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Resume Screening using Natural Language Processing and Multiclass Classification

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ABSTRACT

An important stage in the recruitment process is resume screening. It is currently done manually, labor-intensive, and is prone to human mistake. Term Frequency-Inverse Document Frequency (TF-IDF) is used for feature extraction and a One-vs-Rest (OvR) framework is applied for multiclass classification. Resumes are preprocessed using natural language processing (NLP) techniques. The processed text is subsequently converted from categorical features into numerical feature vectors by the TF-IDF vectorizer [2,3,5] , which measures each resume's phrase relevance in relation to the whole dataset. By fitting one classifier per class, the K-NN classifier, set up in an OvR method, uses these vectors as inputs to handle multiple job role classifications. Using a labeled resume dataset, this system is assessed and shown to be able to accurately and effectively classify job prospects into suitable jobs. The method emphasizes how streamlining the hiring process with a combination of NLP and machine learning tools can improve efficiency in choosing candidates. This screening method increases the accuracy of resume reviews while also requiring less time and effort.

Keywords: NLP, TF-IDF, OvR, KNN, Multiclass Classification

I. INTRODUCTION

A.Overview

Companies employ resume screening, which is similar to a preliminary review of job applications, to sift through a large number of resumes and identify the top candidates for their open positions. By doing this, they ensure that the correct personnel are chosen for the task and save time. Resume screening, whether carried out by humans or algorithms, is crucial for locating the most eligible applicants as soon as possible. It speeds up the hiring process and assists businesses in concentrating on the best applicants. Resume screening is used by businesses in a variety of sectors, including technology and healthcare, to assist them handle the volume of job applications they get. It's especially helpful for jobs where a large number of candidates are vying for the same post.

B.Problem Definition

The employment procedure that is too labor-intensive and prone to mistakes due to the volume of resumes it cannot process. For businesses looking for effective candidate selection procedures in the cutthroat job market of today, the amount of incoming resumes presents a major obstacle. Conventional manual resume screening techniques are frequently time-consuming, biased, and difficult. However, there is a potential chance to efficiently streamline this procedure with the advent of Natural Language Processing (NLP) techniques and machine learning algorithms Some of the problems that have arisen include the challenges of extracting relevant profiles from a large number of resumes, the requirement for a more efficient and standardized screening process, and the need for a solution that minimizes manual processing while ensuring accurate candidate selection based on job descriptions.

C.Objectives

This research presents a novel resume screening method based on TF-IDF word representation and K-Nearest Neighbors (KNN) One-vs-Rest classification. Our approach uses natural language processing (NLP) to extract valuable information from unstructured resume text, and the KNN One-vs-Rest classifier uses job eligibility criteria to classify resumes into predetermined groups. Furthermore, by measuring a word's significance in a resume in relation to the entire corpus, TF-IDF word representation improves feature extraction and increases classification accuracy.

This research is important because it has the potential to transform hiring procedures and help companies and job seekers alike. Employers stand to benefit from lower time and resource costs related to manual screening while also enhancing the caliber and impartiality of candidate selection. Conversely, job candidates gain from an impartial and open review procedure that guarantees equal chances based on merit rather than unimportant variables.

In this study, we offer a thorough overview of the used methodology, including assessment metrics, KNN One-vs-Rest model training, TF-IDF word representation, and data preprocessing. The outcomes of our experiments show how effective and scalable our method is in a variety of datasets and sectors. We also go over the potential applications, difficulties, and future possibilities of using TF-IDF word representation and KNN One-vs-Rest classification in real-world recruitment settings.

Through its ability to connect cutting-edge machine learning methods with real-world applications, this study adds to the current conversation on talent acquisition process optimization in the digital era. We think that our strategy has a great deal of potential to transform resume screening procedures and open the door to more effective, transparent, and fair hiring methods.

II.LITERATURE SURVEY

Numerous studies highlight the significance of automatically reviewing resumes in the recruiting process. Shortlisting resumes is a vital step. Effective talent acquisition leads to improved selection of applicants for specific job roles. Automated resume shortlisting saves time, maintains consistency, and minimizes bias, resulting in efficient and fair applicant selection. Several researches and articles have analyzed resume screening methods and machine learning algorithms to compare their performance.

Table 1. Insight about various papers published in previous years

Year	Title	Dataset	Algorithm/Approaches	Remarks
[1] Dr. Ambareesh S et al. (2024)	Resume Shortlisting Using NLP	A collection of 2452 resumes is gathered in the dataset.	The core steps in the system include parsing resume to text, performing NLP creating a NER model and using NER model to calculate P, R and F score to generate final score to sort resume based on final score.	Natural Language processing (NLP) based resume shortlisting research has shown great potential for accelerating the hiring process.
[2] Anuska Mukherjee et al. (2024)	Resume Ranking and Shortlisting with DistilBERT and XLM	Data set consists of a total 1008 candidates in 26 job categories.	It utilizes distilBERT model and the XLM (Cross-lingual Language Model).	Test accuracy of 95% was achieved.
[3] Asim Wahedna et al. (2024)	Resume Screening–Testing For Data Stability	Dataset consists of 532 different resume pdf files, all provided by a third party source.	NLP techniques used for resume extraction, such as Named Entity Recognition, along with the machine learning algorithms such as cosine similarity.	This model provided an accuracy of 74%.
[4] B.Surendiran et al. (2023)	Resume Classification Using ML Techniques	Dataset having 3446 resumes in 48 different professions from a different of fields.	Machine learning algorithms such as decision Tree, Random Forest, KNN, Support Vector are researched.	Random forest classifiers gave the highest accuracy (91%).
[5] Muskan Sharma et al. (2023)	Resume Classification using Elite Bag-of-Words Approach	Dataset consists of a 1738 training samples and 744 testing samples of resumes.	For the vectorization of resumes , Elite bag-of-words are used.	It gave test accuracy of 62.6%.
[6] Bhoomika SP et al. (2023)	2Q-Learning Scheme for Resume Screening	Dataset consists of a labeled resumes.	It uses a 2Q-Learning-based approach with natural language processing.	This model provided a higher accuracy than the existing traditional string-matching approaches.
[7] Yumula Mani Harsha et al.	Automated Resume Screener using	CSV(comma-separated values) file	It is based on Natural Language Processing (NLP) and automated	A user interface was developed.

(2022)	Natural Language Processing (NLP)	having various skills under various roles.	Machine Learning.	
[8] S Bharadwaj et al. (2022)	Resume Screening using NLP and LSTM	Dataset consists of 962 resumes and 25 job categories.	This system worked on NLP and LSTM.	90% of the selection process of resumes can be achieved in future.
[9] Rasika Ransing et al. (2021)	Screening and Ranking Resumes using Stacked Model	The data is in CSV format which includes two columns that are Roles and Resumes.	Machine Learning algorithms such as KNN, Linear SVC, and XGBoost.	Highest accuracy was achieved by XG Boost (85%).
[10] Vishruth R G et al. (2020)	Resume Scanning and Emotion Recognition System based on Machine Learning Algorithms	The dataset used was a Javascript object notion.	Comprises three modules: Resume scanning, Chatbot implementation, and Emotion Recognition	66% accuracy was achieved.

III. PROPOSED METHODOLOGY

A.Dataset:

The dataset consists of 962 resumes from various fields and professions. This dataset is designed for analyzing and classifying resumes based on their content into different job categories.There are 25 categories,including Health and fitness, Python Developer, Java Developer, Testing, DotNet Developer, Web Designing, HR, Hadoop, ETL Developer, Data Science, Sales, Mechanical Engineer, Database, Electrical Engineering, PMO, Business Analyst,Operations Manager, Automation Testing, Arts, Network Security Engineer, SAP Developer, Civil Engineer,DevOps Engineer,Blockchain and Advocate.

B.Model Workflow

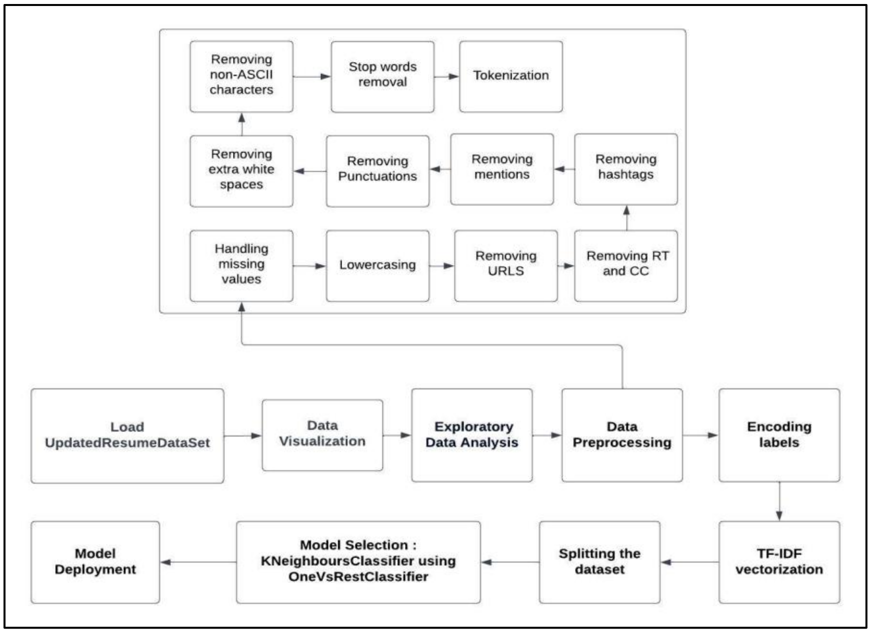

Fig 1. Workflow diagram

Fig 1. depicts the steps for creating a machine learning model for resume screening. The procedure starts with intensive data preparation, which involves stages like eliminating non-ASCII characters, stop words, and punctuation; tokenization; deleting mentions, hashtags, URLs, retweets, and additional white spaces; converting text to lowercase; and dealing with missing information. Following preprocessing, the dataset is imported for data visualization and exploratory data analysis to better understand data distribution and linkages. The next stage is to encode labels for classification and use TF-IDF vectorization to convert the text input into numerical features. The dataset is splitted into training and test sets, and a K-Nearest Neighbors classifier is chosen to train the model using the OneVsRest approach. Finally, the trained model is released for usage.

C.Data Visualization

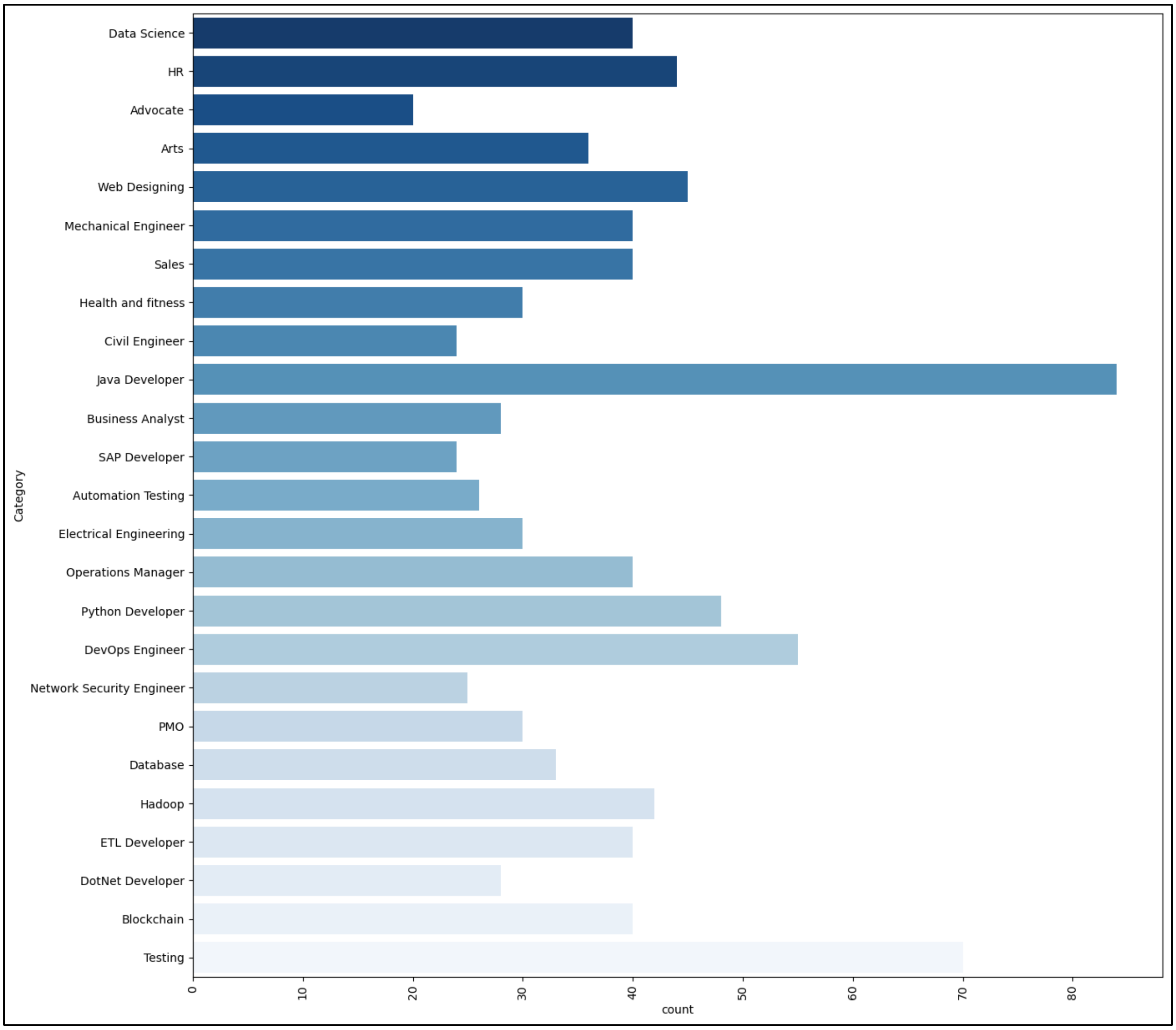

Fig 2. Countplot of Job Categories

Fig 2. shows the numbers for various employment positions, with Java Developer having the highest count of over 80. Python Developer and DevOps Engineer both have substantial numbers, approximately 50 apiece. SAP Developer, Automation Testing, and Electrical Engineering have moderate numbers of 30 to 40. Lower numbers, less than 20, are observed for positions such as DotNet Developer, Testing,Blockchain and ETL Developer.

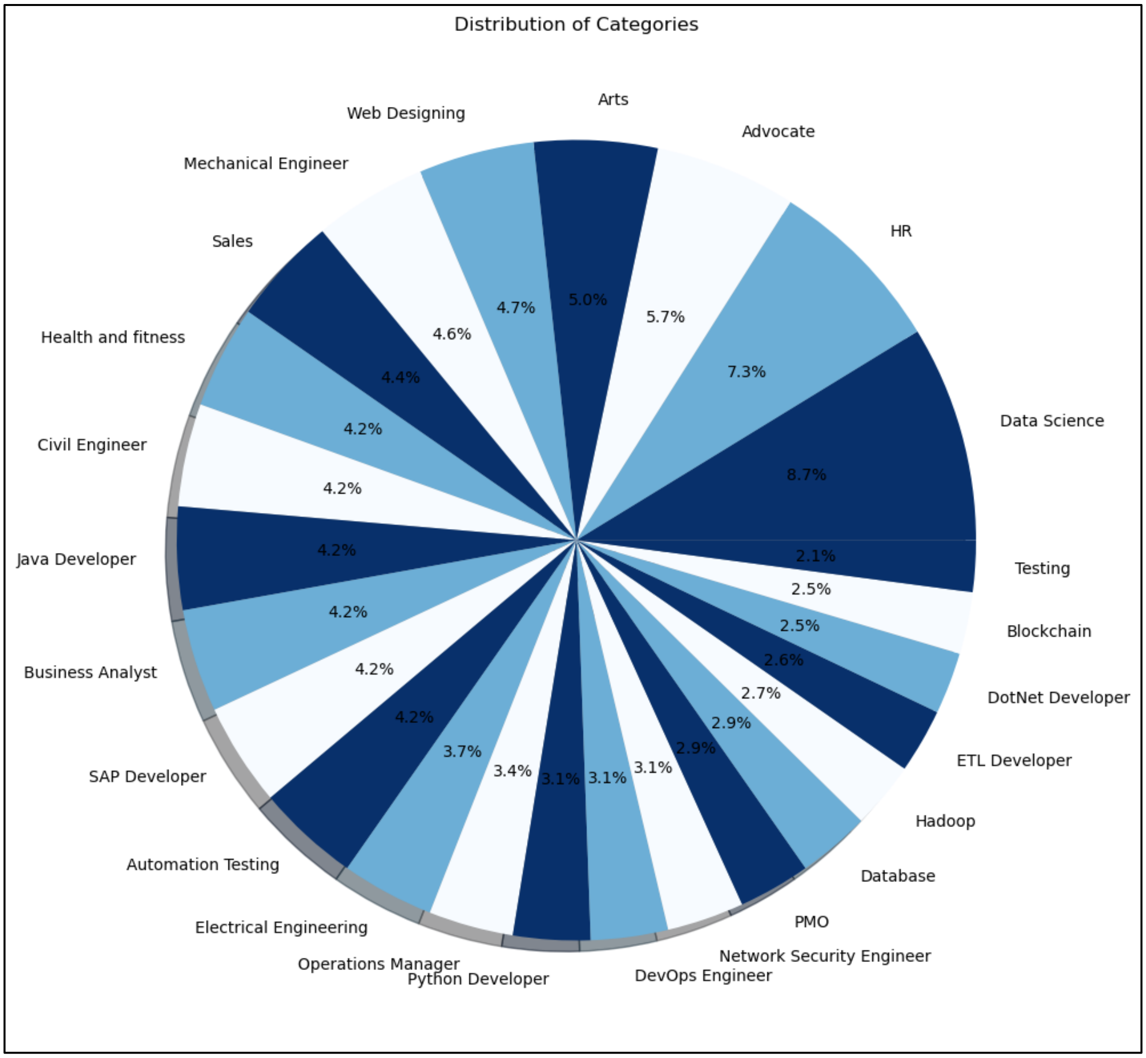

Fig 3. Pie chart Distribution of Categories

This pie chart given in Fig 3. shows the percentage distribution of different employment types. The largest segment, Java Developer, accounts for 8.7% of the total. Data Science and Human Resources follow at 7.3% and 5.7%, respectively. Advocate, Arts, and Web Designing account for roughly 5%, whereas Python Developer, DevOps Engineer, and Network Security Engineer have lesser proportions ranging from 3.1% to 3.4%. The smallest segments are Testing (2.1%) and Blockchain (2.5%), suggesting that these categories have fewer numbers than others.

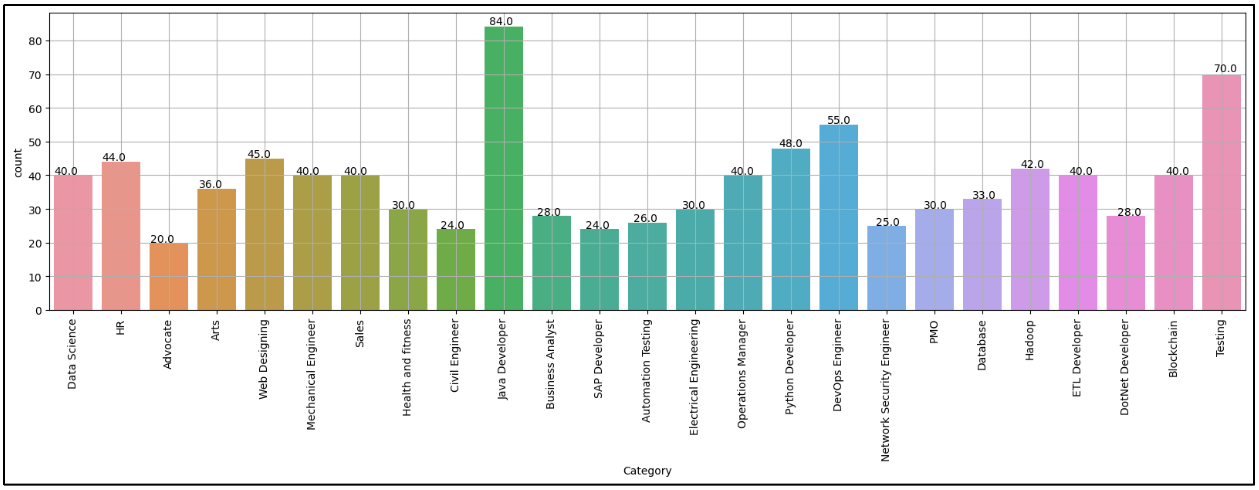

Fig 4. Bar plot of Job Categories

Fig 4. depicts the distribution of resumes across different job categories. Each bar represents a separate category, and its height indicates the number of resumes in that group. Categories such as Java Developer and Testing contain much more resumes, with 84 and 70, respectively, indicating a greater interest or availability in these sectors. Conversely, categories such as Advocate and Civil Engineer have fewer resumes, with counts of 20 and 24, indicating a lesser participation in these fields. This visualization aids in understanding data distribution and identifying groups with the highest or lowest number of resumes, which may be valuable in focused recruiting tactics.

Fig 5. Word Cloud of most frequent words in the cleaned dataset

The word cloud given in Fig 5. depicts the most often used terms in the resume dataset, with bigger words indicating greater frequency. Prominent phrases such as "Experience," "Details," "Data Science," and "Company" indicate that these are significant components frequently stated on resumes. The prominence of terminology like "Machine Learning" and "Deep Learning" emphasizes the importance of technical abilities and modern technology. Furthermore, phrases like "year," "months," and "less" are common indications of employment length and experience level.

C.Data Preprocessing

The process begins by defining a function cleanResume that utilizes regular expressions to systematically eliminate various types of unwanted text. Specifically, the function removes URLs, occurrences of "RT" and "cc", hashtags, and mentions (indicated by '@'). Additionally, it strips away all punctuation marks and non-ASCII characters, ensuring that only standard textual content remains. Furthermore, the function condenses multiple spaces into a single space to maintain uniform spacing. After defining the cleaning function, it is applied to a dataset, presumably a pandas DataFrame named resumeDataSet, which contains a 'Resume' column with raw text data. The apply method is used to invoke the cleanResume function on each resume in the 'Resume' column, and the cleaned text is stored in a new column called 'cleaned_resume'. This preprocessing step standardizes the resumes, making them more suitable for text mining, natural language processing (NLP), or machine learning tasks.

Stop words removal :

The necessity to remove stopwords in NLP depends on the task at hand. For text classification, removing them is one thing that has always been done. This is useful since it allows one to concentrate better on those words which express the meaning of the text itself for example there, book and table as opposed to less meaningful ones like is and on as seen earlier. In these situations all words matter since they are essential in keeping the original meaning intact.

Tokenization:

In NLP, tokenization [4,8] is the process of dividing text into smaller units called tokens, mostly words or sub-words. Many NLP tasks require tokenization as a first step, such as text processing, language modeling and machine translation. This means breaking up a string or piece of text into separate tokens. For instance in a sentence containing many words, it can be seen that there are several tokens in it like the word and sentence and paragraph.The aim of this process is to use a tokenizer to segment unstructured data and natural language texts by treating them as separate entities like individual components. The tokens present in the document can be used as vectors that change an unstructured text document into numerical data structures suitable for machine learning purposes. This process makes it possible for computers to promptly use these tokenized elements to generate practical actions or responses. Or they may be part of machine learning pipelines where more complex decisions would become available so that there could be improved implementations.

Feature extraction by text vectorization:

A. **Label Encoding [9]:** It is used to convert categorical values into numerical values.

B. **Term Frequency-Inverse Document Frequency(TF-IDF):** For featurization, we use TF-IDF. Here, each word is mapped to its frequency in a given dictionary or word map and multiplied by a weight representing how rare this keyword is across all documents. What distinguishes the TF-IDF from the traditional method is its ability to recognize and underline important key terms. There are two parts involved in calculating it.One is creating the Term Frequency (TF) matrix while the other one is constructing Inverse Document Frequency (IDF) matrix. These two matrices are then multiplied together.

F.Modeling

20% of the dataset will be allocated to the test set, while the remaining 80% is used for training the model. The OneVsRestClassifier with K-Nearest Neighbours (KNN) is a multiclass classification approach that trains KNN classifiers separately for each class.The one-vs-Rest technique divides a multiclass classification into one binary classification issue for each class. In this technique, each classifier separates one class from all others, presenting the issue as binary classification. During prediction, the classifiers work together to identify the class of a new data point by choosing the class with the greatest confidence score from each binary classifier.KNN classifier make predictions by grouping individual data points .This approach takes use of the simplicity of KNN and extends it to multiclass classification by successfully merging several binary judgements.

IV.RESULTS AND DISCUSSION

The performance metrics for a K-Neighbors Classifier utilizing the OneVsRestClassifier approach,in Fig 6., as measured for a resume screening assignment achieves an astounding 99% accuracy, demonstrating outstanding generalization. The complete classification report contains precision, recall, and F1-scores for each of the 25 resume categories, with the majority of categories receiving perfect scores (1.00) on all metrics. Categories with minor variances, such as category 2 (precision: 1.00)

```
Accuracy of KNeighbors Classifier on training set: 0.99
Accuracy of KNeighbors Classifier on test set: 0.99

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

           0       1.00      1.00      1.00         3
           1       1.00      1.00      1.00         3
           2       1.00      0.80      0.89         5
           3       1.00      1.00      1.00         9
           4       1.00      1.00      1.00         6
           5       0.83      1.00      0.91         5
           6       1.00      1.00      1.00         9
           7       1.00      1.00      1.00         7
           8       1.00      0.91      0.95        11
           9       1.00      1.00      1.00         9
          10       1.00      1.00      1.00         8
          11       0.90      1.00      0.95         9
          12       1.00      1.00      1.00         5
          13       1.00      1.00      1.00         9
          14       1.00      1.00      1.00         7
          15       1.00      1.00      1.00        19
          16       1.00      1.00      1.00         3
          17       1.00      1.00      1.00         4
          18       1.00      1.00      1.00         5
          19       1.00      1.00      1.00         6
          20       1.00      1.00      1.00        11
          21       1.00      1.00      1.00         4
          22       1.00      1.00      1.00        13
          23       1.00      1.00      1.00        15
          24       1.00      1.00      1.00         8

    accuracy                           0.99       193
   macro avg       0.99      0.99      0.99       193
weighted avg       0.99      0.99      0.99       193
```

Fig 6. Classification Report for Classifier OneVsRestClassifier

V.CONCLUSION

In order to automate the procedure and boost productivity, we created a machine learning model for resume screening in this project. We trained a OneVsRestClassifier utilizing a K-NeighborsClassifier base estimator on TF-IDF features extracted from cleaned resume text following extensive data exploration, preprocessing, and feature engineering.The model demonstrated strong generalization performance, achieving 99% accuracy on the test set. The model was able to correctly identify resumes across many classes. By implementing this model in actual resume screening procedures, one may guarantee uniform candidate evaluation, minimize manual labor, and streamline operations.Scalability is made possible by automation, which enables businesses to manage high resume quantities effectively while upholding quality standards.

VI.FUTURE WORK

Future advancements to the resume screening model will include hyperparameter tuning, research into advanced algorithms and ensemble approaches, and the use of complex text embeddings. Scalability and real-time processing through cloud integration, continuous learning, and ethical concerns will all help to strengthen and fair the model. These innovations will ensure high accuracy, simplify recruiting procedures, and respond to changing market trends.

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