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PRIMARY RESEARCH

Computerized resume screening system for HR management

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Abstract
The selection of skilled employees has become an intimidating task for human resource management and any other job openings recruitment because a job opening has more than thousands of applicants during a recruitment period. It becomes an incredibly challenging job to check all resumes for every applicant. To solve this, a resume screening technology of artificial intelligence may take place. The use of natural language processing and text mining as resume screening technology could ease this daunting task of the recruitment process. Applicants' resumes will be read by the system instead of human recruiter teams and the model would work to classify the resume based on the organization's requirements. Related Key terms and keywords will be stored in the system. The system will search the pre-defined keyword throughout the resume and a score will be given based on keyword match between resume and system, and a clear visualization will be done by decomposing the applicant's resume according to requirement matched. Through this, the model will show the total score earned by each resume as well as the individual score earned by each area. As a result, recruiters may take the decision about the right talent acquisition by looking into the result.

I. INTRODUCTION

A. Problem Statement

Currently, the employee recruitment process is mostly done by human recruiters by checking the applicant's resume per individual whether it meets the requirements or not. It is used to becoming a tedious job that all recruiters must be dedicated to scanning every resume according to the requirements. To the consideration of limitations of human abilities, there are many cons that have been identified in the manual recruitment process such as human biases, a random assumption of recruiters about applicants, and a big amount of time consumed by the recruiter teams [1]. Moreover, the existing AI technique of resume screening also does not exclude full human biases and still, it is taking more time to skim relevant information from every resume to select talent acquisition as most of the existing techniques are not keyword-based resume screening techniques [2]. Through statements above, it may Interrupt an organization to select the most fitted and skilled employees as well as it leads to a job opening to spend more money on the workforce in the recruiters' team. Hence, a system that is clever enough to sort all of these resumes without error and in a timely manner is required, which is exactly the aim of this paper.

B. Project Objective

1. To study the existing traditional recruitment process of resume checking and identify its limitations.
2. To develop an AI technique to filter the resume that will more fitted techniques over human recruiters.
3. To identify the proper talent acquisition through screening technique and suggest the resumes that matched the

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content.

C. Significance of Project

Artificial intelligence for resume screening technology allows recruiters to better leverage their resume tracking system, providing the ability to hire more efficiently, shortlist more accurately, and screen resumes with more fairness by avoiding human biases [3]. However, it will be a critical component for the recruiters as their enhanced technology leads to talent acquisition. The model and experiment of this AI-based resume screening will find the results by reading different resumes providing scores that will be tightly connected with the applicant tracking system. It will add a new layer to the recruitment process to recruit proper experts for the organization. In the context of time, the organization will minimize manual recruitment time by screening the thousands of resumes at a time without recruitment teams and biases which will have a few costs compared to manual recruitment. Moreover, applicants will also know how an AI system reads the resumes and they can make their respective resumes good manner by excluding unnecessary information that the machine does not pick during the keyword search.

II. PREVIOUS WORKS REVIEW

Due to the high number of applicants for a single job opening, the application of artificial intelligence is one of the advanced technologies that may be used in the recruitment process to make the selection of employees easier. To solve this, An AI resume screening process can make talent acquisition effective and faster. The Artificial intelligence-based automated resume screening technique will classify the skilled employees by screening their resume based on requirements given by the human resource management such as educational background, experiences, and searching skilled in specific content [4, 5, 6].

The AI-based technique may filter more than thousands of resumes in a minute without any human biases and assumptions. Using Artificial Intelligence, redundant data of the resume will be ignored by the system as it will search specific content in the resume based on text categorization and information retrieval from the resume. [7] proposed an information retrieval method using a convolutional neural network with a Siamese adoption that effectively captures the underlying semantics that enable to project proper resumes and job descriptions closer together and dissimilar resumes and job descriptions to be projected further distant in the semantic space. The approach uses a retrieval model and ranking technique to measure similarity between resume and job description.it has given a better result as the paper has experimented with more than thousands of resumes with a big number of job descriptions. Moreover, the general solution is that companies are proposed to use Applicant Tracking System (ATS) as an artificial intelligence technique of classification model. An applicant tracking system essentially automates resume screening using keyword matches and knockout questions. The system Classified the variable as dependent and independent variables. It can screen each applicant as a false positive based on keyword filling and screen out the applicants as a false negative. This automated screening enhances the standard of hiring experts in recruitment as it is reducing false positives and false negatives because applicants cannot handle the ATS via keyword filling or stuffing and applicants with proper qualifications no longer slide through keyword screening respectively [8, 9]. It may also add value to candidates' resumes by including publicly available information about their prior employment and social media presence. Uses of AI in the applicant tracking system to resume screening usually can handle massive volumes of data. In fact, AI relies on a large amount of data to generate reliable suggestions about which candidates should forward to the next level or suggestions to recruit experts.

[10] proposed a complete survey that contained the many methods that the researcher had utilised for the recommendation system in the previous few years. They talked about how recommendation systems are commonly used in real-time applications. Collaborative filtering, Content-based filtering, Knowledge-based filtering, and Hybrid techniques are the four basic types of recommendation services that this proposed system mentioned. It also indicated that Malinowski used an Expectation Maximisation (EM) algorithm for the job suggestion, which considers both the applicant's resume and the job description of the company [11]. In addition, as Artificial intelligence brings a remarkable change in recruitment in the context of time consumption and selecting the quality expert without biases, to make it more fast and easy recruitment, the use of text mining and natural language processing can be applied for developing a resume screening system [12]. The algorithm identifies the best-fit employees for a job opening following the threshold and pre-defined criteria through organization and score gain by the developed model. An AI model with a combination of text mining and natural language processing usually looks at applicants' resumes and matches them with job opening requirements. In evaluating phases of the model, the system sorts all the resumes based on score gain from matching with keywords given by the recruiters. It is a straight-

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forward AI model that any company may use to recruit employees without human biases [5].

Moreover, in the context of resume filtering, the technique of calculating tf-idf is also an artificial intelligence technique to match resumes with job descriptions in an unbiased way by mitigating the socio-linguistic bias, it is proposed a fair selection of experts in a job opening without having human biases due to sociolinguistic behaviour [13] [13, 14]. The term frequency-inverse dense frequency (tf-idf) technique is used to improve information retrieval from resume by combining a term weighting system with term frequency (tf) to de-emphasize similar terms and using term frequency method as baseline, the system provides a ranking of resumes similar to given term job opening [15].

Hence, analysis of traditional resume screening and various artificial intelligence of resume screening, traditional resume screening is a time-consuming process to screen per resumes by recruiters which have been considered a tedious job. Whereas artificial intelligence of resume screening is offering an inconceivable way of screening the resume without time-consuming and human biases as well as screening multiple resumes at a time. However, by the above paper review, the existing screening process has some limitations as it is not fully free of human biases and a lack of proper detection of applicant's expertise area by reading their resume through a machine. To make the screening process easier, a specific keyword detection-based resume screening using natural language processing may take place which will do the job with a shorter period and ensure most skilled employees without human biases.

METHODOLOGY

In this experiment, artificial intelligence, in combination with text mining and natural language processing (NLP) will be used to create programmed like a tracking tool that can objectively screen resumes in a minute to find the right resume for a job opening using specific keyword detection from resume based on job opening requirement and their specific criteria, or scores. In this experiment, the machine will read only one resume at a time. Therefore, the tool searches for certain keywords, as well as sorting and scoring resumes deciding which resume should be considered for recruitment and which is not while each organization may have its own resume screening criteria that determines what experts they are looking for. The keywords are stored in a Python dictionary which will be detected based on keyword match in the screening resume. However, In this experiment, keywords are set up for nine specific employment fields for recruitment. Hence, the model and experimental process are presented in graphical way below:

1. Resume Collection
2. Text Preparation (Extraction, Cleaning)
3. Model Creation
4. Experimental Score Visualization
5. Final Resume Decomposition

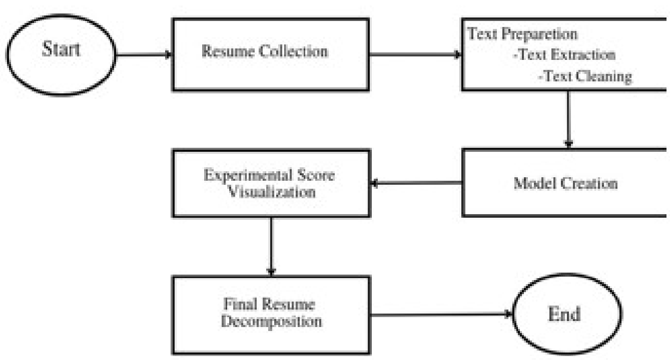

Fig. 1. Flowchart of method

A. *Resume Collection*

Data collection is the act of obtaining and analysing data on certain variables in a structured manner. In all academic domains, data collecting is an important part of the research process. Therefore, In the context of this resume screening method, all the resumes have been collected from the open sources data link online such as LinkedIn, Canva free template resumes and Kaggle resume datasets. LinkedIn helps a lot to collect resumes as it is a major platform for employment that people upload their resume to find attention from recruiters, every resume of employment concentration is available in LinkedIn. It provides numerous resumes by searching respective domains. Also, a resume dataset from Kaggle has been collected.

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B. Text Preparation

Text preparation is the practice of cleaning and preparing text data in natural language processing. It includes various tasks to extract the text from a pdf file and make the text clean and machine readable. Many text preparation tasks are handled by the Python libraries NLTK and re. For text preparation for this method, re libraries have been used. As part of text preparation, two segmentations can be explained.

Text Extraction

Text Extraction or text mining is an artificial intelligence technique that employs natural language processing to convert the free (unstructured) text in documents and databases into normalized text because structured data is suitable for analysis or as input to an experiment. However, as the collected resume will have many distinctive styles according to the applicant's personal design, the resume will be going through the text extraction phase. To make it readable by the machine, whole text will be extracted from every pages of resume to a new encode file where all the resume design will be removed and the content will be converted to lowercase

C. Text Cleaning

Text cleaning is the process of preparing raw text for Natural Language Processing, which allows computers to interpret human language. Therefore, Clean text is a natural language processing that has been organized into a machine-readable format. Text cleaning is the process of preparing the text by removing stop words, Unicode, spaces from the resume content, and simplifying complicated words to their core form. However, after extracting the text from the document, text cleaning has been done to remove spaces, comma, Unicode, stop words and all the numeric values contained in the document to make the text machine readable so that the python interpreter can read the resume keyword by keyword.

III. MODEL CREATION

After text extraction and text cleaning, the resume texts are well prepared for the experiment. In this step, a dictionary will be created with proper key terms and key values. However, the key terms and values depend on the job opening requirements and their job description based on what kind of employee that they are looking for. Dictionary is basically built with the combination of key-value pairs. For this project, nine kinds of employment fields will be chosen to select employees such as data scientist, software engineer, etc. To create the dictionary, nineteen key terms will be finalised and with their respective value as keyword. The purpose of the keyword is that it will be compared with the resume text to find the keyword similarity between resume and dictionary. The key term and keyword are chosen by analysing related resumes on online open source resumes from LinkedIn, Kaggle resume datasets and Canva free template resumes that are related to respective fields that this project will recruit.

A. Experimental Score Visualization

Resume text has been extracted to the form of machine readable format. The key term and keyword have been set up. In the context of experimental score visualization, the resume
extracted text will be compared by every keyword in the dictionary. There is a scoring system in which Every keyword will hold one score if any word of resume matches with a dictionary keyword. The total score will be shown besides the respective key term in the result section using a data frame. Finally, all the scores will be added and the final score will be shown for the examinee resume. As a result, the total score will pop up by summation of each area.

Domain/Area	Score Earned
Software	10
Programming	4
Experience	3
Management Skill	3
Personal Skill	3
Sales & Marketing	2
Accounting	1
Data science	1
Machine Learning	1
Statistics	1
Data Analytics	1
Web Skill	1
Data Analyst	0
Graphic	0
Content skill	0
Graphical content	0
Finance	0
Health/ Medical	0

Fig. 2. A software engineer's Score Frame

B. Final Resume Decomposition

In this section, Python Interpreter will save a result as a pie chart which will clearly visualize a decomposition of the concentrated area by an applicant in the percentage system. Findings will be decomposed dividing each area that will be evaluated by the organization to know the applicant's concentration area. For example, a software engineer has 31% knowledge in software and 12% in programming and 57%

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in combination with other concentration areas.

C. Experimental setup

The method has been understood and the necessary steps are explained. Therefore, in this segment, the flow of code will be explained, and results will be shown accordingly. Also, the result will be analysed after the result has been found.

1) Flow of Experiment The experiment is conducted through the following experimental process. First of all, the resume will be opened by a python interpreter and every resume text will be read using a python file reader. Also, it will count the number of pages that a resume contains. The process has been explained accordingly.

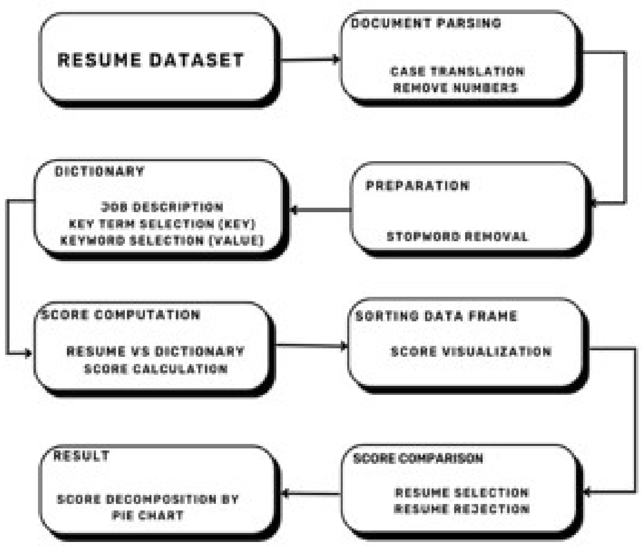

Fig. 3. Ai based Resume screening process

D. Document Parsing

1) Case translation Case translation is a part of text extraction. When the resume has been read by the machine, all the strings of the resume will be converted to the lowercase from a mixture of uppercase and lowercase. The purpose of doing case translation is to match the similarities between resume and keyword as all the keyword declaration has been done in lowercase format.

2) Remove Numbers It is a text analytics technique that transforms the unstructured text to the normalized form of text using natural language processing. by encoding the text from resume, all the text will be extracted in a suitable form by removing resume's uses of all numeric numbers and the spaces between text.

4.2

E. Preparation (Stop word Removal)

As the text had been extracted in the previous segment. Now, the text is pre-processing to clean the text. In the context of text preparation, it will remove the punctuations from whole content such as comma, stop words and Unicode as well as all the styles used in resume. To remove the punctuation, the Python translate method will do the job. By this, the model will have an extracted and clean document from the resume.

F. Dictionary

In this section, a python dictionary will be created with nineteen key terms and related keywords from specific employment sectors. To design the dictionary following steps are being considered.

1) Job Description Job description is a requirement or work responsibilities of a company. To recruitment of employees, companies are looking for specific keywords in the applicant's resume based on job description. Job description is designed by work responsibilities and respective job requirements. Most of the time the dictionary is created from job description's key terms and keywords.

2) Key term and Keyword First of all, dictionaries are Python's implementation of a data structure that is more generally known as an associative array. A dictionary consists of a collection of key-value pairs. Each key-value pair maps the key to its associated value. Therefore, in the process of this experiment, Key will work as Key term which refers to an individual's parents field where keywords will be declared as a value (key-value pairs). To experiment the model, nine employment fields have chosen to recruit which are:

1. Junior Data Scientist
2. Software Engineer
3. Junior Data Analyst
4. Web & Graphic Designer
5. Account Executive
6. Sales Representative
7. Content Creator
8. Senior Accountant
9. General Surgeon

To choose the key term, many key terms have been collected based on above recruitments, most of the key terms chosen by analysing related resumes on online open source resumes from LinkedIn, Kaggle resume datasets and Canva free template resumes that are related to respective fields above. For example, for Junior Data Scientist, the key terms (key) selection are "Data Science", "Programming", "Statistics", "Machine Learning". Moreover, the selection of keyword (value) is most important which is done by extracting respective keywords from Kaggle resume datasets and surfing on google search engine to find related keywords for the key term. Also, a deep search on the respective LinkedIn profile and collect the keywords as they are mentioned for their expertise field. For instance, for a Junior Data Scientist, if the key terms (key) are "Data Science" then the respective keywords (value) are 'algorithm', 'analytics', 'Hadoop', 'machine learning', 'data mining', 'python', 'statistics', 'data', 'statistical analysis', 'data wrangling', 'Algebra', 'Probability', 'visualization'. To view in graphical way of key term and keyword selection for a junior data scientist recruitment is following:

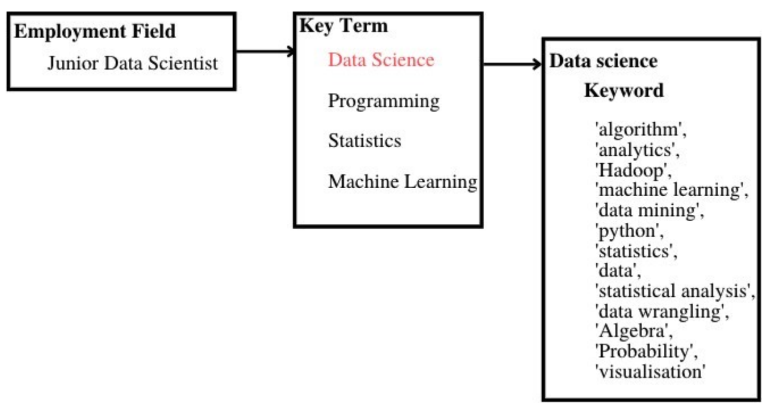

Fig. 4. key term and Keyword selection

Therefore, nineteen key terms have been initialized with their respective keywords where three key terms will be considered compulsory that every applicant must have these two (language, personal Skill) key terms along with their specific employment key terms. However, this dictionary can be customized to add and remove any key terms or keywords according to job opening hiring criteria at any time for any other field. In addition, key terms and keywords have been added to run the code and test the result successfully. More key terms and keywords may be expanded, in my future work to make it as a real life product for other fields as well.

G. Score Computation

Calculation of the score is interrelated with resume text and dictionary keywords. The interpreter will search the matching keyword in the resume to make a score calculation. In this experiment, there are nineteen key terms with respective keywords. Once the machine has read the resume, score has been calculated in per area comparing between resume and selected keyword in the dictionary. For each keyword match between resume and dictionary keyword, one score will be counted and the system will check the matched keyword belongs which key term, after check, score will show besides the key term accordingly. Finally, each area key term will have an individual score based on their keyword similarity in resume. Following is the flow of score computation:

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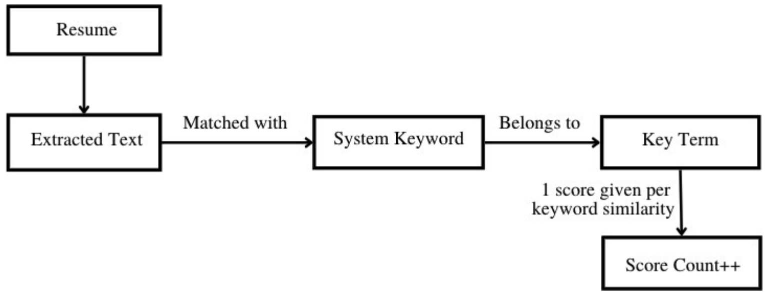

Fig. 5. The process of score calculation

In Figure 5, the resume is open and read. Extracted text from resume has been compared with stored keywords in the dictionary. If there is any keyword matched, it will check the keyword to check it belongs to which key term. Therefore, it will count 1 score accordingly for per keyword similarity.

H. Sorting Data Frame with Score Visualization

After getting all individual scores for each key term, using a data frame, a model will be shown the all scores besides their respective key term in a descending order and a summation of each key term score will pop up. The total score and individual area score will be used in score comparison in the next step to resume selection or rejection for recruitment. As the score calculation is done, the data frame will be sorted and the final score will be displayed (figure 2).

I. Score Comparison to select the resume

To check the applicants resume performance to recruit, total scores and individual area scores are compared with a conditional score comparison. For this experiment, resume comparisons have been set up in a different way. There are ten resumes that will be experimented with for nine employment fields. For each recruitment, there will be different comparison criteria. For example, to recruit a junior data scientist, score comparison will be conducted in the following criteria. The resume must meet one of three categories to a valid junior data scientist recruitment. Conditional statements are in below:

- Total scores should be greater than or equal to 50 and statistical skill must earn greater than or equal 9 and Personal Skill should be greater than or equal to 2 and Language must have at least one. Or,
- Total scores should be greater than or equal 40 and data science skills must earn greater than or equal 10. and Personal Skill should be greater than or equal to 2 and Language must have at least one. Or,
- Total scores should be greater than or equal 60 and statistical skill must earn greater than or equal 8 and Language must have at least one.

If any of the one condition is true, the system will pop up a message to recruit. Otherwise, the terminal will be given a red alert status if resumes do not meet the requirement. Hence, By looking at data frame results, recruiters may evaluate how many key terms were included in each concentration area from a given list by scores summary data frame, total scores, and individual area scores. However, only two employment field's score comparison has been discussed, either acceptance and rejection of a junior data scientist or a software engineer. For software engineer, it is also followed by same criteria but different recruitment has their respective conditioned setup. So, for Software Engineer recruitment, the conditional statement is

- Total scores should be greater than or equal 20 and having a match of two or more than 2 fields of experiences and Personal Skill must be greater than 2 and Language must have at least one and Software skill must match greater than or equal 10. By following above criteria, software resume either accepted or rejected as data scientist resume behaves during score comparison.

IV. RESULT (SCORE DECOMPOSITION BY PIE CHART)

In the end, The acceptance or rejection result has been found in the previous step after score comparison and it has printed the message of recruit or rejection. In this step, This is a score visualization using a pie chart which will provide a clear aspect of an applicant's specialization. In this segmentation, the model will produce a visualization by decomposing the resume by area that will visualize the percentage of the applicant's concentration area correspondence with the resume. Recruiters may investigate it to get an initial aspect of the applicant's resume. If an applicants has the five different knowledge mentioned in the resume, the pie chart will decompose it into percentage that how many percent each area holds such as a programmer resume may composed like he has programming 50%, language 5%, statistics 20%, personal skill 20% and tools 5% of individual skill

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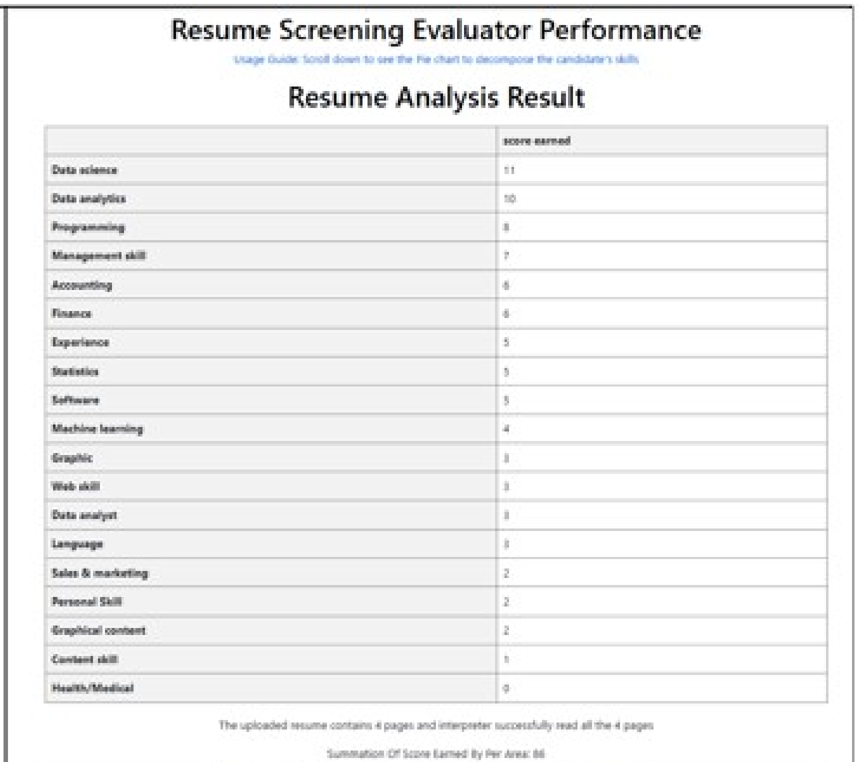
V. RESULT AND ANALYSIS

In this section, ten resumes have been experimented followed by the above experimental set up. However, there is ten resumes from various employment fields, which are Junior Data Scientist – 2 Software Engineer - 1 Junior Data Analyst- 1
Web & Graphic Designer - 1 Account Executive – 1 Sales Representative - 1 Content Creator - 1 Senior Accountant - 1 General Surgeon – 1

In the result section there are ten (10) distinctive results have been found for each employment field as mentioned above. The four result have been attached below and result's explanation have been added below

VI. RESULT

Employment Field - 1	Score and result
Data scientist (Accepted)	

Resume decomposition by domain

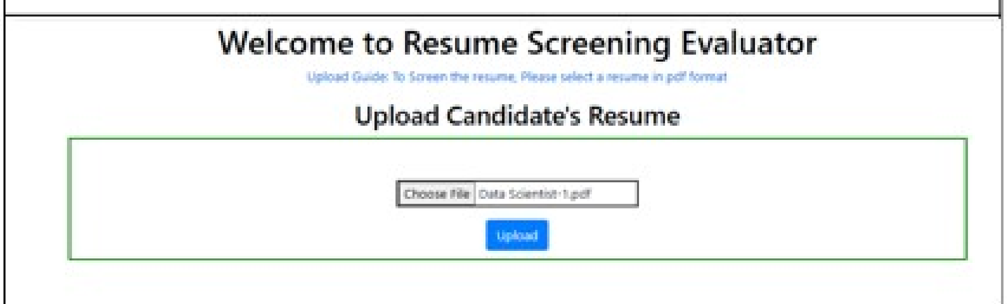
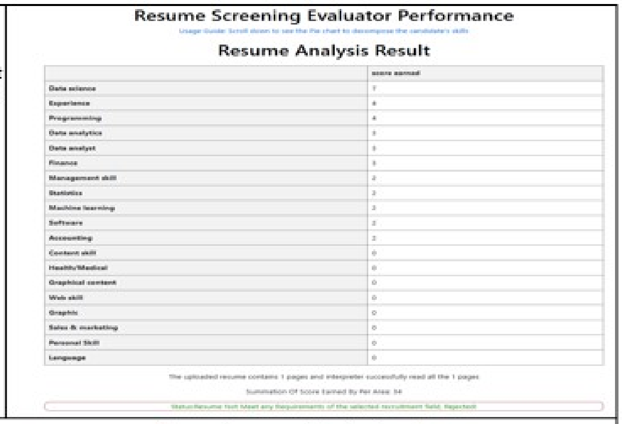
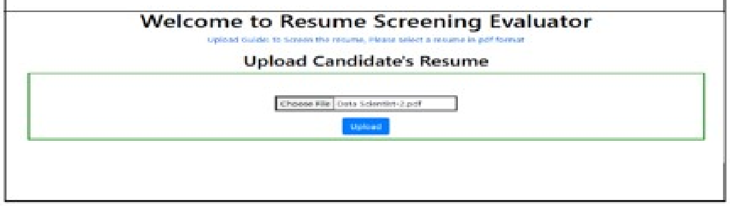


Fig. 6

Employment Field - 2	Score and result status
Data scientist (Rejected)	
Resume decomposition by domain	
	

Resume Screening Evaluator Performance

Usage Guide: Scroll down to see the Pie chart to decompose the candidate's skills

Resume Analysis Result

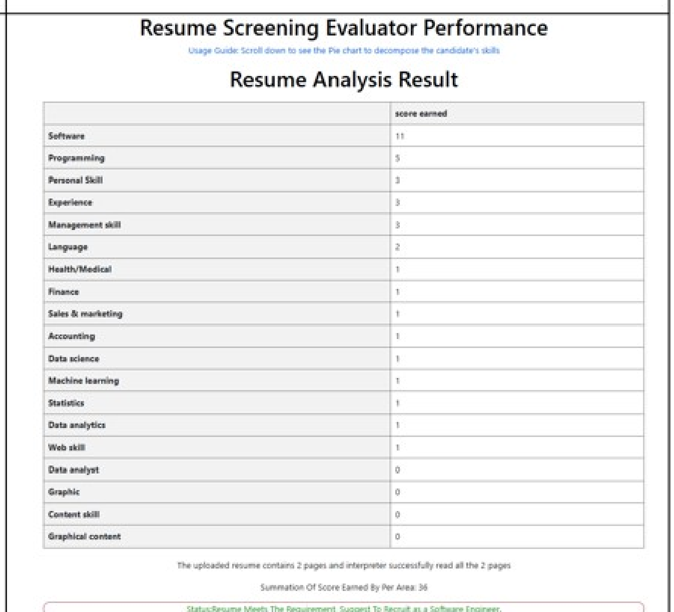
	score earned
Data science	7
Experience	4
Programming	4
Data analytics	3
Data analyst	3
Finance	3
Management skill	2
Statistics	2
Machine learning	2
Software	2
Accounting	2
Content skill	0
Health/Medical	0
Graphical content	0
Web skill	0
Graphic	0
Sales & marketing	0
Personal Skill	0
Language	0

The uploaded resume contains 1 pages and interpreter successfully read all the 1 pages

Summation Of Score Earned By Per Area: 34

Status:Resume Not Meet any Requirements of the selected recruitment field, Rejected

Fig. 7

Employment Field - 3	Score and result status
Software Engineer (Accepted)	
Resume decomposition by domain	

Resume Screening Evaluator Performance

Usage Guide: Scroll down to see the Pie chart to decompose the candidate's skills

Resume Analysis Result

	score earned
Software	11
Programming	5
Personal Skill	3
Experience	3
Management skill	3
Language	2
Health/Medical	1
Finance	1
Sales & marketing	1
Accounting	1
Data science	1
Machine learning	1
Statistics	1
Data analytics	1
Web skill	1
Data analyst	0
Graphic	0
Content skill	0
Graphical content	0

The uploaded resume contains 2 pages and interpreter successfully read all the 2 pages

Summation Of Score Earned By Per Area: 36

Status:Resume Meets The Requirement, Suggest To Recruit as a Software Engineer.

Fig. 8

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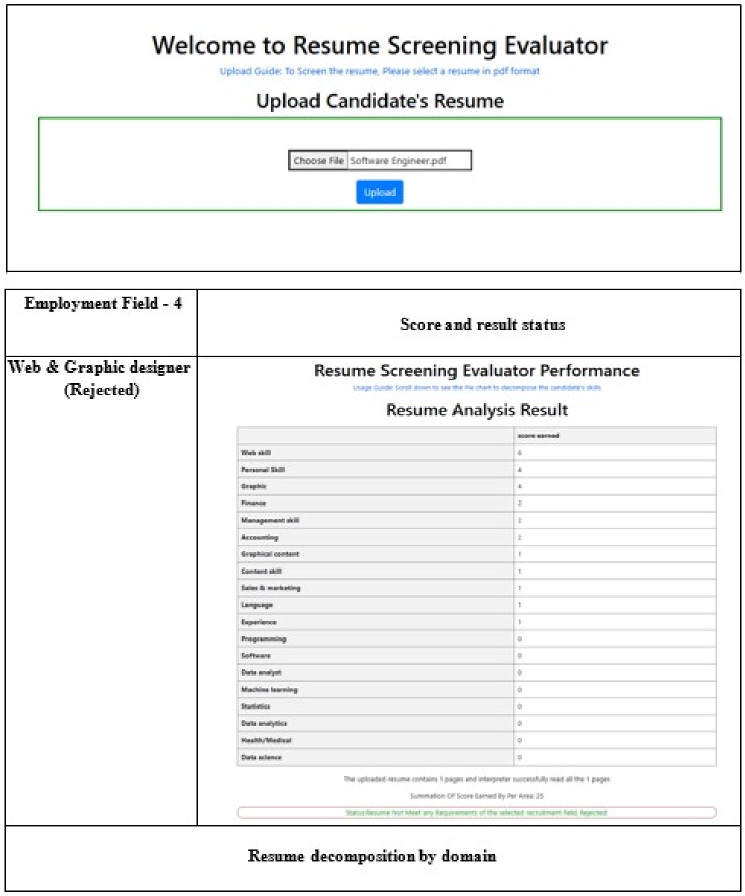

Fig. 9

A. *Result Analysis*

In the result section, we can see there are ten results with ten different statements. After screening the ten resumes, the result has been shown that five resumes are accepted for recruitment and others are rejected by the model and every resume decomposes by using a chart as well. However, for the result analysis, The first two results will be discussed. The first two results are for a junior data scientist recruitment (result 1: figure 6,7,8), (result 2: figure 9,10,11). It provides a status saying that the resume meets the requirements and the second is stated that the resume does not meet the requirements. Therefore, to elaborate this result, there is a significant impact of keyword setup in the model dictionary. As this model is set up for nine employment fields of recruitment, data scientist recruitment is one of them. Among nineteen key terms, there are some key terms that have been set up with data scientist related keywords. Once the machine has read the data science resume, score has been calculated in per area comparing between resume and selected keyword in the dictionary. Moreover, to check the applicants resume performance to recruit, total scores along with individual scores are compared with Conditional score comparison. For this model, referring to above results, resume comparisons have been set in three categories to a valid junior data scientist recruitment and based on recruitment criteria explained in the experimental setup. For the first result, there all criteria meets between resume and system which resulted that system has popped up a message to recruit in figure 8. Otherwise, the terminal will be given a red alert status that resumes do not meet the requirement as it is shown in the figure 10. Furthermore, in the result, there is also a core visualization in the per area in percentage. As an outcome, it is also an important result visualization that will provide a clear aspect of an applicant's specialization. In this segmentation, the model has produced visualization by decomposing resume by area with a pie chart that has visualized the percentage of area matched correspondence with job opening requirements (figure 11).

Hence, there are two approaches to analyse these findings. By looking at data frame results, recruiters may evaluate how many key terms were included in each concentration area from a given list by scores, summary data frame, total scores, and individual area scores. On the contrary, by looking at the pie chart (figure 8 or 11), recruiters can identify

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applicants' major concentration area and evaluate to what area applicants may be considered for positions or applicants may have direct rejection. The number of keywords in the dictionary in each concentration area has a significant impact on the pie chart scores as well. As it is mentioned that the term can make changes anytime based on organization requirement because to talent acquisition, bring expertise, and examine applicant's qualifications, it depends on job type and their specific requirement setup. On the other hand, the software engineer result also followed by same criteria but different recruitment has their
respective conditioned setup such as for Software Engineer recruitment, the conditional statement is total scores should be greater than or equal 20 and should have 2 or more keyword from experiences key term and Personal Skill must be greater than 2 and Language must have at least one and Software skill must matches greater than or equal 10. As a result, In (Figure: 12,13,14), following all the criteria, software resume has been accepted for recruitment and area concentration also showing that resume having 31% of software skill. Hence, similarly, referring to all figures, all of ten resumes have distinct criteria to accept. Otherwise, there will be a rejection of the resume if one criteria is not matched.

B. Progress and Future work

In the context of resume screening using Artificial Intelligence, the concept of how artificial intelligence works in resume screening has been understood. Through literature review, the various techniques of resume screening have been acknowledged. However, using natural language processing and text mining, the architecture of the model has been understood and the workflow of code goes well in my opinion. Therefore, using python language, a model has been developed which has run successfully and given desired output by reading ten resumes (result 1- result 10). During requirement set up to verify applicants resume, the key term and keyword had been set up for recruiting nine employment sector such as junior data scientist, software engineer and all the field mentioned, although it is able to read any resume in pdf format with the scoring result and score visualization by each area of concentration.
Furthermore, for future work, more and more suitable key terms and keywords will be added in the dictionary if the recruitment field is extended. For a real life product, model evaluation and train is another important criteria to have. As future work, evaluation will be added into experimental setup. Moreover, more conditional statements will be extended in the model because now the model returns one score for one keyword match, if there is more keyword added, the score criteria will be changed based on new term addition in the dictionary. However, in this project, ten employment areas have been covered but it is planned that features will be added to make the model a more generalized screening model to check all kinds of recruitment in the future.

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