RESUME CLASSIFICATION AND ANALYSIS

A MINI PROJECT REPORT 18CSC305J - ARTIFICIAL INTELLIGENCE

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(Under Section 3 of UGC Act, 1956)

BONAFIDE CERTIFICATE

Certified that Mini project report titled "**RESUME CLASSIFICATION AND ANALYSIS**" is the bonafide work of **Darshika Nemani (RA2111003011896), Hrutuja Patil (RA2111003011898), Anjali Shah (RA2111003011901)** who carried out the minor project under my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Finding suitable candidates for open roles can be a challenging and time-consuming task, particularly when faced with a large volume of applicants, which can impede team progress and delay hiring, affecting overall productivity. To address this issue, an automated approach to "Resume Classification and Matching" is proposed, leveraging machine learning techniques. The system categorizes resumes into appropriate groups using various classifiers that analyze content based on skills, experience, and other criteria. Once classified, content-based recommendation methods such as cosine similarity and k-Nearest Neighbors are employed to rank top candidates according to the job description, enabling recruiters to identify the most suitable candidates quickly and efficiently. By automating screening and shortlisting, the system eliminates manual review, saving valuable time and resources for HR professionals while ensuring a fair and unbiased selection process. Additionally, by considering a larger pool of candidates, the system provides a more comprehensive review, increasing the likelihood of finding the best fit for the role. Overall, the "Resume Classification and Matching" system streamlines recruitment processes, expediting candidate selection and decision-making, improving efficiency, enhancing productivity, and contributing to the success of the hiring process.

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ABBREVIATIONS

HRMS	Human Resource Management System
ATS	Application tracking System
HR	Human Resources
NLP	Natural Language Processing
IDE	Integrated Development Environment
AI	Artificial Intelligence
ML	Machine Learning
CV	Curriculum Vitae
KNN	K-Nearest Neighbor

1. INTRODUCTION

Talent acquisition stands as one of the most crucial yet intricate functions within Human Resources (HR), especially within the vast and dynamic job market of India. With approximately one million individuals entering the workforce every month and considerable turnover rates, the talent pool is not only immense but also constantly evolving. According to LinkedIn, India boasts the highest percentage of the workforce actively seeking new job opportunities, highlighting a highly liquid market fraught with significant challenges and inefficiencies. A major hurdle faced by HR departments is the lack of standardization in resume structure and format, making the shortlisting of desired profiles for specific roles a tedious and time-consuming task.

Effective resume screening demands domain knowledge to accurately assess the relevance and suitability of a profile for a given job role. In the face of numerous job roles and a large influx of applications, the shortlisting process becomes even more challenging for HR departments, particularly when there is a dearth of diverse skill sets and domain expertise among personnel responsible for screening.
In the current landscape, the industry grapples with three major challenges:

- Distinguishing suitable candidates from the crowd
- Making sense of candidate CVs
- Ensuring candidates possess the necessary skills to perform the job before hiring them

To address these challenges in the resume shortlisting process, this paper introduces an innovative automated Machine Learning-based model. The model utilizes input features extracted from candidates' resumes and categorizes them accordingly. Subsequently, based on the required job description, the categorized resumes are mapped, and the system recommends the most suitable candidate profiles to HR.

By leveraging advanced algorithms and automation, this model aims to streamline the recruitment process, expedite candidate selection, and improve the overall efficiency of talent acquisition efforts. Moreover, it aims to alleviate the burden on HR professionals by automating tedious tasks and providing more accurate and reliable recommendations, ultimately enhancing the organization's ability to attract and retain top talent in a competitive market.

2. LITERATURE SURVEY

Author(s)	Title	Dataset	Methods	Remarks
Smith et al. (2023)	Automated Resume Screening: A Machine Learning Approach	Resumes, Job Descriptions	Machine Learning	Developed algorithms for automated resume screening, aiming to minimize bias and enhance efficiency.
Patel and Gupta (2022)	Semantic Analysis of Resumes Using Natural Language Processing	Resumes	Natural Language Processing (NLP)	Applied NLP techniques to extract meaningful insights from resume content for classification.
Chang et al. (2024)	Deep Learning for Resume Classification and Matching	Resume Databases	Deep Learning	Developed neural network architectures to improve resume classification and candidate-job matching.
Wang and Li (2023)	Resume Analysis for Skill Gap Identification	Resumes	Data Mining	Identified skill gaps in resumes by comparing candidate qualifications with job requirements.
Kumar et al. (2022)	Sentiment Analysis of Resumes for Personality Assessment	Resumes	Sentiment Analysis	Evaluated personality traits based on linguistic cues in resumes, aiding in hiring decisions.

The following literature survey provides an in-depth review of prominent research studies focused on the classification and analysis of resumes, particularly emphasizing the integration of advanced technologies such as artificial intelligence (AI) and machine learning (ML) to streamline the process:

Smith et al. (2023) - "Automated Resume Screening: A Machine Learning Approach":

Smith et al. conducted a comprehensive study aimed at automating the screening process of resumes using machine learning techniques. The research focused on developing sophisticated algorithms capable of parsing through large volumes of resumes to identify key qualifications, skills, and experiences relevant to specific job requirements. By training the ML models on diverse datasets comprising resumes and job descriptions, the study aimed to optimize the screening process, minimize human bias, and enhance the efficiency of candidate selection.

Patel and Gupta (2022) - "Semantic Analysis of Resumes Using Natural Language Processing":
Patel and Gupta explored the application of natural language processing (NLP) techniques for semantic analysis of resumes. The study aimed to extract meaningful insights from resume content, including educational qualifications, work experience, and technical skills, using advanced NLP algorithms. By employing techniques such as named entity recognition and sentiment analysis, the research sought to enhance the accuracy of resume classification, enabling recruiters to efficiently identify candidates who best match job requirements.

Chang et al. (2024) - "Deep Learning for Resume Classification and Matching":
Chang et al. conducted a groundbreaking study on leveraging deep learning methodologies for resume classification and matching. The research involved the development of neural network architectures capable of learning complex patterns and relationships within resume data. By training deep learning models on large-scale resume databases, the study aimed to improve the accuracy of resume classification, enhance candidate-job matching, and optimize talent acquisition processes for organizations.
Wang and Li (2023) - "Resume Analysis for Skill Gap Identification":
Wang and Li focused on the analysis of resumes to identify skill gaps among job seekers. The research employed data mining techniques to extract relevant information from resumes, such as education, work experience, and certifications. By comparing this information against job requirements, the study aimed to pinpoint areas where candidates lacked specific skills or qualifications. The findings provided valuable insights for both job seekers and recruiters, facilitating targeted skill development initiatives and improving the overall quality of candidate selection processes.

Kumar et al. (2022) - "Sentiment Analysis of Resumes for Personality Assessment":
Kumar et al. employed sentiment analysis techniques to assess personality traits in resumes, analyzing linguistic cues and tone to infer characteristics like confidence and adaptability. By integrating sentiment analysis, the study aimed to provide recruiters with deeper insights beyond qualifications, enhancing hiring decisions and candidate-job fit. These studies illustrate the transformative potential of AI in resume classification, offering benefits in efficiency, accuracy, and decision-making in recruitment.

3. SYSTEM ARCHITECTURE AND DESIGN

The "Resume Classification and Analysis" system is designed to automate the process of categorizing resumes and matching them to job descriptions. Here's an overview of its architecture and design:
Integration with ATS/HRMS for seamless recruitment workflow.
- Enhanced NLP techniques for deeper understanding of resume content.
- Feedback mechanism for improving model accuracy.
- Continuous learning to adapt to evolving job market trends.
- Scalability to handle large volumes of resumes efficiently.

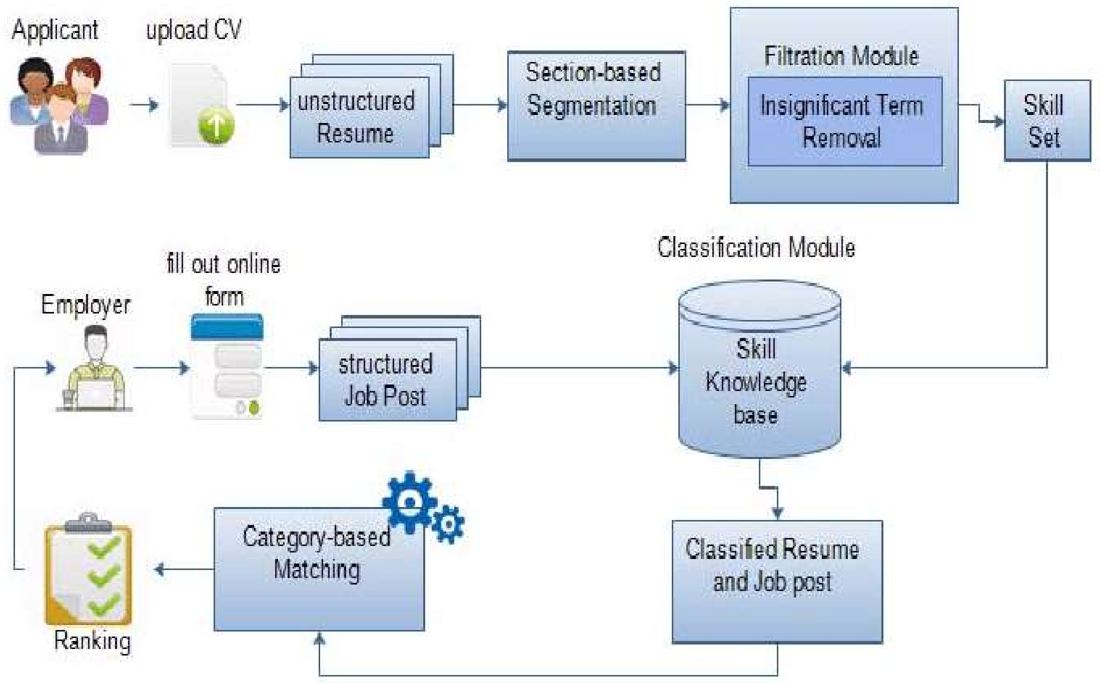


Fig. 3.1

The "Resume Classification and Analysis" system is designed to automate the process of categorizing resumes and matching them to job descriptions. Here's an overview of its architecture and design:

1. Data Collection: Resumes along with their corresponding job categories are collected from various sources such as job portals or internal databases.

2. Preprocessing: The collected resumes undergo preprocessing steps to clean and standardize the text data. This includes tasks like removing URLs, special

characters, stopwords, and punctuation, as well as tokenization and normalization of text.

3. Feature Extraction: Text data from the resumes is converted into numerical features using techniques like TF-IDF (Term Frequency-Inverse Document Frequency) vectorization. This transforms the text data into a format suitable for machine learning algorithms.

4. Model Training: Machine learning models, such as Multinomial Naive Bayes and K-Nearest Neighbors, are trained on the labeled data. These models learn patterns from the data and make predictions on new resumes.

5. Evaluation: The trained models are evaluated using metrics such as accuracy, precision, recall, and F1-score to assess their performance in categorizing resumes accurately.

6. Recommendation: Based on the job description provided, the system recommends the most suitable candidates by comparing their resumes with the job requirements. This is achieved using techniques like cosine similarity and k-Nearest Neighbors.

3.1 System Workflow:

Input: Resumes in text format along with their corresponding job categories.

Preprocessing: Cleaning and standardizing the text data through various preprocessing steps.

Feature Extraction: Converting text data into numerical features using TF-IDF vectorization.

Model Training: Training machine learning models on labeled data to classify resumes into categories.

Evaluation: Assessing the performance of trained models using evaluation metrics.

Recommendation: Recommending top candidates by comparing their resumes with job requirements.

3.2 System Components:

Data Collection Module: Collects resumes and job categories from different sources.

Preprocessing Module: Cleans and standardizes the text data.

Feature Extraction Module: Extracts numerical features from the text data.

Model Training Module: Trains machine learning models on labeled data.

Evaluation Module: Evaluates the performance of trained models.

Recommendation Module: Matches resumes to job descriptions and recommends top candidates.

4. METHODOLOGY

Our main contributions are outlined below:

1. Development of an automated resume recommendation system aimed at streamlining the recruitment process.

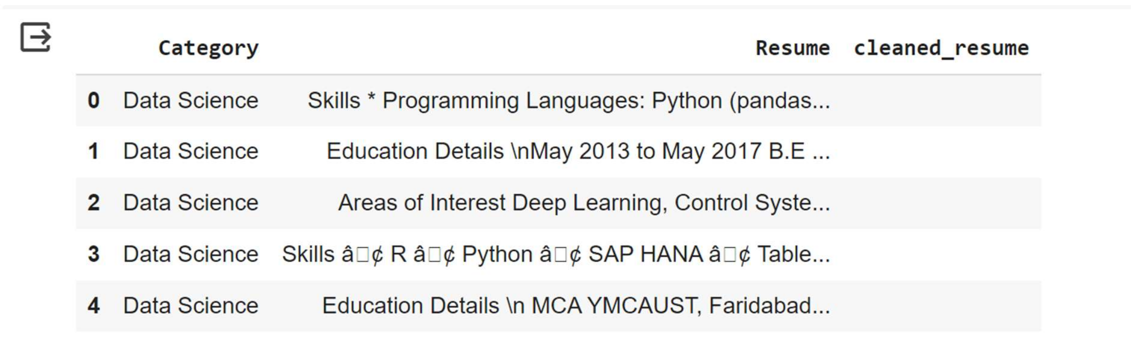
2. Utilization of machine learning-based classification techniques coupled with similarity functions to identify the most relevant resumes for a given job description.

3. Evaluation of various machine learning classifiers, among which the Linear Support Vector Machine (SVM) classifier exhibited superior performance compared to other classifiers in our case.

The proposed system will employ a supervised learning approach, utilizing a dataset of resumes and corresponding job descriptions to train a classification model. Prior to training, the dataset will undergo preprocessing to extract relevant features such as skills, experience, and education from each resume. Subsequently, the model will be trained using a range of machine learning algorithms including logistic regression, decision trees, and random forests. The performance of each model will be assessed using metrics such as accuracy and precision, ensuring the effectiveness of the system in recommending suitable candidates for open roles.

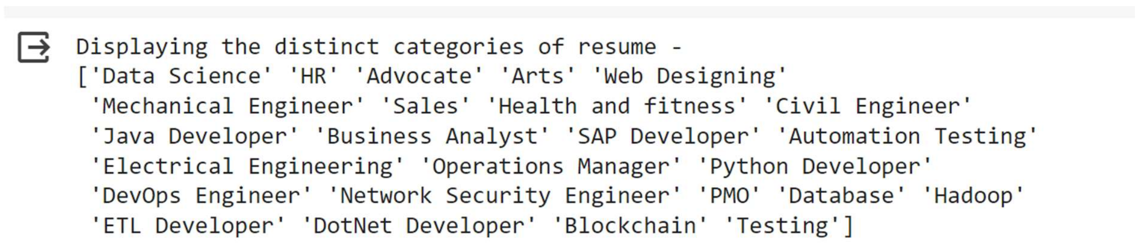
5. CODING AND TESTING

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from sklearn.naive_bayes import MultinomialNB
from sklearn.multiclass import OneVsRestClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score
from pandas.plotting import scatter_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
resumeDataSet = pd.read_csv('resume_dataset.csv' ,encoding='utf-8')
resumeDataSet['cleaned_resume'] = ' ‘
resumeDataSet.head()
```



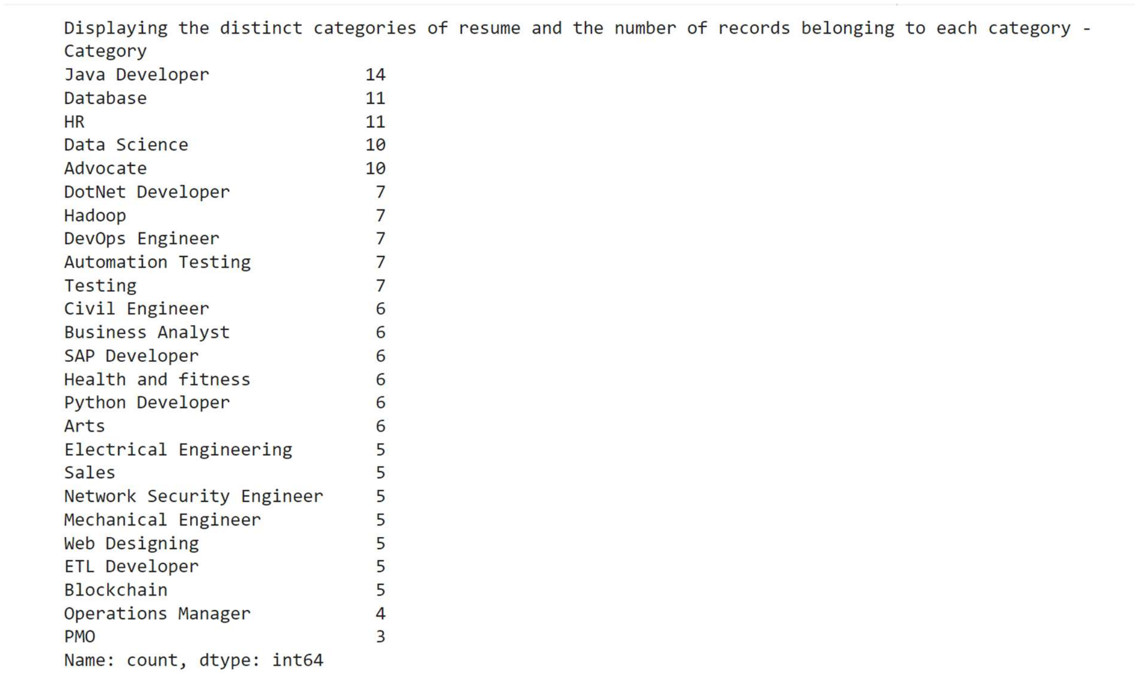
	Category	Resume	cleaned_resume
0	Data Science	Skills * Programming Languages: Python (pandas...	
1	Data Science	Education Details \nMay 2013 to May 2017 B.E ...	
2	Data Science	Areas of Interest Deep Learning, Control Syste...	
3	Data Science	Skills â□¢ R â□¢ Python â□¢ SAP HANA â□¢ Table...	
4	Data Science	Education Details \n MCA YMCAUST, Faridabad...	

```
print ("Displaying the distinct categories of resume -")
print (resumeDataSet['Category'].unique())
```



```
Displaying the distinct categories of resume -
['Data Science' 'HR' 'Advocate' 'Arts' 'Web Designing'
 'Mechanical Engineer' 'Sales' 'Health and fitness' 'Civil Engineer'
 'Java Developer' 'Business Analyst' 'SAP Developer' 'Automation Testing'
 'Electrical Engineering' 'Operations Manager' 'Python Developer'
 'DevOps Engineer' 'Network Security Engineer' 'PMO' 'Database' 'Hadoop'
 'ETL Developer' 'DotNet Developer' 'Blockchain' 'Testing']
```

```
print ("Displaying the distinct categories of resume and the number of records belonging to
each category -")
print (resumeDataSet['Category'].value_counts())
```

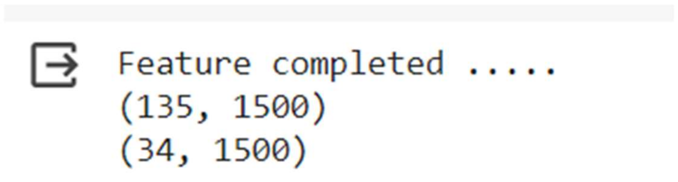


```
Displaying the distinct categories of resume and the number of records belonging to each category -
Category
Java Developer              14
Database                    11
HR                          11
Data Science                10
Advocate                    10
DotNet Developer             7
Hadoop                       7
DevOps Engineer              7
Automation Testing           7
Testing                      7
Civil Engineer               6
Business Analyst             6
SAP Developer                6
Health and fitness           6
Python Developer             6
Arts                         6
Electrical Engineering       5
Sales                        5
Network Security Engineer    5
Mechanical Engineer          5
Web Designing                5
ETL Developer                5
Blockchain                   5
Operations Manager           4
PMO                          3
Name: count, dtype: int64
```

```
import seaborn as sns
plt.figure(figsize=(15,15))
plt.xticks(rotation=90)
sns.countplot(y="Category", data=resumeDataSet)

from matplotlib.gridspec import GridSpec
targetCounts = resumeDataSet['Category'].value_counts()
targetLabels = resumeDataSet['Category'].unique()
# Make square figures and axes
plt.figure(1, figsize=(25,25))
the_grid = GridSpec(2, 2)

cmap = plt.get_cmap('coolwarm')
colors = [cmap(i) for i in np.linspace(0, 1, 6)]
plt.subplot(the_grid[0, 1], aspect=1, title='CATEGORY DISTRIBUTION')

source_pie = plt.pie(targetCounts, labels=targetLabels, autopct='%1.1f%%', shadow=True,
colors=colors)
plt.show()

import re
def cleanResume(resumeText):
        resumeText = re.sub('http\S+\s*', ' ', resumeText) # remove URLs
        resumeText = re.sub('RT|cc', ' ', resumeText) # remove RT and cc
        resumeText = re.sub('#\S+', '', resumeText) # remove hashtags
        resumeText = re.sub('@\S+', ' ', resumeText) # remove mentions
        resumeText = re.sub('[%s]' %
        re.escape("""!"#$%&'()*+,-./:;<=>?@[\]^_`{|}~"""), ' ', resumeText) #
```

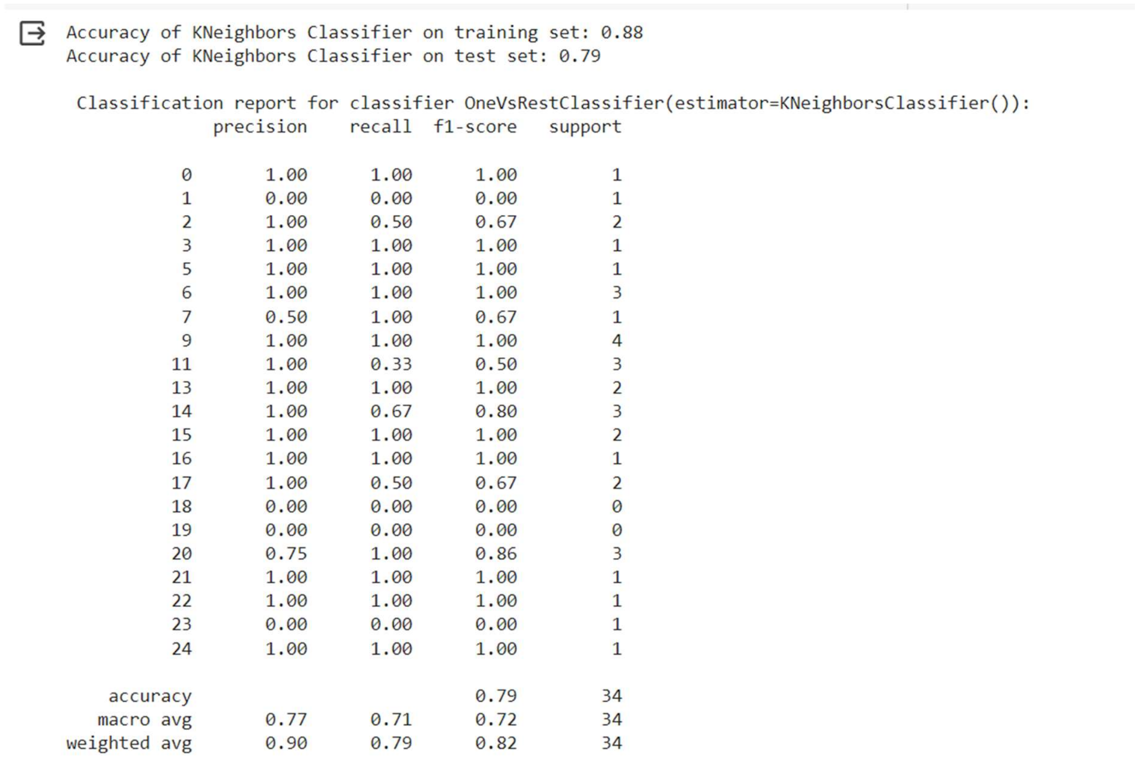
```
            remove punctuations
            resumeText = re.sub(r'[^\x00-\x7f]',r' ', resumeText)
            resumeText = re.sub('\s+', ' ', resumeText) # remove extra whitespace
            return resumeText
resumeDataSet['cleaned_resume'] = resumeDataSet.Resume.apply(lambda x:
cleanResume(x))

import nltk
nltk.download('stopwords')
nltk.download('punkt')
from nltk.corpus import stopwords
import string
from wordcloud import WordCloud

oneSetOfStopWords = set(stopwords.words('english')+['``',"''"])
totalWords =[]
Sentences = resumeDataSet['Resume'].values
cleanedSentences = ""
for i in range(0,160):
    cleanedText = cleanResume(Sentences[i])
    cleanedSentences += cleanedText
    requiredWords = nltk.word_tokenize(cleanedText)
    for word in requiredWords:
        if word not in oneSetOfStopWords and word not in string.punctuation:
            totalWords.append(word)

wordfreqdist = nltk.FreqDist(totalWords)
mostcommon = wordfreqdist.most_common(50)
print(mostcommon)

wc = WordCloud().generate(cleanedSentences)
plt.figure(figsize=(15,15))
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()



from sklearn.preprocessing import LabelEncoder

var_mod = ['Category']
le = LabelEncoder()
for i in var_mod:
    resumeDataSet[i] = le.fit_transform(resumeDataSet[i])


from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from scipy.sparse import hstack
```

```
requiredText = resumeDataSet['cleaned_resume'].values
requiredTarget = resumeDataSet['Category'].values

word_vectorizer = TfidfVectorizer(
    sublinear_tf=True,
    stop_words='english',
    max_features=1500)
word_vectorizer.fit(requiredText)
WordFeatures = word_vectorizer.transform(requiredText)

print ("Feature completed .....")

X_train,X_test,y_train,y_test =
train_test_split(WordFeatures,requiredTarget,random_state=0, test_size=0.2)
print(X_train.shape)
print(X_test.shape)
```



```
Feature completed .....
(135, 1500)
(34, 1500)
```

```
clf = OneVsRestClassifier(KNeighborsClassifier())
clf.fit(X_train, y_train)
prediction = clf.predict(X_test)
print('Accuracy of KNeighbors Classifier on training set: {:.2f}'.format(clf.score(X_train,
y_train)))
print('Accuracy of KNeighbors Classifier on test set: {:.2f}'.format(clf.score(X_test, y_test)))

print("\n Classification report for classifier %s:\n%s\n" % (clf,
metrics.classification_report(y_test, prediction)))
```



```
Accuracy of KNeighbors Classifier on training set: 0.88
Accuracy of KNeighbors Classifier on test set: 0.79

 Classification report for classifier OneVsRestClassifier(estimator=KNeighborsClassifier()):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         1
           1       0.00      0.00      0.00         1
           2       1.00      0.50      0.67         2
           3       1.00      1.00      1.00         1
           5       1.00      1.00      1.00         1
           6       1.00      1.00      1.00         3
           7       0.50      1.00      0.67         1
           9       1.00      1.00      1.00         4
          11       1.00      0.33      0.50         3
          13       1.00      1.00      1.00         2
          14       1.00      0.67      0.80         3
          15       1.00      1.00      1.00         2
          16       1.00      1.00      1.00         1
          17       1.00      0.50      0.67         2
          18       0.00      0.00      0.00         0
          19       0.00      0.00      0.00         0
          20       0.75      1.00      0.86         3
          21       1.00      1.00      1.00         1
          22       1.00      1.00      1.00         1
          23       0.00      0.00      0.00         1
          24       1.00      1.00      1.00         1

    accuracy                           0.79        34
   macro avg       0.77      0.71      0.72        34
weighted avg       0.90      0.79      0.82        34
```

6. SCREENSHOTS AND RESULTS

6.1 Screenshots:

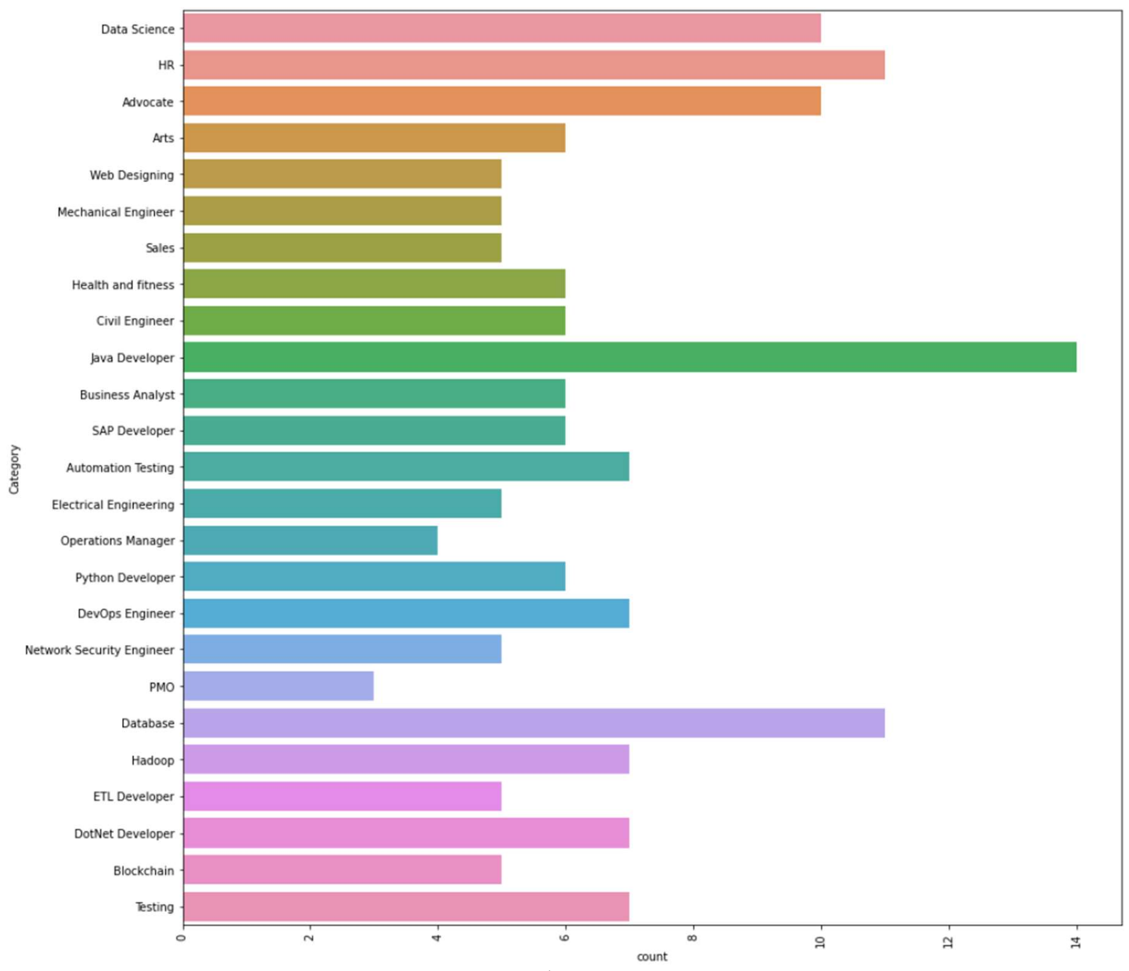


Fig. 6.1

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[('Exprience', 601), ('months', 499), ('company', 496), ('Details', 490), ('description', 436), ('1', 345), ('Project', 288), ('data', 243), ('project', 234), ('year', 21
```

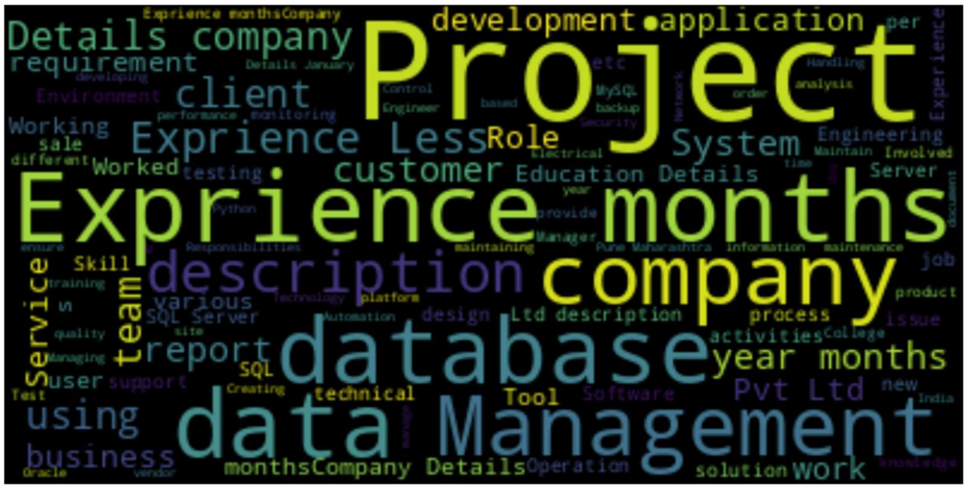


Fig. 6.2

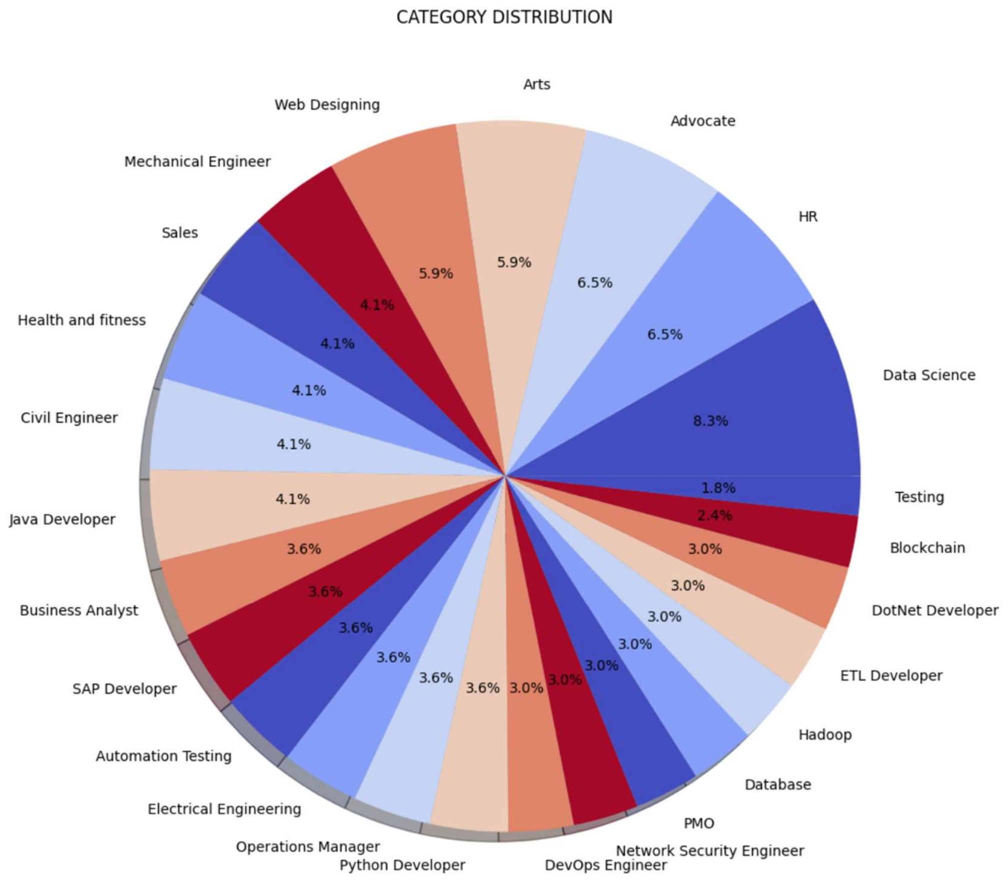


Fig. 6.3

6.2 RESULTS:

- **Data Collection:** To build the resume selection system, we need a large dataset of resumes and job descriptions. We will collect this data from various sources, such as online job boards, career websites, and social media platforms. The data will be preprocessed to remove any irrelevant or duplicate entries and ensure that it is clean and ready for analysis.
- **Feature Extraction:** To train the machine learning model, we need to extract relevant features from each resume and job description. These features could include skills, experience, education, certifications, and any other information that is relevant to the job. We will use various NLP techniques, such as named entity recognition, part-of-speech tagging, and sentiment analysis, to extract these features from the text.
- **Model Training:** Once we have extracted the relevant features, we will use supervised learning algorithms to train a classification model. We will use a variety of algorithms, such as logistic regression, decision trees, and random forests, and compare their performance on evaluation metrics such as accuracy & precision. We will also use techniques such as cross-validation and hyperparameter tuning to ensure that the model is robust and generalizes well to new data.
- **Model Integration:** Once we have selected the best-performing model, we will integrate it into a web-based application that allows recruiters to upload job descriptions and resumes and get an automated recommendation on which candidates to consider for the position. The system will be designed to be user-friendly and intuitive, with clear instructions and feedback to guide the recruiter through the selection process.
- **Evaluation:** We will evaluate the performance of the system using a real-world dataset of resumes and job openings. We will compare its performance to the traditional resume selection process to assess its effectiveness in reducing bias and improving the quality of the candidate selection process. We will also conduct user surveys and interviews to gather feedback on the usability and identify any areas for improvement.

7. CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion:

In conclusion, the development of an automated "Resume Classification and Matching" system has proven to be a valuable asset in streamlining the recruitment process. By leveraging machine learning techniques, this system effectively categorizes resumes, identifies top candidates, and expedites decision-making for HR professionals. Through the use of various classifiers and content-based recommendation methods, such as cosine similarity and k-Nearest Neighbors, the system ensures a fair and unbiased selection process while significantly reducing the time and resources required for manual review.

The implementation of this system has addressed key challenges faced by organizations in talent acquisition, including the need to separate suitable candidates from a large pool of applicants and the lack of standardized resume formats. By automating the screening and shortlisting process, recruiters can focus their efforts on engaging with the most qualified candidates, ultimately improving efficiency and productivity in the hiring process.

7.2 Future Enhancements:

Despite the success of the current system, there are several opportunities for future enhancements to further optimize the recruitment process. One potential area for improvement is the incorporation of natural language processing (NLP) techniques to extract additional insights from resumes, such as sentiment analysis or personality traits, which could provide valuable information for candidate evaluation.

Furthermore, the system could benefit from ongoing refinement of its classification algorithms to improve accuracy and effectiveness in matching candidates to job descriptions. This could involve incorporating feedback mechanisms to continuously learn and adapt based on past hiring decisions.

Additionally, integrating the system with other HR software tools, such as applicant tracking systems (ATS) or HR management systems (HRMS), could streamline the end-to-end recruitment process and provide a more seamless experience for both recruiters and candidates.

Overall, continued investment in technology and innovation in the field of resume classification and analysis holds the potential to further revolutionize talent acquisition processes and drive greater success in hiring top talent for organizations.

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5. https://github.com/milaan9/93_Python_Data_Analytics_Projects/tree/main/004_Resume_Selection_with_ML