal line
plt.plot([0, 1], [0, 1], linestyle='--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend()
plt.show()
```

```
Average AUC: 0.56
```



In [88]:

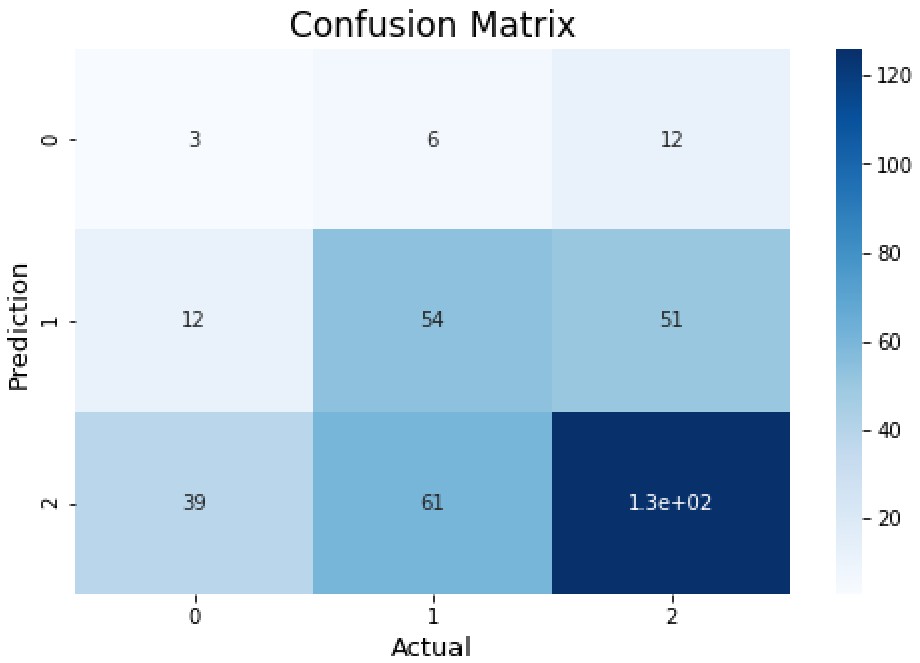
```
# Creating a Decision Tree Classifier with default hyperparameters
dt = DecisionTreeClassifier()
dt.fit(x_train_smote, y_train_smote)
y_pred = dt.predict(x_test)
print('Classification report: \n', classification_report(y_test, y_pred))
```

```
Classification report: 
               precision    recall  f1-score   support

           0       0.06      0.14      0.08        21
           1       0.45      0.46      0.45       117
           2       0.67      0.56      0.61       226
```

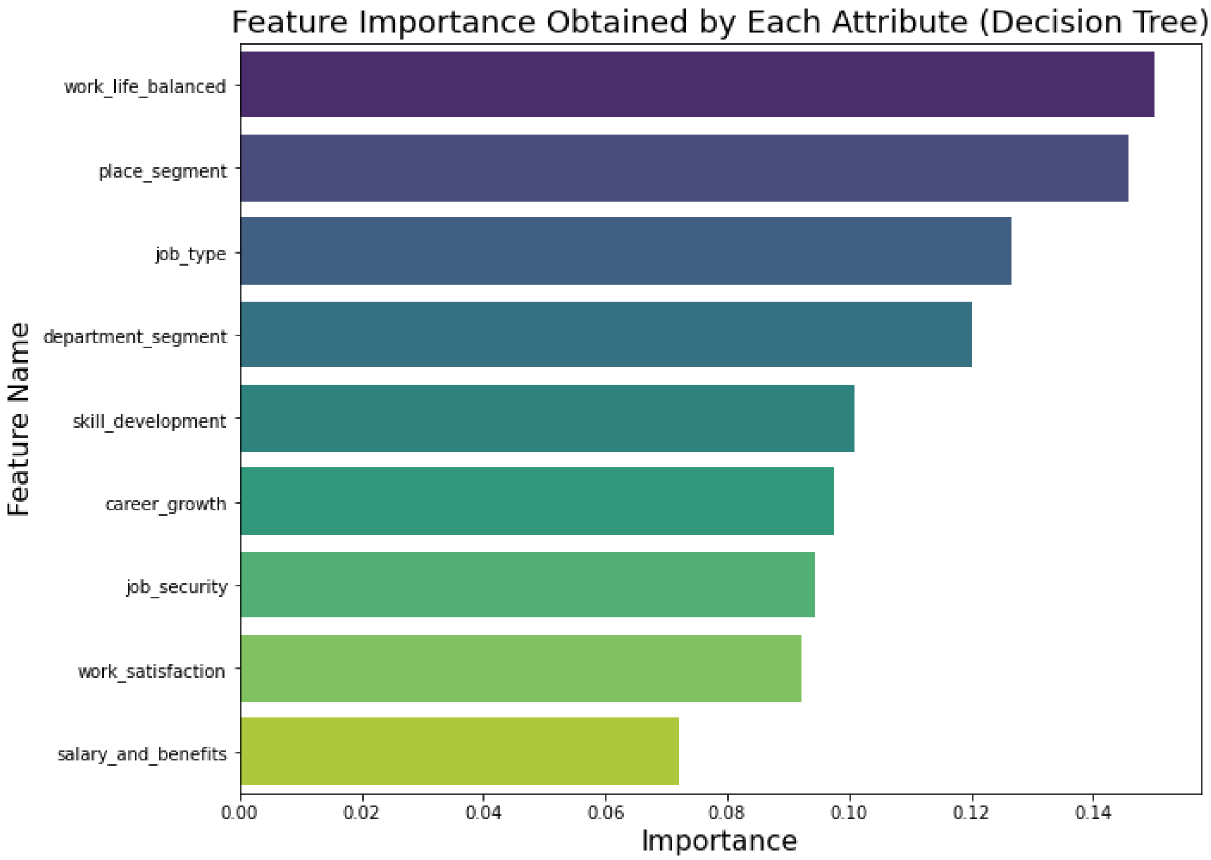
```
    accuracy                          0.50       364
   macro avg       0.39      0.39     0.38       364
weighted avg       0.56      0.50     0.53       364
```

In [89]:
```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,5))
sns.heatmap(cm, annot=True, cmap='Blues')
plt.ylabel('Prediction', fontsize=13)
plt.xlabel('Actual', fontsize=13)
plt.title('Confusion Matrix', fontsize=17)

# Displaying additional performance metrics
print('Accuracy: ', accuracy_score(y_test, y_pred))
print('F-1: ',(f1_score(y_test, y_pred, average='micro')))
print('Precision: ',(precision_score(y_test, y_pred, average='micro')))
print('Recall: ',(recall_score(y_test, y_pred, average='micro')))
```

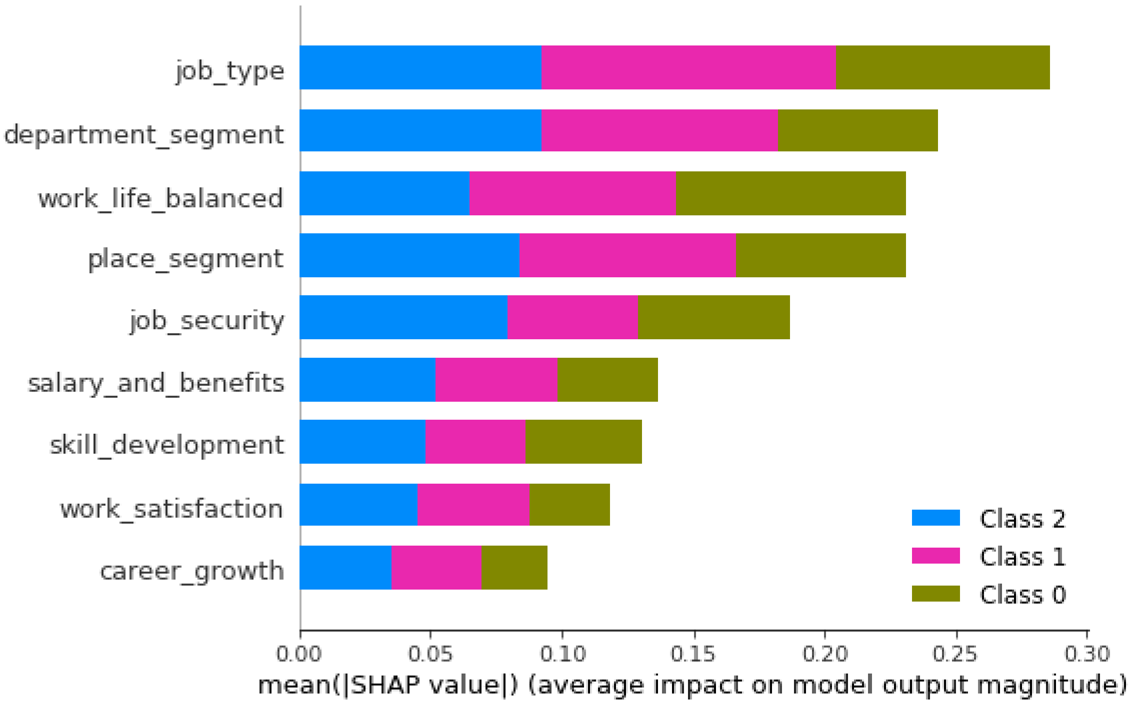
```
Accuracy:  0.5027472527472527
F-1:  0.5027472527472527
Precision:  0.5027472527472527
Recall:  0.5027472527472527
```



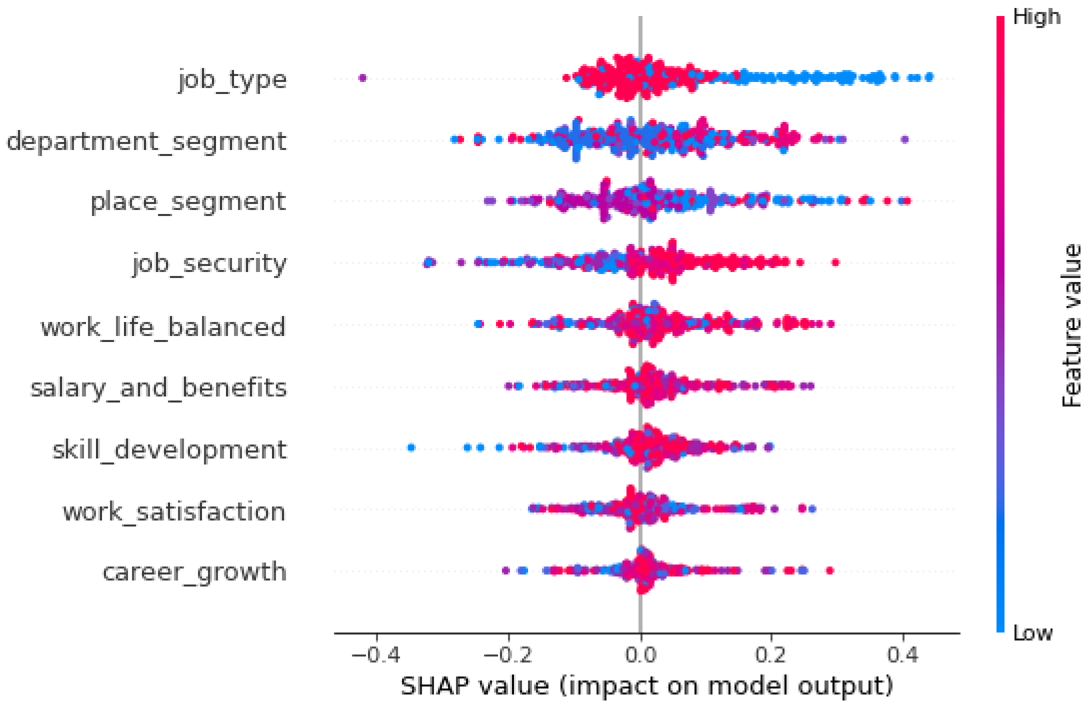
In [90]:
```
# Creating a DataFrame for feature importance
feature_names = ['job_type', 'work_life_balanced', 'skill_development', 'salary_and_
feature_df = pd.DataFrame({
    'Feature Name': feature_names,
    'Importance': dt.feature_importances_
})
# Sorting features based on importance
feature_imp = feature_df.sort_values(by='Importance', ascending=False)

# Plotting a bar plot for feature importance
plt.figure(figsize=(10,8))
sns.barplot(data=feature_imp, x='Importance', y='Feature Name', palette='viridis')
plt.title('Feature Importance Obtained by Each Attribute (Decision Tree)', fontsize=
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [91]:
```
# Creating a DataFrame for x_test with feature names as columns
x_test_df = pd.DataFrame(x_test, columns=feature_names)

# Creating a TreeExplainer for the Decision Tree model
explainer = shap.TreeExplainer(dt)

# Generating SHAP values for x_test
shap_values = explainer.shap_values(x_test)

# Plotting a summary plot for SHAP values
shap.summary_plot(shap_values, x_test_df)
```

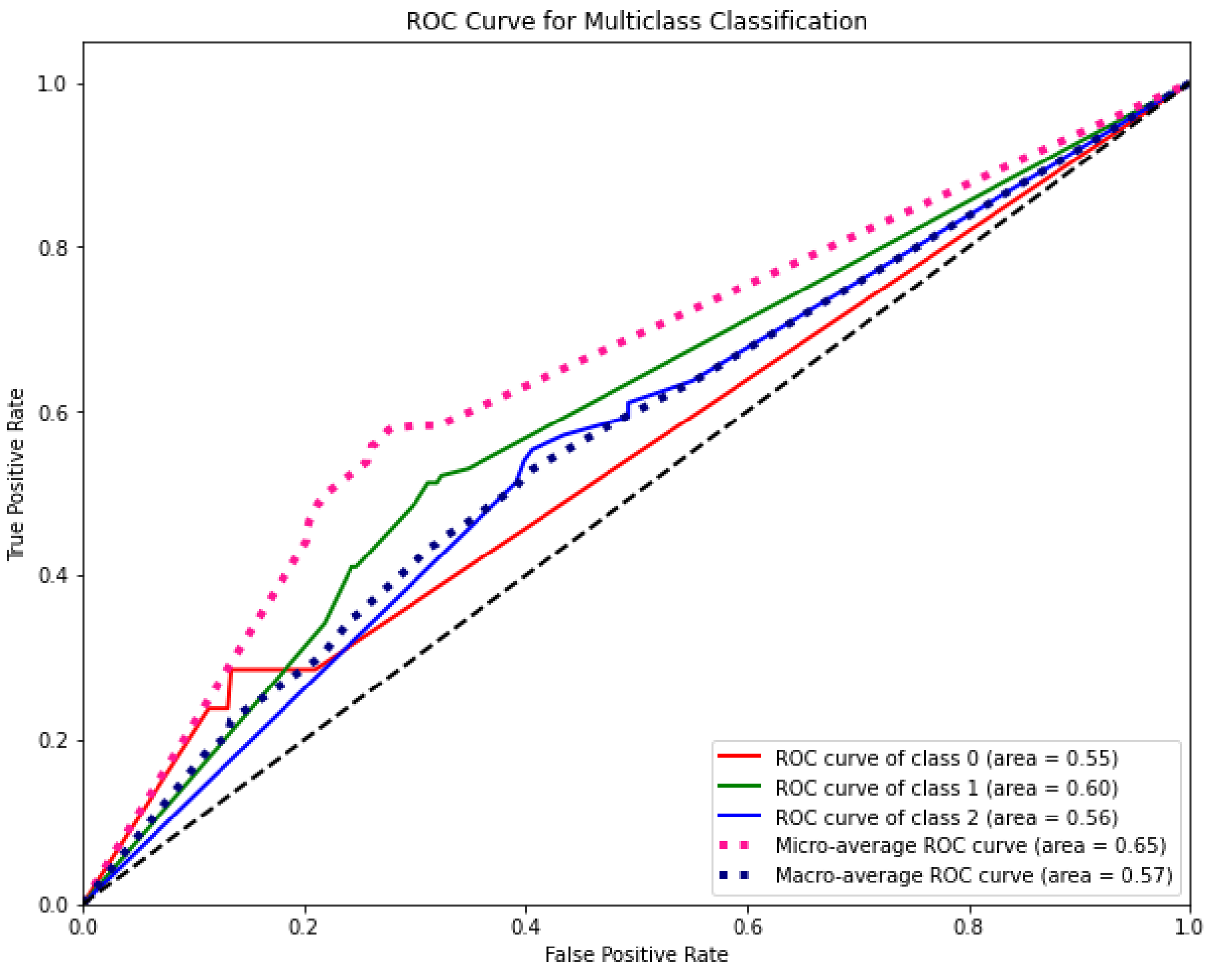


In [92]:
```
explainer = shap.TreeExplainer(dt)
shap_values = explainer.shap_values(x_test)
shap.summary_plot(shap_values[2], x_test_df, feature_names=feature_names)
```



In [93]:
```
# Calculate the number of classes
num_classes = len(np.unique(y_test))

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

# Fit the classifier and obtain predicted probabilities
y_score = dt.fit(x_train_smote, y_train_smote).predict_proba(x_test)

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), y_score.ravel())
roc_auc_micro = auc(fpr_micro, tpr_micro)

# Compute macro-average ROC curve and ROC area
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(num_classes)]))
mean_tpr = np.zeros_like(all_fpr)
for i in range(num_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

mean_tpr /= num_classes

fpr_macro = all_fpr
tpr_macro = mean_tpr
roc_auc_macro = auc(fpr_macro, tpr_macro)

# Plot the ROC curve
```

```
plt.figure(figsize=(10, 8))

colors = ['red', 'green', 'blue']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='ROC curve of class {0} (area = {1:0.2f})'
                   ''.format(i, roc_auc[i]))

plt.plot(fpr_micro, tpr_micro, color='deeppink', linestyle=':', linewidth=4,
         label='Micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_micro))

plt.plot(fpr_macro, tpr_macro, color='navy', linestyle=':', linewidth=4,
         label='Macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_macro))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend(loc="lower right")
plt.show()
```

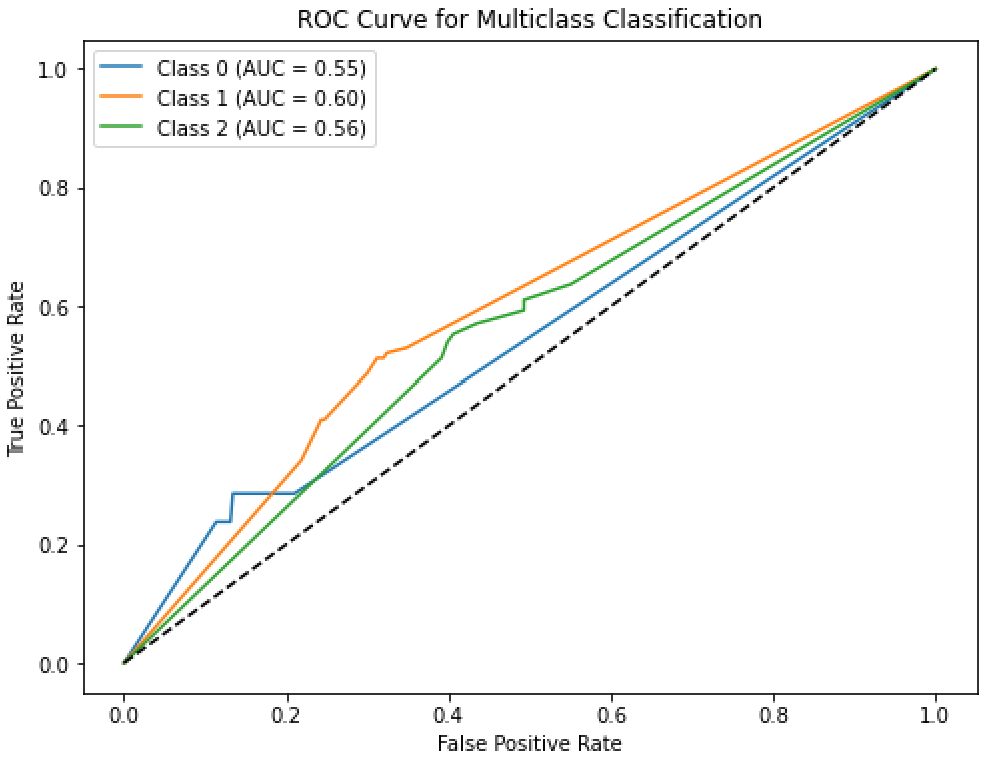


In [94]:

```
# Predicted probabilities for each class
y_pred_proba = dt.predict_proba(x_test)

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
```

```
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Calculate the average AUC
average_auc = np.mean(list(roc_auc.values()))

# Plot the ROC curve for each class
plt.figure(figsize=(8, 6))
for i in range(num_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Print the average AUC
print(f'Average AUC: {average_auc:.2f}')

# Plot the diagonal line
plt.plot([0, 1], [0, 1], linestyle='--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend()
plt.show()
```

```
Average AUC: 0.57
```



Random Forest

In [95]:

```
rf = RandomForestClassifier()
rf.fit(x_train_smote, y_train_smote)
y_pred = rf.predict(x_test)
print('Classification report: \n', classification_report(y_test, y_pred))
```

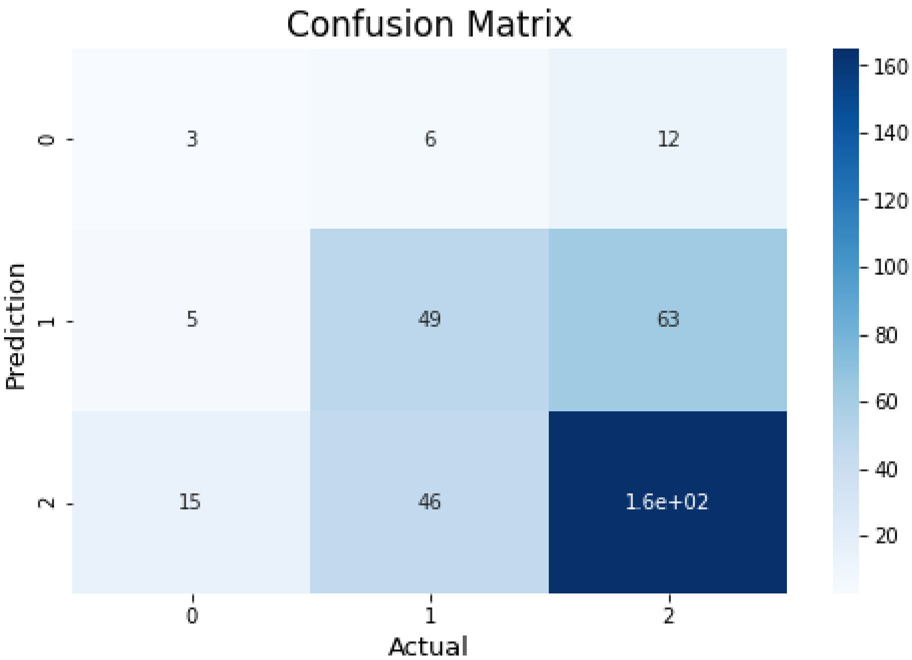
```
Classification report:
               precision    recall  f1-score   support

           0       0.13      0.14      0.14        21
```

```
           1       0.49      0.42      0.45       117
           2       0.69      0.73      0.71       226

    accuracy                           0.60       364
   macro avg       0.43      0.43      0.43       364
weighted avg       0.59      0.60      0.59       364
```

In [96]:

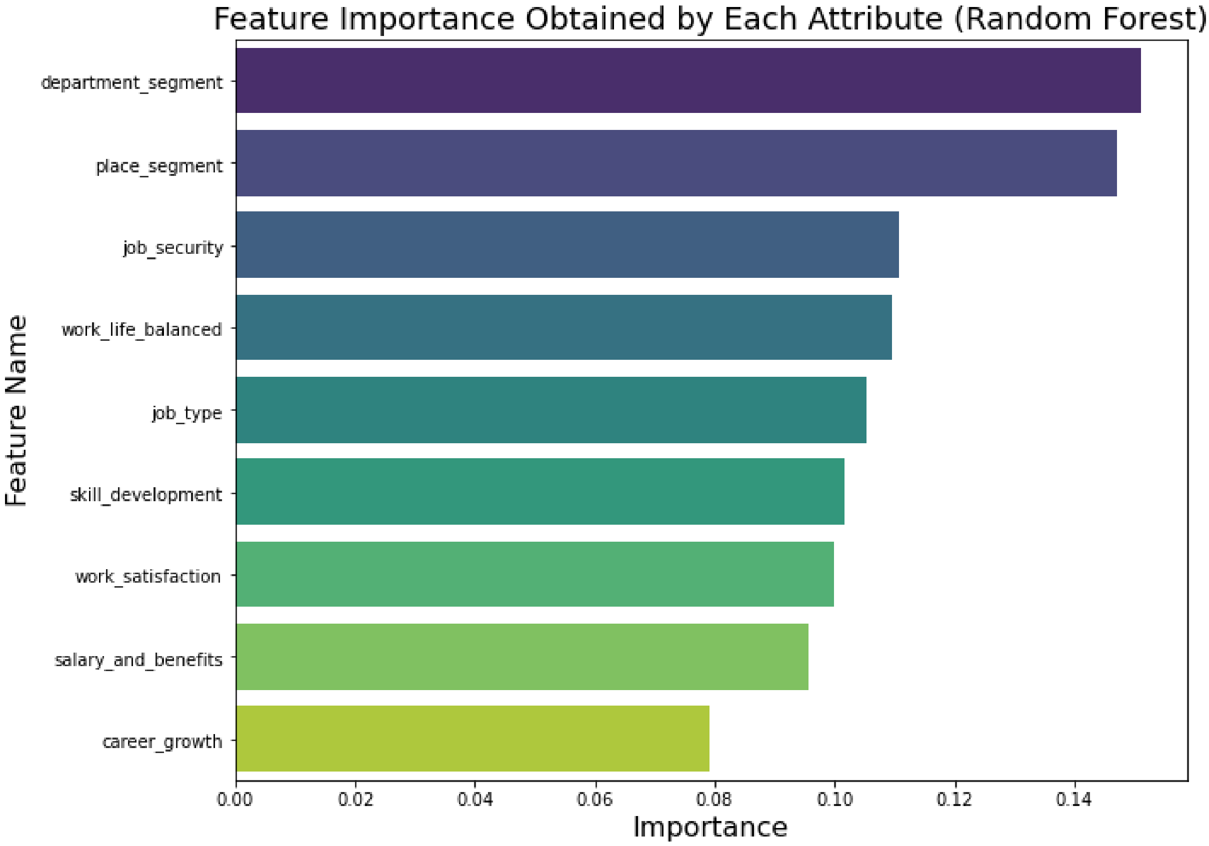
```python
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,5))
sns.heatmap(cm, annot=True, cmap='Blues')
plt.ylabel('Prediction', fontsize=13)
plt.xlabel('Actual', fontsize=13)
plt.title('Confusion Matrix', fontsize=17)

print('Accuracy: ',accuracy_score(y_test, y_pred))
print('F-1: ',(f1_score(y_test, y_pred, average='micro')))
print('Precision: ',(precision_score(y_test, y_pred, average='micro')))
print('Recall: ',(recall_score(y_test, y_pred, average='micro')))
```

```
Accuracy:  0.5961538461538461
F-1:  0.5961538461538461
Precision:  0.5961538461538461
Recall:  0.5961538461538461
```



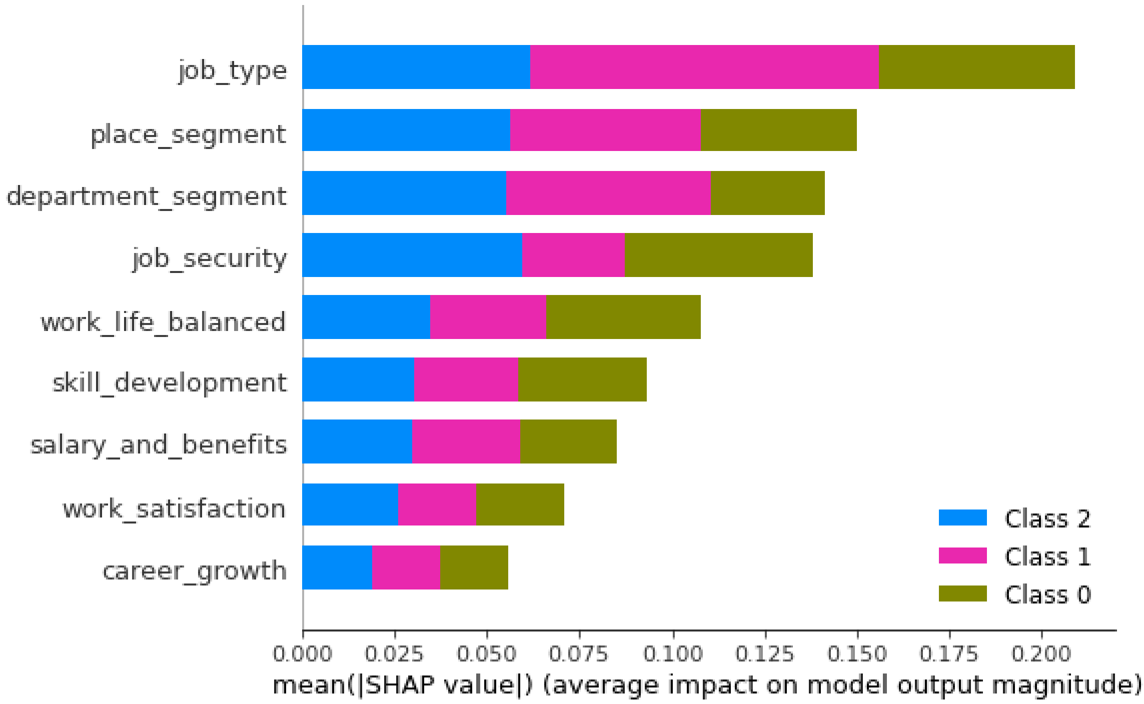
In [97]:

```python
# Creating a DataFrame for feature importance
feature_names = ['job_type', 'work_life_balanced', 'skill_development', 'salary_and_
feature_df = pd.DataFrame({
    'Feature Name': feature_names,
    'Importance': rf.feature_importances_
})
# Sorting features based on importance
feature_imp = feature_df.sort_values(by='Importance', ascending=False)

# Plotting a bar plot for feature importance
plt.figure(figsize=(10,8))
sns.barplot(data=feature_imp, x='Importance', y='Feature Name', palette='viridis')
plt.title('Feature Importance Obtained by Each Attribute (Random Forest)', fontsize=
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [98]:

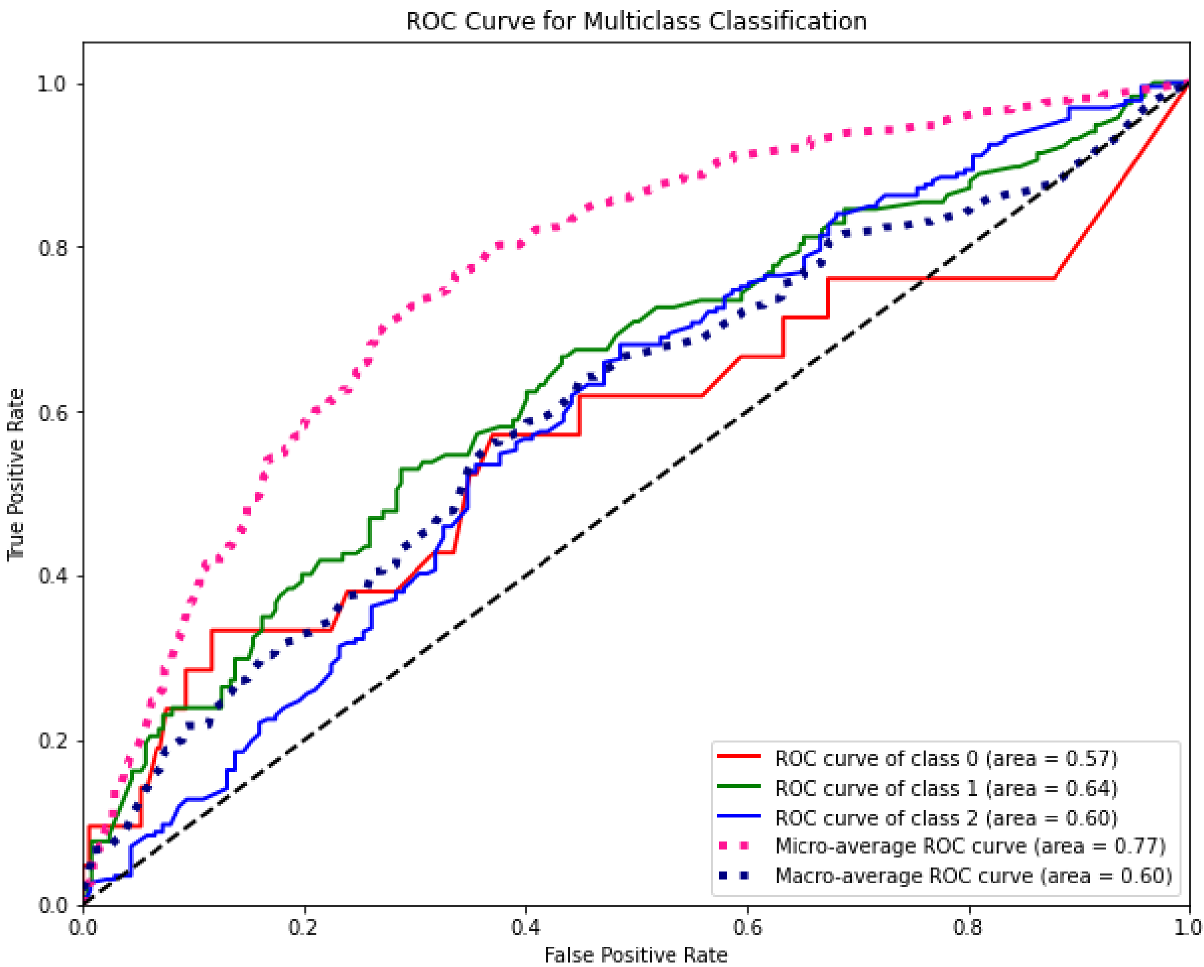
```
# Creating a DataFrame for x_test with feature names as columns
x_test_df = pd.DataFrame(x_test, columns=feature_names)

# Creating a TreeExplainer for the Random Forest Classifier model
explainer = shap.TreeExplainer(rf)

# Generating SHAP values for x_test
shap_values = explainer.shap_values(x_test)

# Plotting a summary plot for SHAP values
shap.summary_plot(shap_values, x_test_df)
```



In [99]:
```
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(x_test)
shap.summary_plot(shap_values[2], x_test_df, feature_names=feature_names)
```

In [100…
```
# Calculate the number of classes
num_classes = len(np.unique(y_test))

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

# Fit the classifier and obtain predicted probabilities
y_score = rf.fit(x_train_smote, y_train_smote).predict_proba(x_test)

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), y_score.ravel())
roc_auc_micro = auc(fpr_micro, tpr_micro)

# Compute macro-average ROC curve and ROC area
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(num_classes)]))
mean_tpr = np.zeros_like(all_fpr)
for i in range(num_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

mean_tpr /= num_classes

fpr_macro = all_fpr
tpr_macro = mean_tpr
roc_auc_macro = auc(fpr_macro, tpr_macro)

# Plot the ROC curve
```

```
plt.figure(figsize=(10, 8))

colors = ['red', 'green', 'blue']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='ROC curve of class {0} (area = {1:0.2f})'
                   ''.format(i, roc_auc[i]))

plt.plot(fpr_micro, tpr_micro, color='deeppink', linestyle=':', linewidth=4,
         label='Micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_micro))

plt.plot(fpr_macro, tpr_macro, color='navy', linestyle=':', linewidth=4,
         label='Macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_macro))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend(loc="lower right")
plt.show()
```

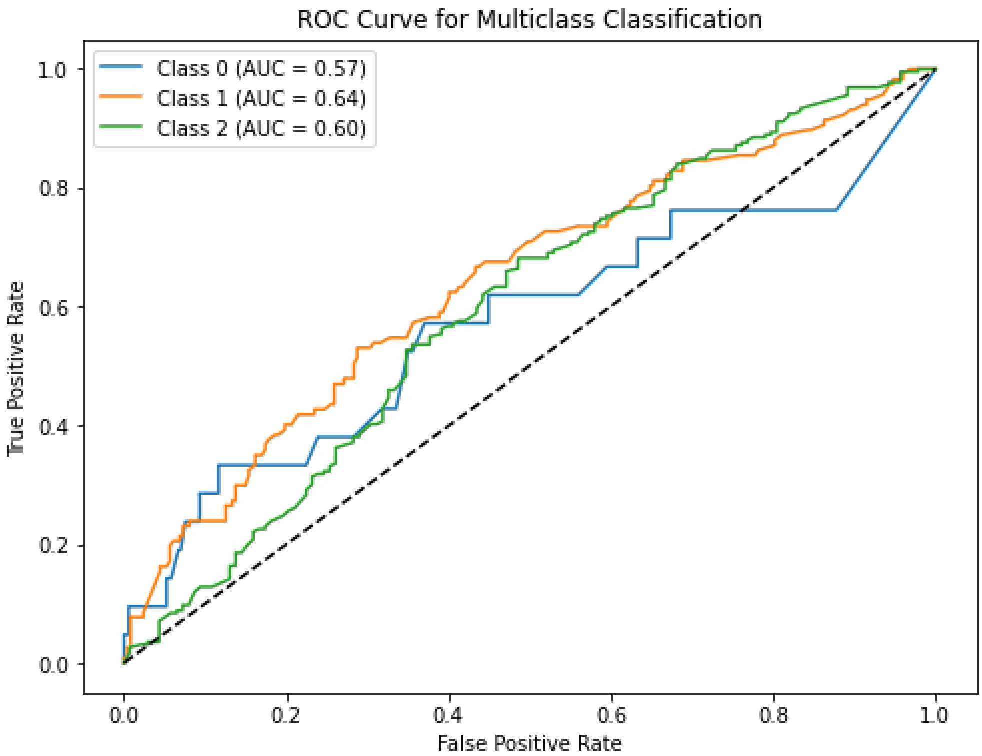


In [101…

```
# Predicted probabilities for each class
y_pred_proba = rf.predict_proba(x_test)

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
```

```
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Calculate the average AUC
average_auc = np.mean(list(roc_auc.values()))

# Plot the ROC curve for each class
plt.figure(figsize=(8, 6))
for i in range(num_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Print the average AUC
print(f'Average AUC: {average_auc:.2f}')

# Plot the diagonal line
plt.plot([0, 1], [0, 1], linestyle='--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend()
plt.show()
```

```
Average AUC: 0.60
```



SVM

In [102…

```
svm = SVC(probability=True, kernel='linear', decision_function_shape='ovr')
svm.fit(x_train_smote, y_train_smote)
y_pred = svm.predict(x_test)
print('Classification report: \n', classification_report(y_test, y_pred))
```

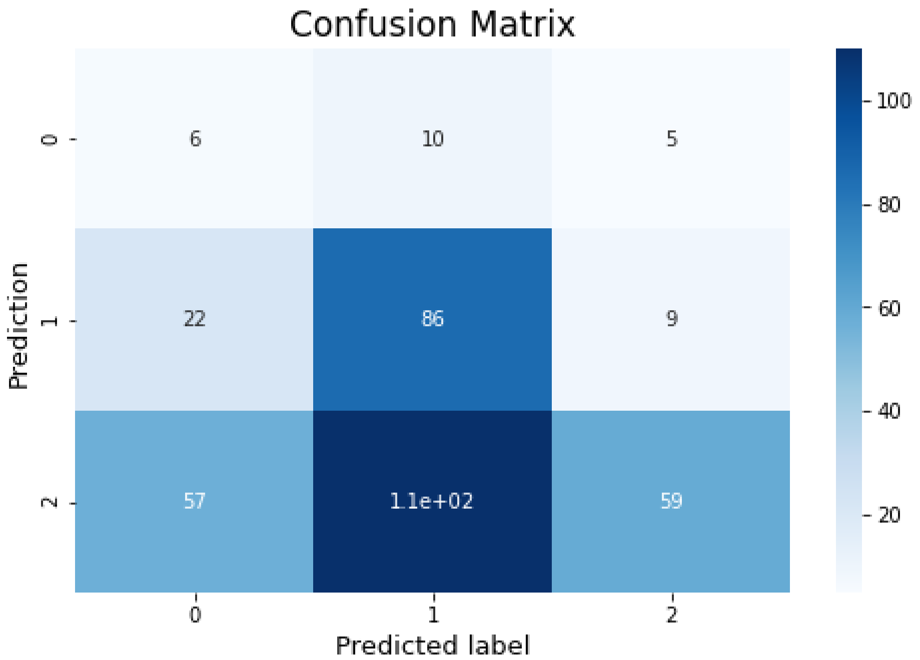
```
Classification report:
               precision    recall  f1-score   support

           0       0.07      0.29      0.11        21
```

```
           1       0.42      0.74      0.53       117
           2       0.81      0.26      0.39       226

    accuracy                           0.41       364
   macro avg       0.43      0.43      0.35       364
weighted avg       0.64      0.41      0.42       364
```

In [103…

```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,5))
sns.heatmap(cm, annot=True, cmap='Blues')
plt.ylabel('Prediction', fontsize=13)
plt.xlabel('Predicted label', fontsize=13)
plt.title('Confusion Matrix', size=17)

print('Accuracy: ', accuracy_score(y_test, y_pred))
print('F-1: ',(f1_score(y_test, y_pred, average='micro')))
print('Precision: ',(precision_score(y_test, y_pred, average='micro')))
print('Recall: ',(recall_score(y_test, y_pred, average='micro')))
```

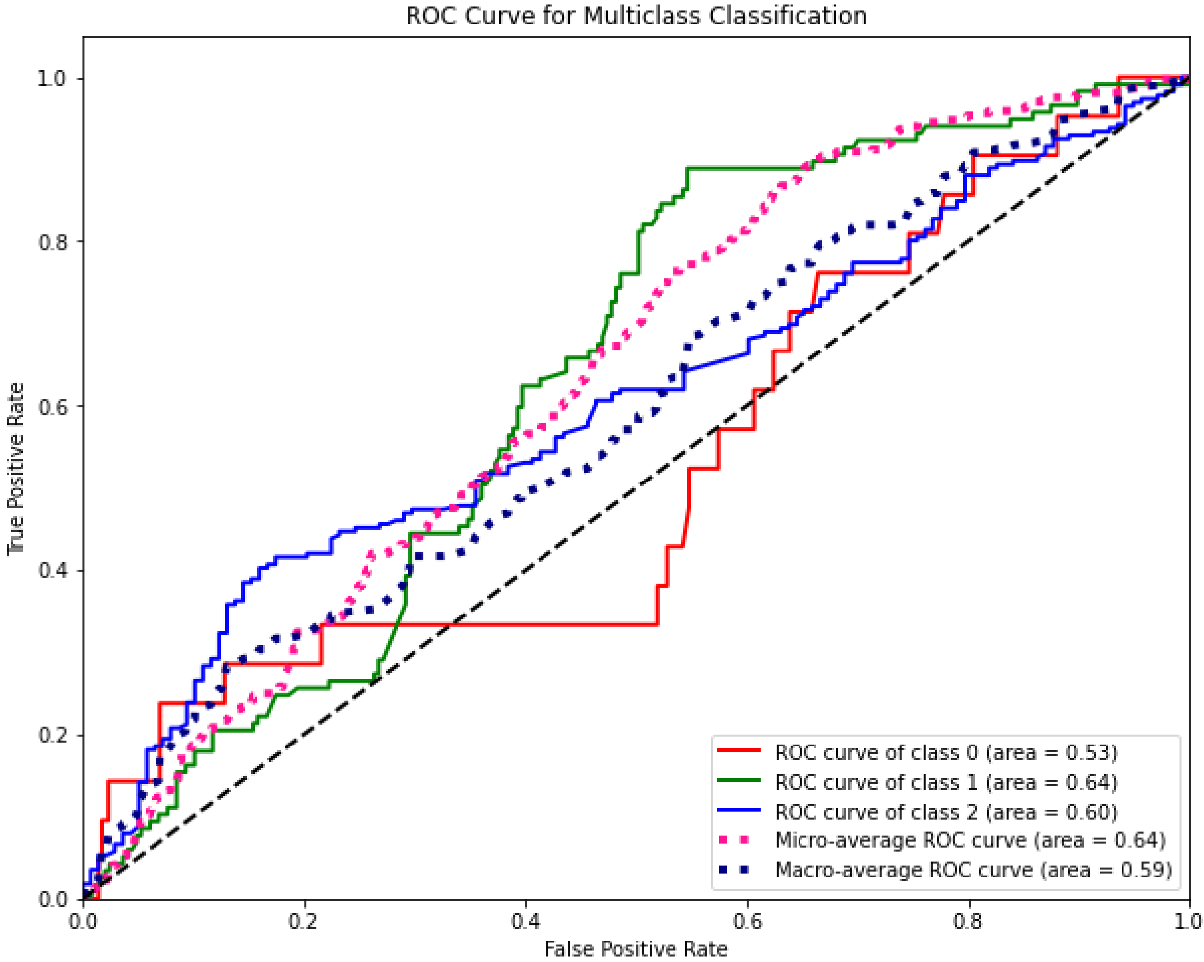
```
Accuracy:  0.41483516483516486
F-1:  0.41483516483516486
Precision:  0.41483516483516486
Recall:  0.41483516483516486
```



In [104…

```
# Calculate the number of classes
num_classes = len(np.unique(y_test))

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

# Fit the classifier and obtain predicted probabilities
y_score = svm.fit(x_train_smote, y_train_smote).predict_proba(x_test)

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
```

```
# Compute micro-average ROC curve and ROC area
fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), y_score.ravel())
roc_auc_micro = auc(fpr_micro, tpr_micro)

# Compute macro-average ROC curve and ROC area
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(num_classes)]))
mean_tpr = np.zeros_like(all_fpr)
for i in range(num_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

mean_tpr /= num_classes

fpr_macro = all_fpr
tpr_macro = mean_tpr
roc_auc_macro = auc(fpr_macro, tpr_macro)

# Plot the ROC curve
plt.figure(figsize=(10, 8))

colors = ['red', 'green', 'blue']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='ROC curve of class {0} (area = {1:0.2f})'
                   ''.format(i, roc_auc[i]))

plt.plot(fpr_micro, tpr_micro, color='deeppink', linestyle=':', linewidth=4,
         label='Micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_micro))

plt.plot(fpr_macro, tpr_macro, color='navy', linestyle=':', linewidth=4,
         label='Macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_macro))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend(loc="lower right")
plt.show()
```

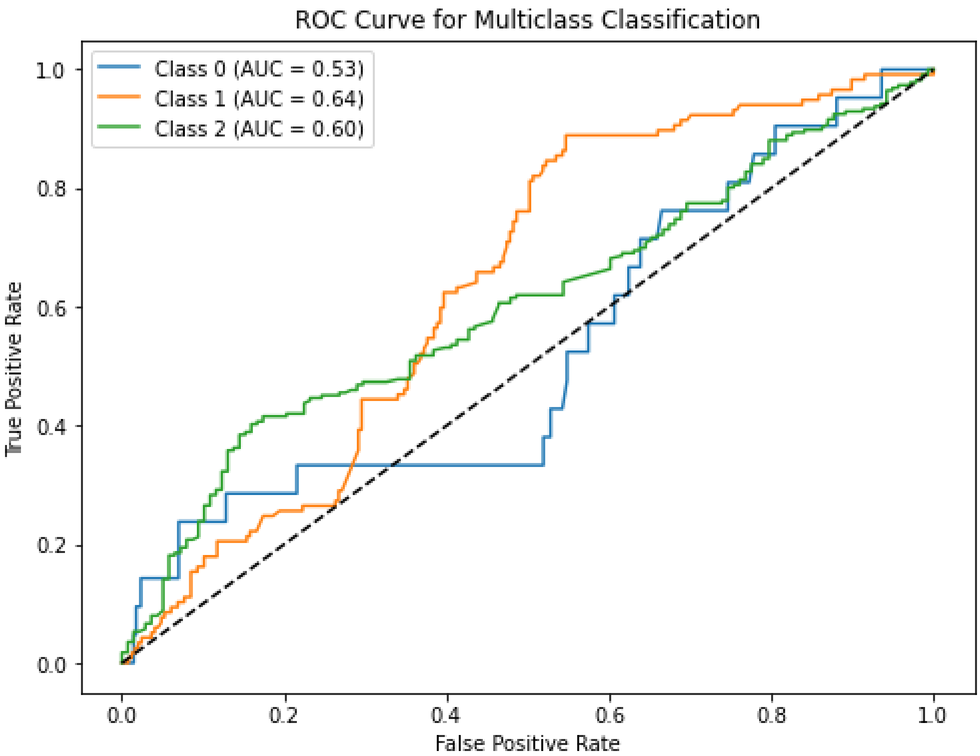


In [105…

```
# Predicted probabilities for each class
y_pred_proba = svm.predict_proba(x_test)

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Calculate the average AUC
average_auc = np.mean(list(roc_auc.values()))

# Plot the ROC curve for each class
plt.figure(figsize=(8, 6))
for i in range(num_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Print the average AUC
print(f'Average AUC: {average_auc:.2f}')

# Plot the diagonal line
plt.plot([0, 1], [0, 1], linestyle='--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
```

```
plt.legend()
plt.show()
```

```
Average AUC: 0.59
```



XGBoost

In [106…

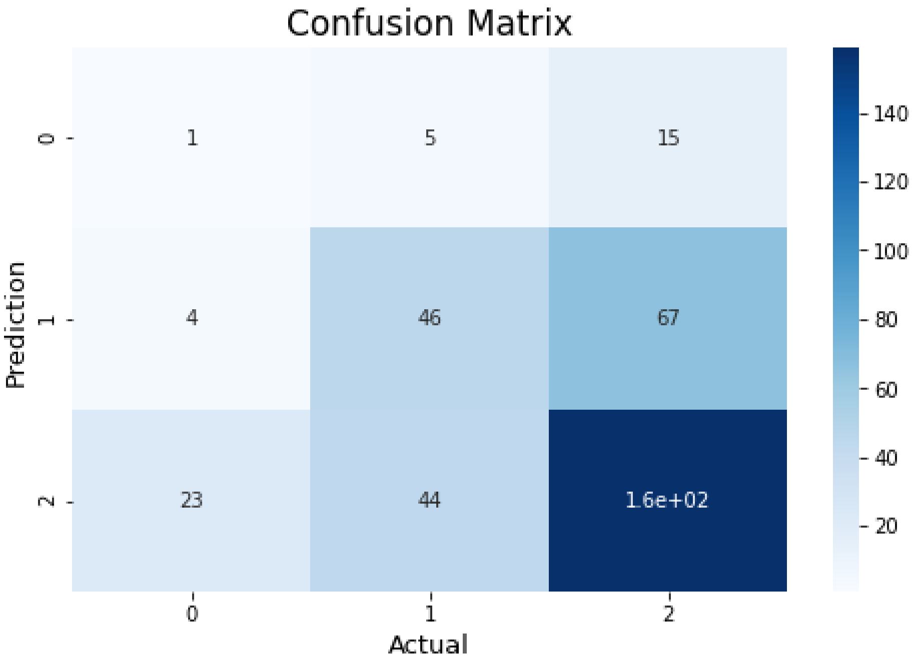
```
xgboost = xgb.XGBClassifier()
xgboost.fit(x_train_smote, y_train_smote)
y_pred = xgboost.predict(x_test)
print('Classification report: \n', classification_report(y_test, y_pred))
```

```
Classification report:
               precision    recall  f1-score   support

           0       0.04      0.05      0.04        21
           1       0.48      0.39      0.43       117
           2       0.66      0.70      0.68       226

    accuracy                           0.57       364
   macro avg       0.39      0.38      0.39       364
weighted avg       0.57      0.57      0.56       364
```

In [107…

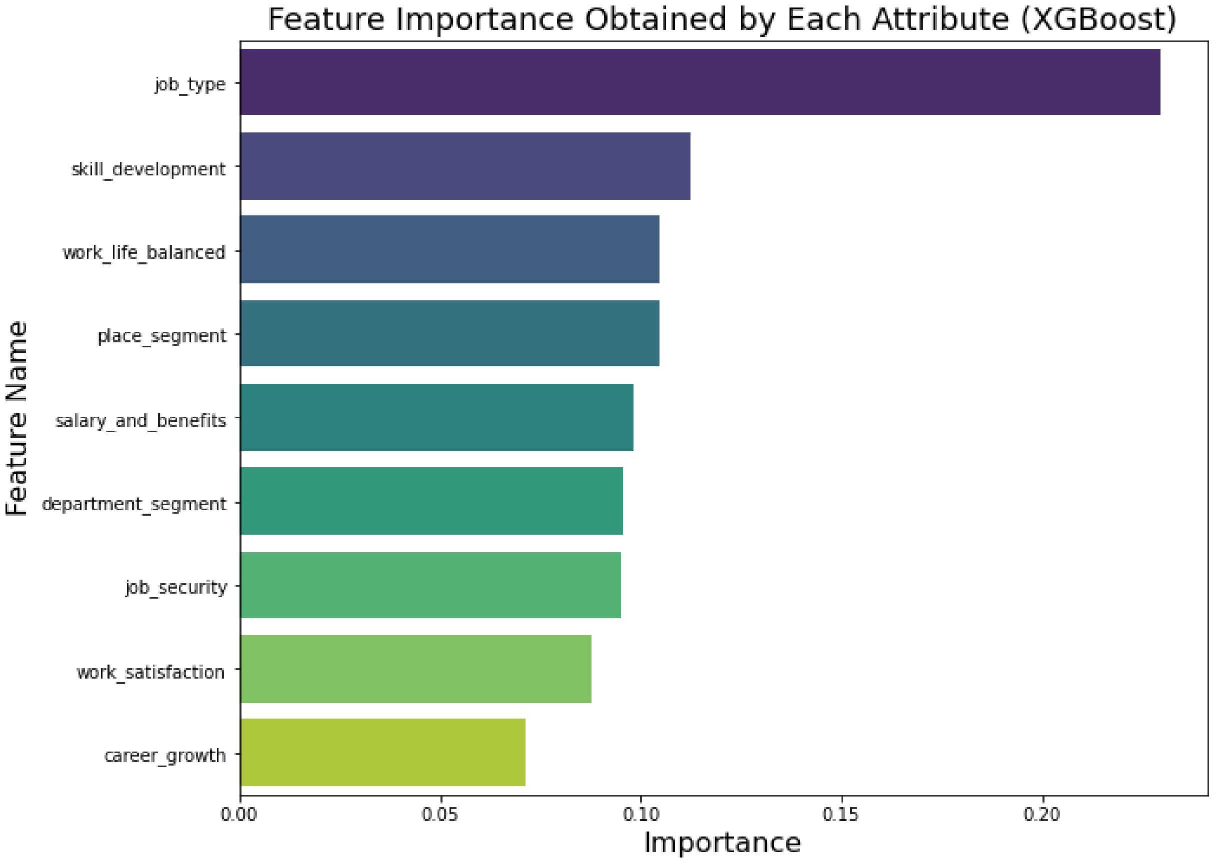
```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,5))
sns.heatmap(cm, annot=True, cmap='Blues')
plt.ylabel('Prediction', fontsize=13)
plt.xlabel('Actual', fontsize=13)
plt.title('Confusion Matrix', fontsize=17)

print('Accuracy: ',accuracy_score(y_test, y_pred))
print('F-1: ',(f1_score(y_test, y_pred, average='micro')))
print('Precision: ',(precision_score(y_test, y_pred, average='micro')))
print('Recall: ',(recall_score(y_test, y_pred, average='micro')))
```

```
Accuracy:  0.5659340659340659
F-1:  0.5659340659340659
Precision:  0.5659340659340659
Recall:  0.5659340659340659
```



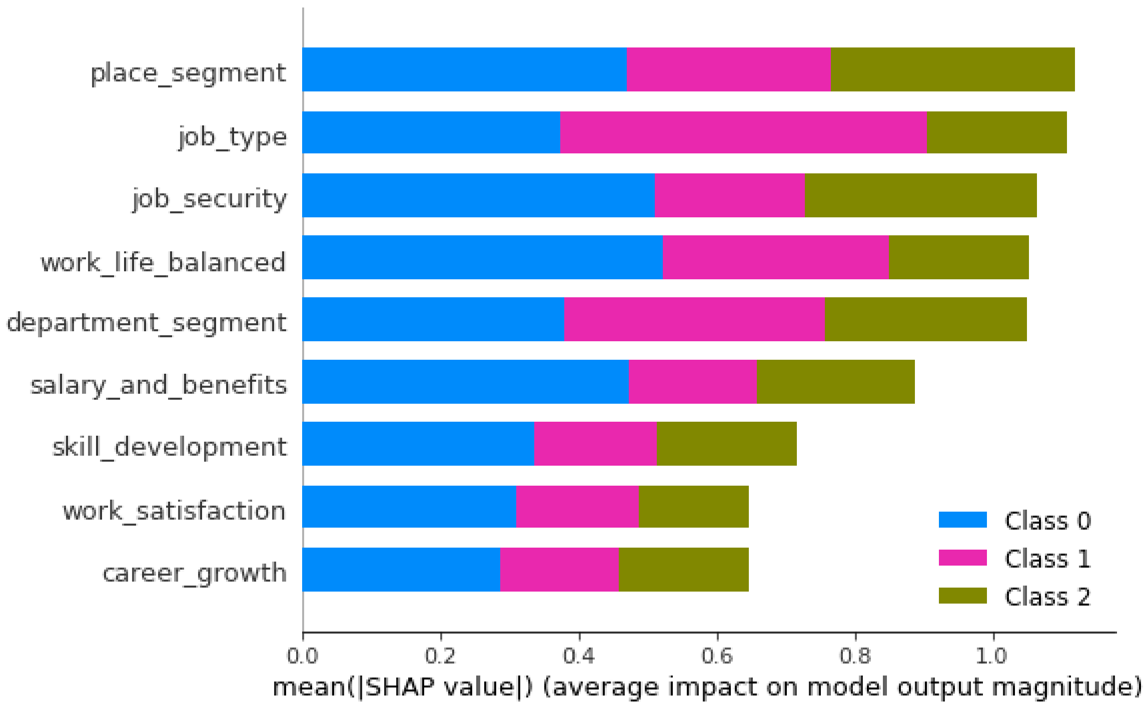
In [108…

```
# Creating a DataFrame for feature importance
feature_names = ['job_type', 'work_life_balanced', 'skill_development', 'salary_and_
feature_df = pd.DataFrame({
    'Feature Name': feature_names,
    'Importance': xgboost.feature_importances_
})
# Sorting features based on importance
feature_imp = feature_df.sort_values(by='Importance', ascending=False)

# Plotting a bar plot for feature importance
plt.figure(figsize=(10,8))
sns.barplot(data=feature_imp, x='Importance', y='Feature Name', palette='viridis')
plt.title('Feature Importance Obtained by Each Attribute (XGBoost)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



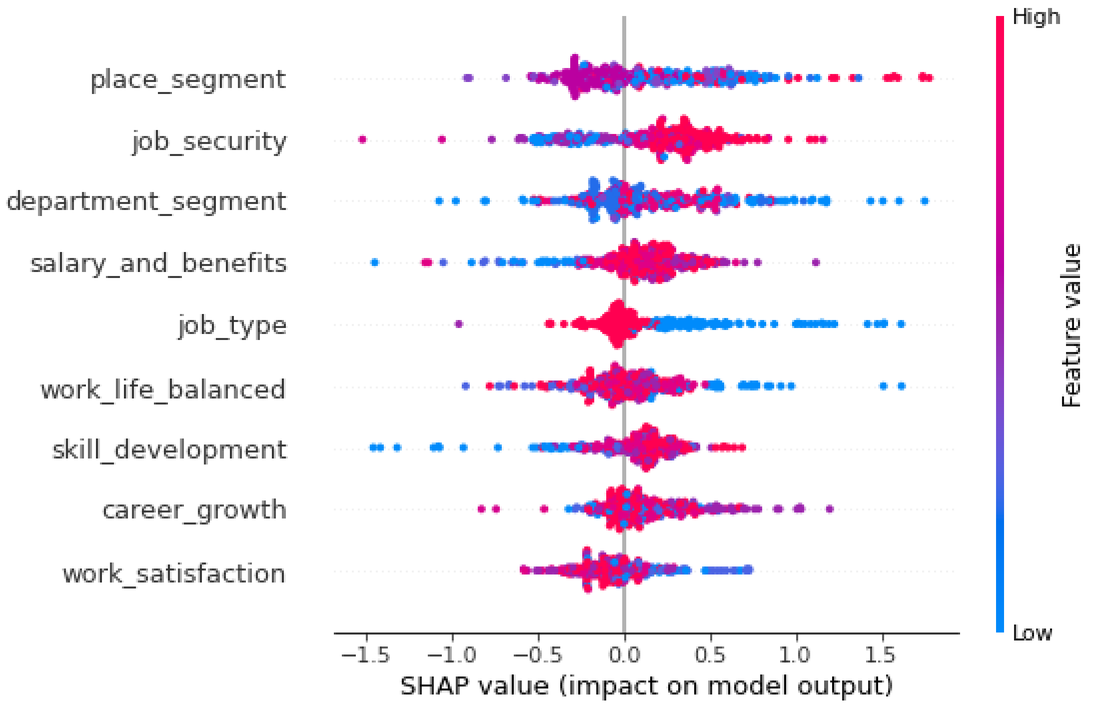
In [109…

```
# Creating a DataFrame for x_test with feature names as columns
x_test_df = pd.DataFrame(x_test, columns=feature_names)

# Creating a TreeExplainer for the XGBoost Classifier model
explainer = shap.TreeExplainer(xgboost)

# Generating SHAP values for x_test
shap_values = explainer.shap_values(x_test)

# Plotting a summary plot for SHAP values
shap.summary_plot(shap_values, x_test_df)
```



In [110…

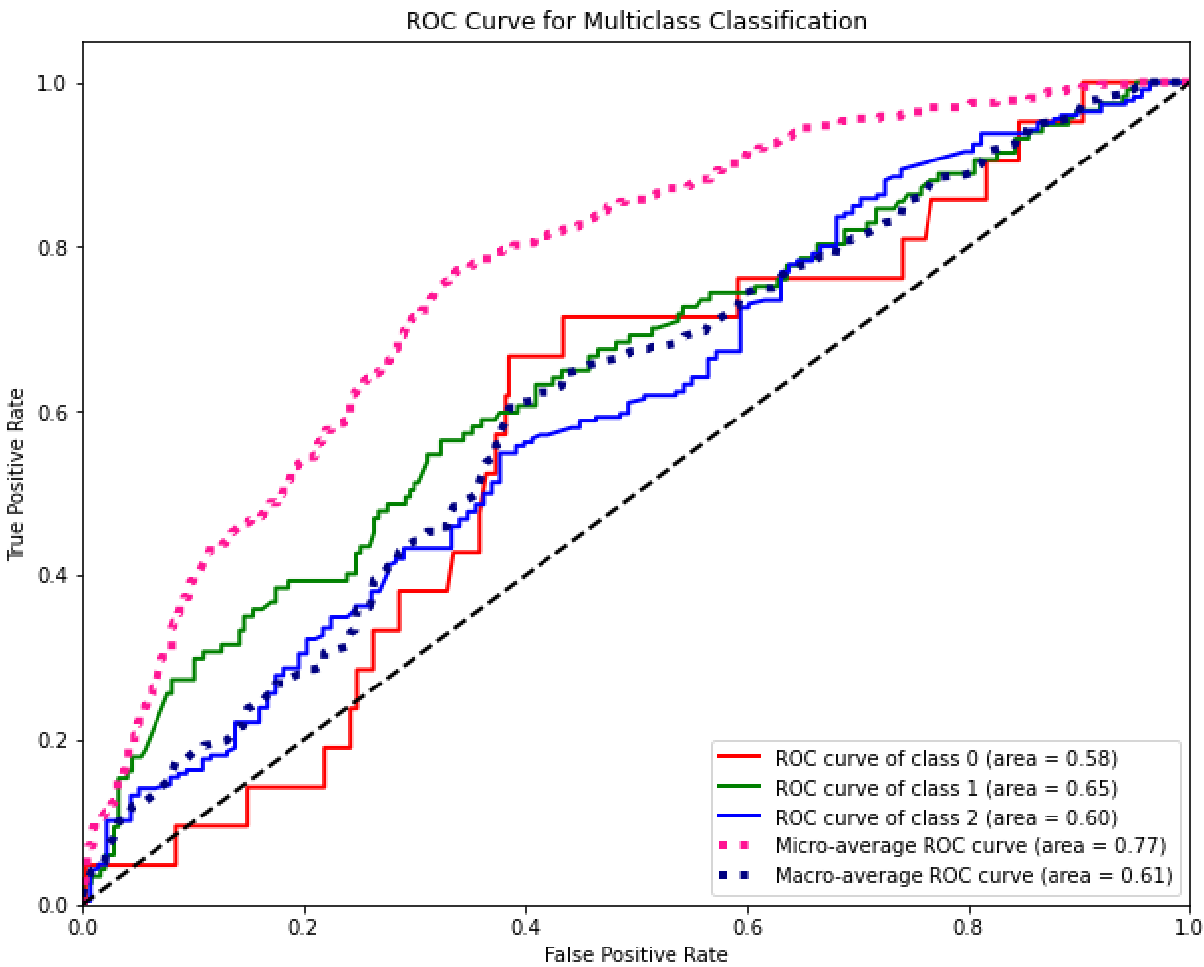
```
explainer = shap.TreeExplainer(xgboost)
shap_values = explainer.shap_values(x_test)
shap.summary_plot(shap_values[2], x_test_df, feature_names=feature_names)
```



In [111…

```
# Calculate the number of classes
num_classes = len(np.unique(y_test))

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

# Fit the classifier and obtain predicted probabilities
y_score = xgboost.fit(x_train_smote, y_train_smote).predict_proba(x_test)

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), y_score.ravel())
roc_auc_micro = auc(fpr_micro, tpr_micro)

# Compute macro-average ROC curve and ROC area
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(num_classes)]))
mean_tpr = np.zeros_like(all_fpr)
for i in range(num_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

mean_tpr /= num_classes

fpr_macro = all_fpr
tpr_macro = mean_tpr
roc_auc_macro = auc(fpr_macro, tpr_macro)

# Plot the ROC curve
```

```
plt.figure(figsize=(10, 8))

colors = ['red', 'green', 'blue']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='ROC curve of class {0} (area = {1:0.2f})'
                   ''.format(i, roc_auc[i]))

plt.plot(fpr_micro, tpr_micro, color='deeppink', linestyle=':', linewidth=4,
         label='Micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_micro))

plt.plot(fpr_macro, tpr_macro, color='navy', linestyle=':', linewidth=4,
         label='Macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc_macro))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend(loc="lower right")
plt.show()
```

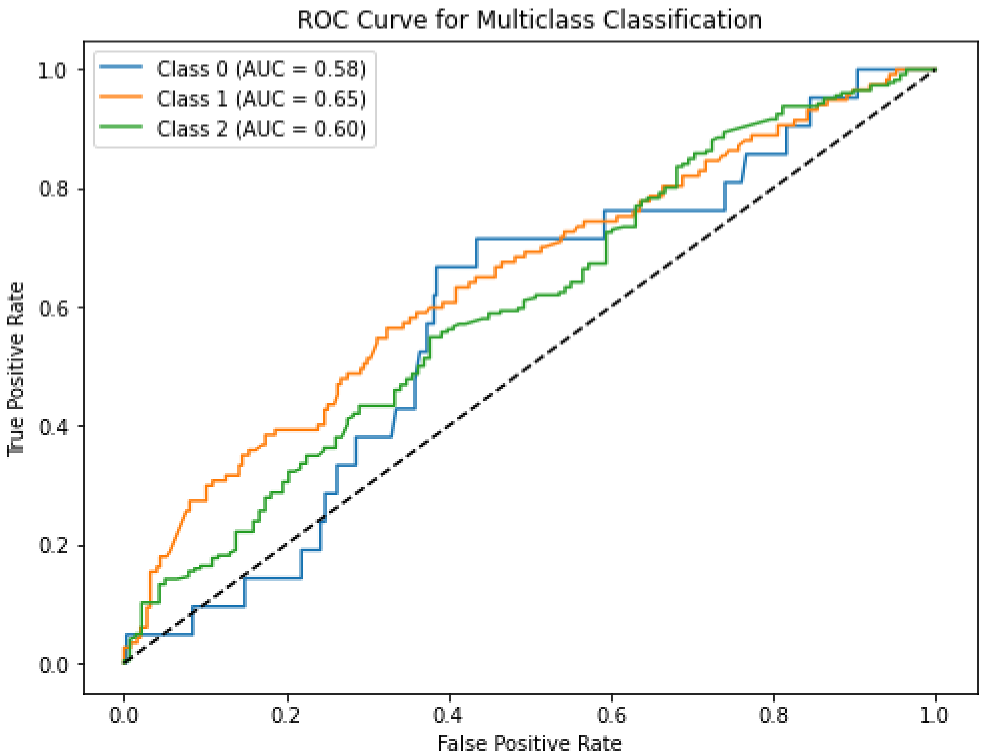


In [112…

```
# Predicted probabilities for each class
y_pred_proba = xgboost.predict_proba(x_test)

# Binarize the labels
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

# Initialize dictionaries and arrays for ROC calculations
fpr = dict()
```

```
tpr = dict()
roc_auc = dict()

# Compute ROC curve and ROC area for each class
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Calculate the average AUC
average_auc = np.mean(list(roc_auc.values()))

# Plot the ROC curve for each class
plt.figure(figsize=(8, 6))
for i in range(num_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Print the average AUC
print(f'Average AUC: {average_auc:.2f}')

# Plot the diagonal line
plt.plot([0, 1], [0, 1], linestyle='--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Multiclass Classification')
plt.legend()
plt.show()
```

```
Average AUC: 0.61
```



The Decision Tree, after hyperparameter tuning, achieves an accuracy of 51%, while its default version gives 50%. Random Forest shows the highest performance with an accuracy of 60%, whereas SVM performs lower with only 41%. XGBoost obtains an accuracy of 57%.

Looking at the confusion matrix, the Decision Tree, Random Forest, and XGBoost models tend to predict positive and neutral sentiments well, but there are also a considerable number of false positives and false negatives.

In terms of feature importances, attributes like work_life_balanced, place_segment, and job_type consistently play a decisive role in all models, indicating the importance of these aspects in influencing employee sentiments.

SHAP Plot analysis depicts that almost all models (except SVM) have a similar pattern, especially regarding attributes job_type and job_security. However, SVM, being a complex model, is challenging to interpret through this method.

Examining the ROC Curve, the Decision Tree model shows good performance for all three classes, while the other models exhibit some difficulty in distinguishing negative sentiments.

The observed subpar performance of the models can be attributed to several factors. One of them is that the distribution of values in the features tends to be limited to the range of 1 to 5, which can reduce the complexity and variability in the data. There is also an issue of class imbalance that might affect the models, especially if one class is dominant compared to others.

Future strategies:

1. Focus on improving the representation of minority classes for models that still struggle to predict those classes.
2. Reevaluate SVM parameters or consider another model to enhance performance.
3. Further explore patterns seen in the SHAP plots to gain deeper insights.
4. Fine-tune the models and consider using ensemble methods to improve accuracy and model generalization.
5. Consider normalizing or scaling features to a broader range like 0-1 to help the model capture more variability.
6. Data expansion, if possible, by adding variations to the data through sampling or generating synthetics, can assist the model in seeing more diverse cases.