IntelCV: An Intelligent Skilled Resume Selection Method for Job Purposes

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Approval Certificate

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Declaration

This is to certify that the work entitled **"IntelCV: An Intelligent Skilled Resume Selection Method for Job Purposes"** is the outcome of the research carried out by me under the supervision of Dr. Mohammad Nurul Huda, Professor & Head of the Dept. of CSE.

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Abstract

In today’s companies recruit a significant number of employees each year and face the challenge of evaluating a vast quantity of resumes from candidates. Consequently, the HR department finds it challenging to filter the CVs that best match the company's requirements. This thesis addresses this challenge by rigorously comparing the accuracy of an automated job-resume matching system against human-led decisions, specifically focusing on filtering applicants based on their skill sets. The study employs preprocessing techniques to standardize text and advanced Natural Language Processing (NLP) techniques to extract skills from 122 potential resumes across 10 technical job positions. Using Cosine similarity, Jaccard index, and Jaro-Winkler distance, the research analyzes the similarity between job descriptions and resumes. The decisions made by the automated system are then compared with the decision made by human assessors, and their alignment is meticulously evaluated. Furthermore, leveraging K-means clustering, the study categorizes resumes into "good," "average," and "poor" groups, providing recruiters with efficient tools to identify the most qualified candidates. This research aims to shed light on the strengths and limitations of machine-based decision-making in recruitment, offering insights into enhancing efficiency, optimizing time usage, reducing biases, and improving candidate evaluations. Through the evaluation of three similarity measurement algorithms, the study identifies that Cosine similarity and Jaro-Winkler distance provide high accuracy results, while the Jaccard index yields lower results. The achieved research results contribute to a deeper understanding of automated systems' efficacy in the recruitment landscape, leading to the development of more informed and effective talent acquisition strategies, especially when compared to time-consuming and biased manual recruiting processes.

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Chapter 1

Introduction

In today's competitive job market, talent acquisition has become a critical aspect of organizational success. Companies face the daunting challenge of sifting through a large pool of resumes to identify the most suitable candidates for their vacancies. To streamline this process and alleviate the burden on HR departments, automated systems have emerged as a promising solution. These systems leverage natural language processing (NLP) techniques and similarity measurement algorithms to assess the degree of alignment between job descriptions and the skills mentioned in resumes.

1.1 Motivation

The increasing volume of job applications necessitates an efficient and accurate approach to identify the right candidates for specific positions. Automated resume evaluation systems offer a potential solution by leveraging advanced NLP and machine learning techniques. However, to fully embrace such technology, it is crucial to comprehensively evaluate its accuracy, reliability, and alignment with human judgment. This research is motivated by the need to bridge the gap between machine-generated assessments and human judgments, providing valuable insights for organizations seeking to optimize their talent acquisition processes.

1.2 Research Aims

Evaluate the Accuracy of Automated Resume Evaluation: The primary goal of the research is to assess the accuracy of the automated resume evaluation system by comparing the machine-generated similarity scores with human judgments. By quantifying the alignment between the two, the study aims to determine how well the system approximates human decision-making in the context of talent acquisition.

Compare Similarity Measurement Algorithms: Another objective is to compare the performance of different similarity measurement algorithms, such as cosine similarity, Jaccard similarity, and Jaro-Winkler similarity. The research aims to identify which algorithm yields the best results in aligning with human judgments and effectively capturing the similarity between candidate skills and job descriptions.

Explore Clustering for Candidate Categorization: The study seeks to extend the investigation by applying K-means clustering to categorize resumes into "good," "average," and "poor" similarity clusters. This exploration aims to provide recruiters with a more nuanced understanding of the quality of match between candidate profiles and job requirements, facilitating more efficient talent pool identification.

Provide Insights for Optimizing Talent Acquisition: Through rigorous analysis and evaluation, the research aims to offer valuable insights and recommendations to optimize automated talent acquisition processes. By understanding the strengths and limitations of the automated system, employers and HR professionals can make data-driven decisions in candidate selection and streamline the recruitment process.

Contribute to Advancements in Automated Talent Acquisition: The overarching objective of the research is to contribute to the advancement of automated talent acquisition systems. By identifying areas of improvement and showcasing the potential benefits of such systems, the study aims to encourage further research and development in this domain, leading to more efficient and effective hiring practices in the future.

1.3 Research Contribution

- Rigorous evaluation of automated resume evaluation systems' accuracy in approximating human judgments.
- Comparative analysis of similarity measurement algorithms (cosine, Jaccard, Jaro-Winkler) to identify the most effective one for talent matching.
- Introduction of K-means clustering for categorizing resumes into "good," "average," and "poor" similarity clusters, aiding targeted talent pool identification.
- Valuable insights and recommendations for optimizing talent acquisition processes and enhancing candidate screening.
- Advancements in the field of automated talent acquisition, inspiring further research, and development in technology-driven hiring practices.

1.4 Thesis Organization

This thesis follows a well-structured organization. Chapter 2 presents the background details of the research, covering fundamental techniques and engineering terms. It also includes a comprehensive literature review that discusses automated resume evaluation systems, NLP techniques, similarity measurement algorithms, and clustering approaches, drawing insights from previous works. Chapter 3 focuses on the methodology, outlining data collection and preprocessing, NLP skills extraction, application of similarity measurement algorithms, and threshold setting for binary decisions. Additionally, it explains the human expert rating process for benchmarking and the use of K-means clustering for candidate categorization. In Chapter 4, the experimental evaluation showcases accuracy results, a comparative analysis of similarity algorithms, and insights from clustering for talent pool identification. Chapter 5 presents the conclusion, summarizing research findings, highlighting contributions to automated talent acquisition, and discussing the potential impact of the work. The chapter also acknowledges limitations and outlines future research scopes.

Chapter 2

Background and Literature Review

2.1 Background

Talent acquisition is a critical process for organizations, but the increasing volume of job applications has made manual screening and selection time-consuming. To address this, automated resume evaluation systems have emerged, using NLP techniques and similarity measurement algorithms to compare job descriptions with candidate resumes. However, the accuracy of these systems in approximating human judgment requires rigorous evaluation. Additionally, applying K-means clustering based on similarity scores offers a novel approach to categorize resumes by their level of match with job descriptions. This research aims to comprehensively assess the alignment between machine-generated assessments and human judgments, providing valuable insights for optimizing talent acquisition processes and identifying top candidates effectively.

2.2 Fundamental Terms & Techniques

2.2.1 Natural Language Processing

In this research, Natural Language Processing (NLP) has been instrumental in enabling computers to comprehend and process human language effectively. NLP techniques are employed to extract the entire text from the resumes, followed by preprocessing steps to enhance data quality. The extracted skills from resumes are then compared with the required skills in job descriptions, providing valuable insights into candidate skillsets and their alignment with job requirements. The use of NLP has played a pivotal role in streamlining the talent acquisition process and contributing to the advancement of automated resume evaluation systems.

2.2.2 Similarity Measure Algorithms

In this thesis, skills information extracted from job descriptions and resumes is represented as vectors for comparison using similarity measurement algorithms. After getting the skill set from a certain resume three similarity measure algorithms are implemented for getting the similarity:

- **Cosine Similarity:** A metric used to measure the similarity between two vectors by calculating the cosine of the angle between them. In the context of this thesis, cosine similarity is applied to determine the similarity between skills vectors extracted from the resumes with the job description's required skills. The cosine similarity formula can be expressed as:

$$\mathrm{Sim}\ (\mathrm{A}, \mathrm{B})\ = \cos\ (\theta)\ = \frac{\mathrm{A.B}}{|A||B|} \qquad [2.1]$$

- **Jaccard Similarity:** A measure of similarity between two sets, calculated by dividing the size of the intersection of the sets by the size of their union. In the context of this thesis, Jaccard similarity is used to compare the sets of skills present in job descriptions and resumes. Jaccard similarity formula can be expressed as:

$$J(S, M) = \frac{|S \cap M|}{|S \cup M|} \qquad [2.2]$$

- **Jaro-Winkler Similarity:** A string similarity measure that calculates the similarity between two strings by considering the number of matching characters and the number of transpositions between them. In this thesis, Jaro-Winkler similarity is applied to assess the similarity between job description's requires skills and resume skills. The below formula can be use as Jaro-Winkler:

$$Sim = \frac{1}{3} * (\frac{m}{|s1|} + \frac{m}{|s2|} + \frac{m-t}{m}) \qquad [2.3]$$

Similarity Scores represent the degree of similarity between two vectors or sets. Cosine similarity, Jaccard similarity, and Jaro-Winkler similarity provide similarity scores that indicate the level of match between job descriptions and resumes. Threshold Value is used to convert continuous similarity scores into binary decisions (e.g., Accepted or Rejected) for comparison with human judgments.

2.2.3 Accuracy Measurements

The accuracy formula is a metric used to evaluate the performance of similarity measurement model by comparing its decisions or predictions with the ground truth or human judgments. For comparing the cosine decision and human decision in the context of automated resume evaluation, the accuracy formula can be expressed as:

$$Accuracy = \frac{(Number\ of\ Correct\ Decisions)}{Total\ Number\ of\ Decisions} \qquad [2.4]$$

2.2.4 Clustering

This research extends by applying a popular unsupervised machine learning algorithm used for partitioning data into k clusters based on their similarities. Clustering is a process of grouping similar data points into clusters based on certain criteria. In this research, K-means clustering is applied to group resumes into "good," "average," and "poor" similarity clusters.

2.3 Related works

Automated resume evaluation and talent acquisition have gained significant attention in recent years, prompting research on various aspects related to the comparison of job descriptions and resumes. This literature review provides an overview of key studies focusing on automated resume evaluation systems, natural language processing (NLP) techniques, similarity measurement algorithms, and clustering approaches for talent pool categorization.

Several studies have explored the development and implementation of automated resume evaluation systems to streamline the hiring process. Liu et al. [37] proposed a machine learning-based approach for candidate ranking, leveraging NLP techniques to extract skills information from resumes and job descriptions. Another paper [38] employed deep learning models to evaluate candidate resumes, showcasing improved accuracy compared to manual screening methods. These automated systems have demonstrated promising results in efficiently identifying qualified candidates.

NLP plays a vital role in automated resume evaluation by enabling computers to process and understand human language. Smith et al. [35] applied NLP techniques for named entity recognition, effectively extracting skills and qualifications from resumes. The paper [6] proposes an automated Resume Analyzer system using text mining technology to extract and analyze resume details without human interaction.

With the increasing number of job seekers, job recruiters face the challenge of shortlisting the most suitable profiles from a large pool of resumes [9, 10, 11]. Malinowski et al. (3) utilized the Expectation Maximization (EM) algorithm to create a job recommendation system considering both applicant resumes and organizations' job descriptions. They explored the role of e-recruitment portals in assisting organizations and factors influencing candidate selection. Matching candidate resumes to job descriptions resembles a recommender system, where candidate profiles are recommended for specific positions. Resnick and Varian [33] introduced the concept of recommendation systems, now widely used in various domains, such as product recommendations on e-commerce portals [17, 18], book recommendations [16], news recommendations [25], movie recommendations [27], music recommendation [19], and other factors [20, 21, 42, 23, 26]. A. Satish, P. Vasant [15] applied text mining approach for keyword searching. The output provides extracted text by Soundex Algorithm.

Allan Robey et al. [7] introduced a dual-sided system aimed at alleviating the burden on Human Resource departments in companies. The proposed system is designed to be organization and candidate oriented, ensuring a fair and legal ranking when shortlisting CVs from a large pool. The novel approach involves not only scanning CVs but also conducting aptitude and personality tests for better personality prediction.

In another study, a different approach was employed to extract information from online Chinese resumes. The researchers utilized regular expression and text automatic classification to extract basic details, while a fuzzy logic algorithm was utilized to extract more intricate information [8].

Additionally, Zhang and Wang [36] used sentiment analysis to assess language style and tone in resumes, providing insights into candidates' communication skills and personality traits. NLP techniques have proven crucial in extracting relevant information from both job descriptions and resumes.

R. Tanaz, Raznath[13] used KNN algorithm to classify the resumes according to their respective categories such as HR, Java developer etc. B. Kelkar, R. Shedbate [14] implemented text mining approaches for shortlisting recommended CVs using Document

Object Model (DOM), and Semantic-based object extraction. The output is categorized as high low medium. S. Bagade, J. Rout [16] employ ML algorithms: random forest, KNN, Naïve Bayes, logistic regression, and SVM. The system predicts the personality of the applicants such as Lively, Responsible, etc.

Wei et al. (1) extensively discussed various recommendation techniques and their underlying principles. Al-Otaibi et al. (2) conducted a comprehensive survey on job recommendation services, elaborating on the steps involved in the recruitment process utilized by organizations. On the other hand, Golec & Kahya (4) employed a fuzzy-based model to evaluate candidate relevance in relation to posted job descriptions. Additionally, Paparrizos et al. (5) introduced a hybrid classifier model for job recommendation, incorporating information retrieval, manual attributes, and other factors into the process.

Various similarity measurement algorithms have been explored to quantify the alignment between skills in job descriptions and resumes. Xu et al. [39] compared the performance of cosine similarity, Jaccard similarity, and Jaro-Winkler similarity in resume-job description matching, highlighting Jaro-Winkler's effectiveness in handling spelling variations and abbreviations.

This paper [41] focuses on developing a text similarity system using similarity measurement algorithms such as cosine, Jaccard, Minkowski, Manhattan and Euclidean to compare student scripts with standard answers, achieving high accuracy and reducing bias.

Wu and Yang [40] demonstrated the efficiency of cosine similarity in capturing semantic relationships between candidate skills and job requirements. These algorithms offer valuable tools for assessing the similarity between resumes and job descriptions.

In recent years, clustering techniques, particularly K-means clustering, have been integrated into talent acquisition processes. K-means clustering to group resumes based on their extracted skills, facilitating targeted talent pool identification for specific positions. In the literature, numerous clustering algorithms have been suggested, but the k-means clustering algorithm stands out as the most frequently employed one due to its straightforwardness [41].

Clustering, an unsupervised classification method [30], aims to group similar patterns into categories. Many clustering algorithms have been designed to meet various needs, each with its own strengths and weaknesses. For example, k-means algorithms have been criticized [31] for initial parameter configuration and local optimization issues but demonstrate acceptable performance in large-scale data analytics and adapt well to real-world data sources.

Hierarchical clustering algorithms, a more traditional approach [34], typically generate high-quality outputs but are time-consuming. Additionally, soft clustering solutions, like fuzzy c-means algorithms, allow objects to be assigned to multiple clusters with varying membership grades, identifying overlapping clusters [29].

The introduction of kernel functions aims to enhance clustering for non-linear datasets by mapping low-dimensional data into a high-dimensional feature space [32], but this may increase computational complexity and introduce kernel function selection issues [12].

Overall, the literature review reveals a growing interest in automated resume evaluation systems, with NLP techniques playing a crucial role in information extraction. The comparison of similarity measurement algorithms and the integration of clustering techniques offer valuable insights into talent acquisition processes. However, further research is needed to explore the limitations and potential biases of these automated systems and identify ways to improve their effectiveness in real-world recruitment scenarios.

Chapter 3

Automated Job-Resume Matching: Methodology

3.1 Data Collection

The data collection process for this research involved selecting 10 distinct types of job descriptions, as detailed in Table 3.1. For each job description, on average, 20 resumes were considered to conduct a comprehensive analysis. The chosen job descriptions covered a diverse range of industries and positions, providing a representative sample to evaluate the performance of the automated job-resume matching system. This approach ensured a varied and extensive dataset, enhancing the reliability and generalizability of the research findings.

This research has been conducted examining a total of 122 resumes collected from employees who have been working in various companies across Bangladesh such as, PwC, Colgis BD, Basundhara Limited, Strativ, NRBC. In parallel, the job descriptions for the Job titles listed in the below table have been collected from different job searching portals such as LinkedIn, indeed, Google, and different company websites.

Table 1: Different Type of Jobs for Analyze

Sl. No.	**Job Title**
1	Java Developer
2	Front End Developer
3	Back End Developer
4	UX/UI designer
5	Network Engineer
6	Python Developer
7	Finance Manager
8	Data Scientist
9	Graphics Designer
10	Sales Executive

3.2 Data Preprocessing

Once the resumes are provided as input, we proceed to extract all the text from each resume. To ensure data consistency and quality, we subject the collected resumes to preprocessing techniques. During preprocessing, we perform various steps such as standardizing the text, eliminating noise, and ensuring uniformity.

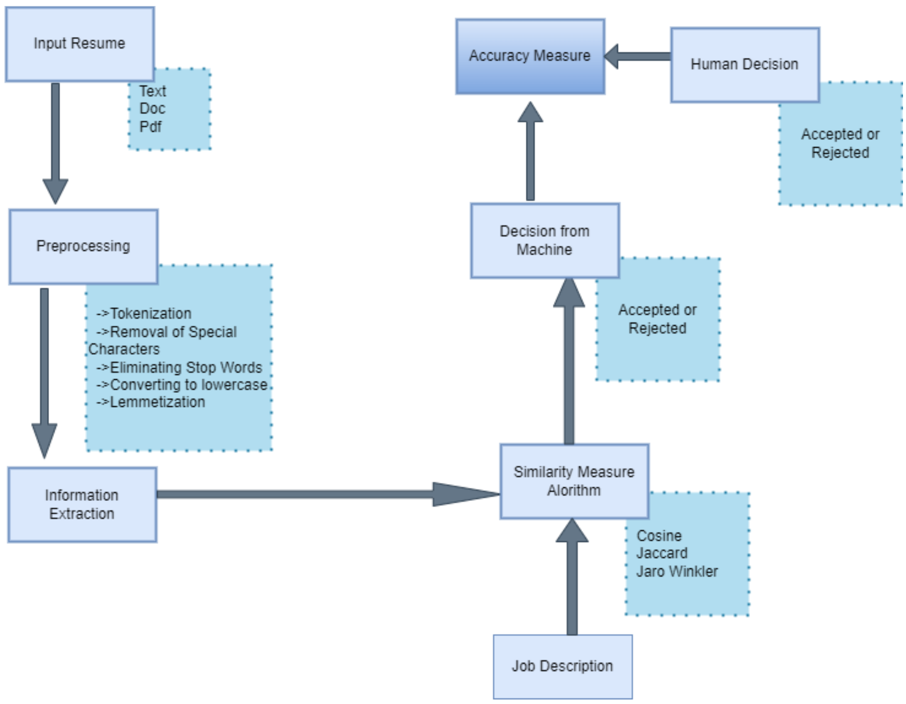


Figure 1: Resume Analyzing with Job Description Process Flow

During the preprocessing phase, we implement the following steps to clean and standardize the text extracted from the resumes:

3.2.1 Tokenization

Tokenization is used to break down the text into individual words or tokens. This allows us to analyze the resumes at a more granular level, facilitating further processing and feature extraction.

Let's assume we have the following excerpt from a resume as our input text:

Resume Text: "I am a highly motivated and skilled software developer with experience in Python, Java, and C++. I have worked on various web development projects using Django and Flask frameworks."

Tokenization Output:

1. "I"
2. "am"
3. "a"
4. "highly"
5. "motivated"
6. "and"
7. "skilled"
8. "software"
9. "developer"
10. "with"
11. "experience"
12. "in"
13. "Python"
14. ","
15. "Java"
16. ","
17. "and"
18. "C++"
19. "."
20. "I"
21. "have"
22. "worked"
23. "on"
24. "various"
25. "web"
26. "development"
27. "projects"
28. "using"
29. "Django"
30. "and"
31. "Flask"
32. "frameworks"

33. "."

In this tokenization example, each word in the resume text is considered a separate token, and punctuation marks are also treated as individual tokens. This process breaks down the resume text into its fundamental units, allowing for further analysis and processing in natural language processing tasks.

3.2.2 Removal of Special Characters

We remove any special characters or symbols present in the text, ensuring that only meaningful words are retained for further analysis.

For example,

"!", "," and "?" are all removed from the text.

3.2.3 Eliminating Stop Words

Common words like "am", "is" "and" etc., which do not carry significant meaning, are removed from the text through stop word removal. This process reduces noise and focuses on the essential content of the resumes.

3.2.4 Converting to Lowercase

To avoid any discrepancies due to case sensitivity, we convert all the text to lowercase, ensuring consistency in our analysis.

3.2.4 Lemmatization

We perform lemmatization, which involves reducing words to their base or root form. This process further standardizes the text, ensuring that different inflections of the same word are treated as the same token.

For example,

"improve", "improving" and "improvements" are all lemmatized to "improve".

By applying these preprocessing techniques, we create a clean and standardized text corpus, which serves as the foundation for further analysis and processing in our research.

3.3 Information Extraction

3.3.1 Email Extraction

A crucial step involves extracting email addresses from the resumes of applicants. Email addresses serve as unique identifiers for individuals and play a significant role in managing applicant records and facilitating communication during the hiring process.

These techniques involve advanced Natural Language Processing (NLP) methods such as tokenization, part-of-speech tagging, and pattern matching. Part-of-speech tagging helps identify specific types of words, such as nouns or proper nouns, which may indicate potential email addresses. Pattern matching involves using regular expressions (re library has been used) to identify email address patterns, such as "applicants_name@gmail.com". The procedure of extracting email is shown in Algorithm 1.

Algorithm 1: Email Extraction

Input : Processed Resume Text of Applicant, resume_text

Output : Applicant's Email, email

```
def extract_email(resume_text):
    email_regex = r"\b[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\.[A-Za-z]{2,}\b"
    email = re.search(email_regex, resume_text)
    if email:
        return email.group(0)
    else:
        return None
email = extract_email(resume_text)
if email:
    print("Email address found in the resume:", email)
else:
    print("No email address found in the resume.")
```

3.3.2 Skill Extraction

To extract relevant skills information from resumes, we utilized advanced Natural Language Processing (NLP) techniques. One of the key tools we employed is the spaCy library, which facilitated tokenization and Custom Entity Recognition. With this technique, we could identify specific skills and qualifications mentioned in the text.

In the context of this research, a JSON file [22] has been utilized, comprising a comprehensive set of 2129 data entries or patterns. Each entry is associated with a unique skill label and delineates rules for automated skill extraction. These rules are finely tuned to identify mentions of various skills, including programming languages, tools, and concepts across diverse domains like machine learning, databases, cloud services etc. The utilization of this JSON file has proven instrumental in enhancing the accuracy and efficiency of automated processes, such as resume parsing and skill tagging within textual data.

The below methodology involves utilizing natural language processing (NLP) techniques to extract skills from a processed resume text based on custom patterns defined in a JSON file.

- **Custom Entity Patterns:** The methodology leverages advanced natural language processing (NLP) techniques to identify and extract specific skills from a processed resume text. These techniques involve defining custom entity patterns in a JSON file, each associated with a unique label and word patterns that represent a skill.

  For example:

  {"label":"SKILL|machine learning",
  "pattern":[{"LOWER":"machine"},{"LOWER ":"learning"}]}

  "label": "SKILL|machine learning"`: This part of the line specifies the label for the custom entity pattern. In this case, the label is "SKILL|machine learning." The label serves as an identifier for the type of entity being recognized. The "SKILL|" prefix is added to indicate that this entity represents a skill. The specific skill being recognized is "machine learning."

  "pattern"`: This part of the line defines the pattern used for recognizing the entity. The pattern is specified as a list of dictionaries. In this case, there is one dictionary in the list.

- {"LOWER": "machine"}: This dictionary contains a single key-value pair. It specifies that the entity must have the word "machine" in lowercase to be recognized as "machine learning."

- {"LOWER": "learning"}: This is another dictionary specifying that the entity must also have the word "learning" in lowercase to match the pattern.

In essence, this line defines a custom entity recognition pattern for identifying the entity labeled as "SKILL|machine-learning." To match this pattern, an entity in the text must contain both "machine" and "learning" in lowercase, signifying that it represents the skill of "machine learning."

- **Add Custom Entity Ruler**: To apply these custom patterns effectively, the algorithm incorporates a custom entity ruler into the spaCy NLP pipeline. This entity ruler is responsible for recognizing and labeling skills in the resume text based on the defined patterns.

- **Text Preprocessing and Recognition:** Prior to skill extraction, the sample resume text undergoes text preprocessing, which includes converting the text to lowercase. This step ensures that the NLP techniques used for entity recognition are case-insensitive, improving pattern matching accuracy.

- **Entity Recognition and Labeling:** The heart of the methodology lies in the entity recognition process facilitated by spaCy. As the text is processed, the custom patterns are used to label recognized entities as skills. These labels are prefixed with "SKILL|" to distinguish them from other entities.

- **Skill Extraction and Uniqueness:** The extracted skills are collected into a set data structure, an NLP technique used to automatically ensure uniqueness and eliminate duplicates. This enhances the quality of the extracted skills data. The final output consists of the extracted skills, which will be used for similarity measurement.

Algorithm 2 integrates advanced NLP techniques for skill extraction by utilizing custom entity patterns, spaCy's entity ruler, and additional text processing to enhance the accuracy and quality of the extracted skills from the resume text.

Algorithm 2: Skills Extraction from Resume

Input : Processed Resume text of Applicant, resume_text

Output : Applicant’s Skill Set, skills

```
nlp = spacy.load("en_core_web_sm")
def add_custom_entity_ruler(nlp, patterns_file):
    entity_ruler = nlp.add_pipe("entity_ruler", after="ner")
    with jsonlines.open(patterns_file) as reader:
    patterns = [line for line in reader]
    entity_ruler.add_patterns(patterns)
def create_skill_set(doc):
    skill_set = set()
    for ent in doc.ents:
        if ent.label_.startswith("SKILL|"):
            skill_set.add(ent.text)
    return skill_set
add_custom_entity_ruler(nlp, 'skill_patterns.jsonl')
resume_text = resume_text.lower()
doc = nlp(resume_text)
for ent in doc.ents:
    if ent.label_.startswith("SKILL|"):
        skill_label = ent.label_.split("|")[-1]
        print(f"Entity: {ent.text}, Label: {skill_label}")
skills = create_skill_set(doc)
print("Extracted Skills:", skills)
```

3.4 Similarity Measure Algorithms

After getting the skill set from the resume and job description, three similarity measurement algorithms - cosine similarity, Jaccard similarity, and Jaro-Winkler similarity – will implement to compare skills information between job descriptions and resumes.

3.4.1 Cosine Similarity

Cosine similarity is a mathematical metric used to measure the similarity between two vectors in a multi-dimensional space. In the context of our research, cosine similarity will be employed as a similarity measurement algorithm to compare the skills information extracted from job descriptions and resumes. It computes the cosine of the angle between two vectors, where a smaller angle indicates a higher similarity.

For example, consider two vectors representing the skills of a job description and a resume. The vectors are transformed into a multi-dimensional space, with each dimension corresponding to a specific skill. Cosine similarity calculates the cosine of the angle between these vectors, yielding a value between -1 and 1. A value close to 1 indicates high similarity, while a value close to -1 implies dissimilarity. A value of 0 indicates no similarity. Algorithm 2 represents how to get a similarity score using cosine similarity.

The formula for computing the cosine similarity between two vectors A and B is as follows:

$$\mathrm{Sim}\ (\mathrm{A}, \mathrm{B}) = \cos\ (\theta) = \frac{\mathrm{A.B}}{|A||B|} \qquad [3.1]$$

Where:

- A · B represents the dot product of vectors A and B.
- ||A|| represents the magnitude (or Euclidean norm) of vector A.
- ||B|| represents the magnitude (or Euclidean norm) of vector B.

Algorithm 3 represents how to get a similarity score using cosine similarity.

Algorithm 3: Cosine Similarity		
Input	:	Required skills from Job Description, job_description_skills
		Extracted Skills from Applicant Resume, resume_skills
Output	:	Similarity Score, cosine_simialrity_scr
1	:	job_description_skills_str = ' '.join(job_description_skills)
2	:	resume_skills_str = ' '.join(resume_skills)
3	:	vectorizer = TfidfVectorizer()

4	:	job_description_vector = vectorizer.fit_transform([job_description_skills_str])
5	:	resume_vector = vectorizer.transform([resume_skills_str])
6	:	cosine_similarity_scr = cosine_similarity(job_description_vector, resume_vector)[0][0]
7	:	print("Cosine Similarity:", cosine_similarity_scr)

In the context of our research, vectors A and B represent the skills information extracted from the job description and the resume, respectively. The cosine similarity formula calculates the cosine of the angle between these vectors, providing a measure of how similar the skills are between the job description and the resume.

By using cosine similarity, we are able to quantitatively assess the degree of similarity between job descriptions and resumes, facilitating an automated comparison process to identify suitable candidates for specific job positions.

3.4.2 Jaccard Similarity

The Jaccard similarity is another similarity measurement used to compare the similarity between two sets of elements. It is defined as the size of the intersection of the sets divided by the size of their union showed in below.

$$J(S,M) = \frac{|S \cap M|}{|S \cup M|} \quad [3.2]$$

Where:

- |A ∩ B| represents the size of the intersection of sets A and B (i.e., the number of common elements between the sets).

- |A ∪ B| represents the size of the union of sets A and B (i.e., the total number of unique elements in both sets).

Algorithm 4 represents how to get a similarity score using jaccard similarity.

Algorithm 4: Jaccard Similarity		
Input	:	Required skills from Job Description, job_description_skills Extracted Skills from Applicant Resume, resume_skills
Output	:	Similarity Score, jaccard_simialrity
1	:	job_descriptios = [value.strip() for value in job_description.split(",")]
2	:	intersection = len(set(extracted_skills).intersection(set(job_descriptions)))

union = len(set(extracted_skills).union(set(job_descriptions)))

jaccard_similarity = intersection / union

print("Jaccard Similarity:", jaccard_similarity)

In the context of our research, sets A and B represent the sets of skills extracted from the job description and the resume, respectively. The Jaccard similarity measures how similar the sets of skills are between the job description and the resume, providing a value between 0 and 1, where 1 indicates complete similarity and 0 indicates no similarity.

3.4.3 Jaro-Winkler Similarity

The Jaro-Winkler similarity is a string similarity measurement used to compare the similarity between two strings. It is particularly effective for comparing strings with small typographical errors or slight variations. The Jaro-Winkler similarity is an extension of the Jaro similarity and is designed to give higher scores to strings that have a common prefix. Algorithm 4 represents how to get a similarity score using jaro winkler similarity. The Jaro-Winkler similarity is calculated based on the number of matching characters and the number of transpositions between the two strings.

The formula for calculating the Jaro-Winkler similarity is as follows:

$$\text{Jaro} - \text{Winkler Similarity } (s1, s2) = \frac{1}{3} * \left(\frac{m}{|s1|} + \frac{m}{|s2|} + \frac{m-t}{m}\right) \qquad [3.3]$$

Where:

- s1 and s2 are the two strings being compared.
- Jaro Similarity (s1, s2) is the regular Jaro similarity between the two strings, measuring the number of matching characters and transpositions.
- prefix_length is the length of the common prefix between the two strings.
- prefix_scale is a constant factor that gives higher weight to the common prefix.

Algorithm 5 represents how to get a similarity score using Jaro Winkler similarity.

Algorithm 5: Jaro Winkler Similarity

Input : Required skills from Job Description, job_description_skills
Extracted Skills from Applicant Resume, resume_skills

Output : Similarity Score, jaccard_simialrity,jw_similarity

combined_skills = " ".join(extracted_skills)

```
job_description_str = job_description.replace(',', ' ')
jw_similarity = jellyfish.jaro_winkler_similarity(combined_skills, job_description_str)
print("Jaro-Winkler Similarity:", jw_similarity)
```

The Jaro-Winkler similarity value ranges between 0 and 1, where 1 indicates high similarity and 0 indicates no similarity. It is commonly used in applications such as record linkage, fuzzy string matching, and duplicate detection.

In the context of our research on automated job-resume matching, the Jaro-Winkler similarity can be applied to measure the similarity between skills extracted from job descriptions and resumes.

By using the Jaro-Winkler similarity in this research, we can improve the accuracy of matching job requirements with candidate skills, especially when there are slight variations or minor differences in the way skills are mentioned in job descriptions and resumes. This can contribute to more reliable and precise automated job-resume matching, ultimately enhancing the efficiency of talent acquisition processes.

3.5 Threshold Determination

In the context of this research on automated job-resume matching, threshold determination is a crucial step to convert the similarity scores obtained from similarity measurement algorithms (e.g., cosine similarity, Jaccard similarity, Jaro-Winkler similarity) into binary decisions (Accepted or Rejected) for candidate matching.

Threshold determination involves setting a value that acts as a cutoff point for the similarity scores. Resumes with similarity scores above the threshold are considered a good match with the job description and are accepted, while those below the threshold are rejected.

Selecting an appropriate threshold value is essential to achieve the desired balance recall in the automated matching process. Two factors are considered:

- A **higher threshold** may lead to more conservative matching, accepting only highly similar resumes, which can result in missing potentially qualified candidates.
- A **lower threshold** may lead to accepting more resumes, but it could also introduce more noise and lower the overall accuracy.

To determine the threshold value, a comprehensive evaluation process is conducted by running a substantial number of resumes through the similarity measurement algorithms (e.g., cosine similarity, Jaccard similarity, Jaro-Winkler similarity). During this evaluation, the algorithms' performance in identifying the most similar and less similar resumes is observed and analyzed.

By examining the outcomes and comparing the results across different algorithms, the most effective threshold value is determined. This value is set to distinguish between acceptable matches (resumes with high similarity scores) and rejections (resumes with low similarity scores). Algorithm 6 represents the procedure of the Machine’s decision-making.

Algorithm 6: Resume Accepted or Rejected Based on Threshold Value

Input : Cosine Similarity Score, cosine_similarity_scr
Jaccard Similarity Score, jaccard_similarity
Jaro Winkler Similarity Score, jw_simialrity

Output : Applicant’s Resume Accepted or Rejected
accepted_textC ← "Accepted" or "Rejected"
accepted_textJ ← "Accepted" or "Rejected"
accepted_textJW ← "Accepted" or "Rejected"

: threshold_cosine ← 0.4
: threshold_jaccard ← 0.25
: threshold_jaroW ← 0.65
: **if** cosine_similarity_scr >= threshold_cosine:
:   accepted_textC = "Accepted"
: **else:**
:   accepted_textC = "Rejected"

```
if jaccard_similarity >= threshold_jaccard:
    accepted_textJ = "Accepted"
else:
    accepted_textJ = "Rejected"
if similarity_score >= threshold_jaroW:
    accepted_textJW = "Accepted"
else:
    accepted_textJW = "Rejected"
```

3.6 Human Expert Rating

To assess the accuracy of the automated system, human experts were actively involved in the evaluation process. Each resume is meticulously reviewed by the human evaluators, who rated the similarity of the resumes to their corresponding job descriptions. This manual rating process provided a crucial benchmark against which the machine-generated similarity scores were compared.

Additionally, the human experts independently made decisions on whether each resume was accepted or rejected for the given job position. By comparing the automated system's results to human judgments, the study aimed to ascertain the system's alignment with human decision-making, ensuring the reliability and effectiveness of the talent acquisition process.

3.7 Model Performance: Accuracy, Precision, Recall, and F1 Score Analysis

Accuracy, Precision, Recall, and F1 Score serve as crucial metrics for assessing the job-resume matching system's performance by comparing machine-generated decisions with human judgments. The evaluation process involves the following calculations:

Accuracy: The machine-generated decisions were compared to human judgments to evaluate the accuracy of each similarity measurement algorithm. The following evaluation metric is used to assess the alignment between human and machine decisions:

Accuracy measures the proportion of correct decisions made by the automated system when compared to human judgments. It is calculated using the formula:

$$Accuracy = \frac{(Number\ of\ Correct\ Decisions)}{Total\ Number\ of\ Decisions} \qquad [3.4]$$

Where,

"Number of Correct Decisions" represents the count of decisions made by the automated system that aligns with human judgments

"Total Number of Decisions" is the overall number of decisions made by both human evaluators and the automated system

Precision: Precision measures the accuracy of positive predictions. It is calculated as the ratio of true positives to the sum of true positives and false positives.

$$Precision = \frac{True\ positives}{True\ Positives + Fales\ Positives} \qquad [3.5]$$

Recall (Sensitivity): Recall quantifies the model's ability to correctly identify all relevant instances. It is calculated as the ratio of true positives to the sum of true positives and false negatives.

$$Recall = \frac{True\ positives}{True\ Positives + Fales\ Negatives} \qquad [3.6]$$

F1 Score: The F1 Score is the harmonic mean of Precision and Recall, providing a balanced measure. It is calculated as the reciprocal of the average of the reciprocals of Precision and Recall.

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall} \qquad [3.7]$$

Confusion matrix: It is often used to describe the performance of a model on a set of data for which the true values are known. It is particularly useful for binary classification problems. The confusion matrix has four entries:

- True Positives (TP): Instances that are actually positive and were correctly classified as positive.
- True Negatives (TN): Instances that are actually negative and were correctly classified as negative.
- False Positives (FP): Instances that are actually negative but were incorrectly classified as positive.
- False Negatives (FN): Instances that are actually positive but were incorrectly classified as negative.

In this evaluation, human decisions are considered correct, and the algorithms' decisions are compared against human decisions to calculate accuracy, precision, recall, and F1 Score. These metrics collectively provide insights into the effectiveness and reliability of the job-resume matching system.

3.8 K-Means Clustering

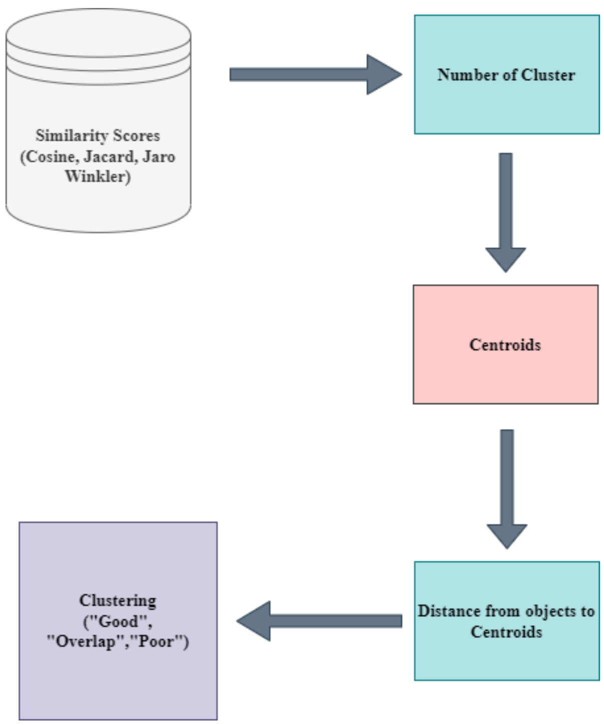


Figure 2: Process of K-Means clustering

K-means clustering is employed to categorize resumes based on their similarity scores obtained from the similarity measurement algorithms. This clustering approach groups resume into clusters representing "good," "average," and "poor" similarity matches with the job description. By doing so, the study gains valuable insights into potential talent pools for specific positions, allowing recruiters to identify candidates more effectively based on their level of alignment with the job requirements.

3.9 Data Analysis

The collected data and results were analyzed to draw meaningful conclusions about the effectiveness and reliability of the automated system. Comparative analysis between the different similarity measurement algorithms and clustering outcomes was conducted to identify strengths and limitations.

3.10 Visualization

Data visualization techniques, implemented with the help of matplotlib and other visualization libraries, are used to present the findings in a clear and intuitive manner.

Overall, this methodology aimed to rigorously evaluate the accuracy and reliability of the automated system in comparison to human judgments while exploring the application of K-means clustering for candidate categorization based on similarity scores.

Chapter 4

Automated Job- Resume Matching: Result & Discussion

4.1 Data Description

The research undertaken involved a comprehensive analysis of 122 resumes sourced from individuals currently employed in diverse companies across Bangladesh. These companies include prominent entities such as PwC, Colgis BD, Basundhara Limited, Strativ, and NRBC. The objective of this study was to gain insights into the employment backgrounds, skills, and qualifications of professionals actively contributing to various sectors within the Bangladeshi workforce.

To ensure a thorough examination, resumes were obtained from employees working across a spectrum of industries and roles within these esteemed organizations. This diverse sample set allowed for a holistic understanding of the skills and experiences prevalent among professionals in the Bangladesh job market.

In tandem with resume analysis, the study incorporated an investigation into job descriptions associated with specific job titles. Information for these job titles was systematically collected from reputable job searching platforms such as LinkedIn, indeed, and Google, as well as from official company websites. By sourcing data from multiple channels, the research aimed to capture a comprehensive view of the expectations and requirements set forth by employers for various positions.

The analysis was performed using Jupyter Notebook, a popular interactive computing environment, and the Python programming language. The system is designed to handle resumes in various formats, including PDF, text, and DOC files. To facilitate this functionality, the following libraries were installed and utilized:

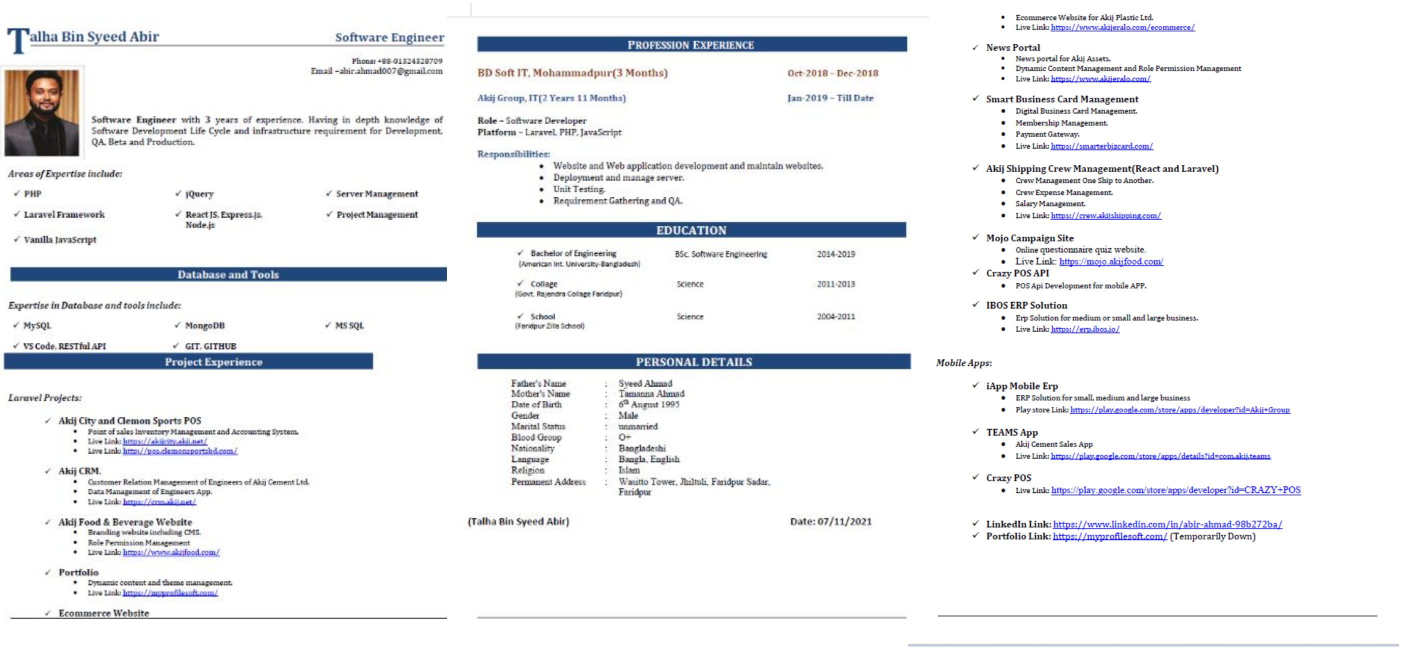
1. docx2txt: To extract text from DOCX files.
2. pdfminer: For extracting text from PDF files.

3. spacy: To perform advanced Natural Language Processing (NLP) tasks such as tokenization and named entity recognition (NER).

4. nltk: For text preprocessing, including stop word removal and lemmatization.

The entire result or output has been explained by taking a sample resume and a job description following a systematic step by step approach. The process starts with resume preprocessing.

4.2 Resume Preprocessing



Talha Bin Syeed Abir
Software Engineer
Phone: +88-01324328709
Email –abir.ahmad007@gmail.com

Software Engineer with 3 years of experience. Having in depth knowledge of Software Development Life Cycle and infrastructure requirement for Development, QA, Beta and Production.

Areas of Expertise include:

- ✓ PHP
- ✓ jQuery
- ✓ Server Management
- ✓ Laravel Framework
- ✓ React JS, Express.js, Node.js
- ✓ Project Management
- ✓ Vanilla JavaScript

Database and Tools

Expertise in Database and tools include:

- ✓ MySQL
- ✓ MongoDB
- ✓ MS SQL
- ✓ VS Code, RESTful API
- ✓ GIT, GITHUB

Project Experience

Laravel Projects:

- ✓ Akij City and Clemon Sports POS
  - Point of sales Inventory Management and Accounting System.
  - Live Link: https://akijcity.akij.net/
  - Live Link: http://pos.clemonsportsbd.com/
- ✓ Akij CRM.
  - Customer Relation Management of Engineers of Akij Cement Ltd.
  - Data Management of Engineers App.
  - Live Link: https://crm.akij.net/
- ✓ Akij Food & Beverage Website
  - Branding website including CMS.
  - Role Permission Management
  - Live Link: https://www.akijfood.com/
- ✓ Portfolio
  - Dynamic content and theme management.
  - Live Link: https://myprofilesoft.com/
- ✓ Ecommerce Website

PROFESSION EXPERIENCE

BD Soft IT, Mohammadpur(3 Months) Oct-2018 – Dec-2018

Akij Group, IT(2 Years 11 Months) Jan-2019 – Till Date

Role – Software Developer
Platform – Laravel, PHP, JavaScript

Responsibilities:

- Website and Web application development and maintain websites.
- Deployment and manage server.
- Unit Testing.
- Requirement Gathering and QA.

EDUCATION

✓ Bachelor of Engineering (American Int. University-Bangladesh)	BSc. Software Engineering	2014-2019
✓ Collage (Govt. Rajendra Collage Faridpur)	Science	2011-2013
✓ School (Faridpur Zilla School)	Science	2004-2011

PERSONAL DETAILS

Father's Name	:	Syeed Ahmad
Mother's Name	:	Tamanna Ahmad
Date of Birth	:	6th August 1995
Gender	:	Male
Marital Status	:	unmarried
Blood Group	:	O+
Nationality	:	Bangladeshi
Language	:	Bangla, English
Religion	:	Islam
Permanent Address	:	Wasitto Tower, Jhiltuli, Faridpur Sadar, Faridpur

(Talha Bin Syeed Abir) Date: 07/11/2021

- Ecommerce Website for Akij Plastic Ltd.
- Live Link: https://www.akijeralo.com/ecommerce/

- ✓ News Portal
  - News portal for Akij Assets.
  - Dynamic Content Management and Role Permission Management
  - Live Link: https://www.akijeralo.com/
- ✓ Smart Business Card Management
  - Digital Business Card Management.
  - Membership Management.
  - Payment Gateway.
  - Live Link: https://smarterbizcard.com/
- ✓ Akij Shipping Crew Management(React and Laravel)
  - Crew Management One Ship to Another.
  - Crew Expense Management.
  - Salary Management.
  - Live Link: https://crew.akijshipping.com/
- ✓ Mojo Campaign Site
  - Online questionnaire quiz website.
  - Live Link: https://mojo.akijfood.com/
- ✓ Crazy POS API
  - POS Api Development for mobile APP.
- ✓ IBOS ERP Solution
  - Erp Solution for medium or small and large business.
  - Live Link: https://erp.ibos.io/

Mobile Apps:

- ✓ iApp Mobile Erp
  - ERP Solution for small, medium and large business
  - Play store Link: https://play.google.com/store/apps/developer?id=Akij+Group
- ✓ TEAMS App
  - Akij Cement Sales App
  - Live Link: https://play.google.com/store/apps/details?id=com.akij.teams
- ✓ Crazy POS
  - Live Link: https://play.google.com/store/apps/developer?id=CRAZY+POS

- ✓ **LinkedIn Link:** https://www.linkedin.com/in/abir-ahmad-98b272ba/
- ✓ **Portfolio Link:** https://myprofilesoft.com/ (Temporarily Down)

Figure 3: A Sample Resume

Resume preprocessing is a crucial step in preparing the resume text for further analysis and comparison. I have taken a sample resume as Figure 1. Following steps are executed for preprocessing the resume:

- **Text Extraction:** Extracting the text content from this resume file, which can be in various formats like PDF, text, or Word documents.
- **Tokenization:** Breaking the text into individual words or tokens, making it easier to process and analyze the content.
- **Stop Word Removal:** Removing common words, known as stop words, such as "and," "the," "is," etc., as they do not carry significant meaning in the context of analysis.

- **Punctuation Removal:** Eliminating punctuation marks like commas, periods, and exclamation points, as they are not relevant for comparing skills or qualifications.
- **Lemmatization:** Reducing words to their base or root form to standardize variations of the same word.

```
Out[22]: "Talha Bin Syeed Abir Software Engineer Phone: +88-01324328709 Email -abir.ahmad007@gmail.com Software Engineer with 3 years of
experience. Having in depth knowledge of Software Development Life Cycle and infrastructure requirement for Development, QA, Be
ta and Production. Areas of Expertise include: PHP jQuery Server Management Laravel Framework React JS, Express.js, Node.js Pro
ject Management Vanilla JavaScript Database and Tools Expertise in Database and tools include: MySQL MongoDB MS SQL VS Code, RE
STful API GIT, GITHUB Project Experience Laravel Projects: Akij City and Clemon Sports POS Point of sales Inventory Management
and Accounting System. Live Link: https://akijcity.akij.net/ Live Link: http://pos.clemonsportsbd.com/ Akij CRM. Customer Relat
ion Management of Engineers of Akij Cement Ltd. Data Management of Engineers App. Live Link: https://crm.akij.net/ Akij Food &
Beverage Website Branding website including CMS. Role Permission Management Live Link: https://www.akijfood.com/ Portfolio Dyna
mic content and theme management. Live Link: https://myprofilesoft.com/ Ecommerce Website Ecommerce Website for Akij Plastic Lt
d. Live Link: https://www.akijeralo.com/ecommerce/ News Portal News portal for Akij Assets. Dynamic Content Management and Role
Permission Management Live Link: https://www.akijeralo.com/ Smart Business Card Management Digital Business Card Management. Me
mbership Management. Payment Gateway. Live Link: https://smarterbizcard.com/ Akij Shipping Crew Management(React and Laravel) C
rew Management One Ship to Another. Crew Expense Management. Salary Management. Live Link: https://crew.akijshipping.com/ Mojo
Campaign Site Online questionnaire quiz website. Live Link: https://mojo.akijfood.com/ Crazy POS API POS Api Development for mo
bile APP. IBOS ERP Solution Erp Solution for medium or small and large business. Live Link: https://erp.ibos.io/ Mobile Apps: i
App Mobile Erp ERP Solution for small, medium and large business Play store Link: https://play.google.com/store/apps/developer?
id=Akij+Group TEAMS App Akij Cement Sales App Live Link: https://play.google.com/store/apps/details?id=com.akij.teams Crazy POS
Live Link: https://play.google.com/store/apps/developer?id=CRAZY+POS LinkedIn Link: https://www.linkedin.com/in/abir-ahmad-98b2
72ba/ Portfolio Link: https://myprofilesoft.com/ (Temporarily Down) PROFESSION EXPERIENCE BD Soft IT, Mohammadpur(3 Months) Oct
-2018 - Dec-2018 Akij Group, IT(2 Years 11 Months) Jan-2019 - Till Date Role - Software Developer Platform - Laravel, PHP, Java
Script Responsibilities: Website and Web application development and maintain websites. Deployment and manage server. Unit Test
ing. Requirement Gathering and QA. EDUCATION Bachelor of Engineering (American Int. University-Bangladesh) BSc. Software Engine
ering 2014-2019 Collage (Govt. Rajendra Collage Faridpur) Science 2011-2013 School (Faridpur Zilla School) Science 2004-2011 PE
RSONAL DETAILS Father's Name : Syeed Ahmad Mother's Name : Tamanna Ahmad Date of Birth : 6th August 1995 Gender : Male Marital
Status : unmarried Blood Group : O+ Nationality : Bangladeshi Language : Bangla, English Religion : Islam Permanent Address : W
asitto Tower, Jhiltuli, Faridpur Sadar, Faridpur (Talha Bin Syeed Abir) Date: 07/11/2021"
```

Figure 4: Processed Text

By performing these preprocessing steps, the resume text becomes clean, consistent, and ready for further analysis, such as skills extraction and similarity comparison with job descriptions. This helps in achieving more accurate and reliable results in automated resume screening and job matching systems.

To analyze the resume, the following job description (Job Post: Back End Developer) has been considered and the skills required for this job description have been identified in Figure 7.

Back End Developer's Job Description

We are hiring!
Job Position: Backend Developer (Full Time)
Salary: 35,000-50,000 BDT (Depending on personal projects and knowledge depth)
Company Name: Wondersoft Solution
Location: House: JA-70, 2nd Floor, Link Road, Gudaraghat, Dhaka-1212
Job Context:
We are seeking a highly motivated, and enthusiastic Software Engineer to join our team. The ideal candidate should have knowledge in JavaScript, Typescript and be familiar with the Express.js, Node.js and NoSQL databases such as MongoDB and mysql database. They should also have knowledge in developing RESTful API's and be familiar with version control systems such as Git.
Nest Js framework knowledge will be plus. Must be a team player. Should maintain API design standard and guide frontend and app team.
Below points will be prioritised:
- 1+ years internship/fulltime experience and have some good github projects
- Server side knowledge NodeJS Projects and experience
- Good at data structure
- Can design database for any requirements
- Write clean and optimized code
- Expertise on developing microservice
- Expertise on Project Management

Office Hours: 10AM - 6PM, Saturday - Thursday.
Apply Method: If you want to be a proper backend developer, Please send your updated resume to tanincse14@gmail.com mentioning the position name in the email subject line (example: Applying for Backend Developer).

```
node.js
javascript
typescript
express.js
nosql
mongodb
mysql
restful api
git
nest js
api design
github
software engineering
database
project management
framework
```

Figure 5: Required Skill Set from the Job Description

4.3 Information Extraction

After getting the preprocessed text, we implemented the email extraction algorithm for getting the email of that particular applicant. Figure 2: is showing the email address that is found in the extracted text.

```
Email address found in the resume: abir.ahmad007@gmail.com
```

Figure 6: Extracted Email Address

For extracting skills from the preprocessed text, we have used advanced Natural Language Processing (NLP) techniques to identify and extract specific skills from the resume text. Here's an overview of the skill extraction process:

Custom Entity Patterns:

- Custom patterns are defined in a JSON file.
- Each pattern is associated with a unique label.
- Example: {"label": "SKILL|project management", "pattern":[{"LOWER":"proect"},{"LOWER ":"management"}]}
- This pattern specifies that the entity must contain both "project" and "management" in lowercase, indicating the skill "machine learning."

Add Custom Entity Ruler:

- A custom entity ruler is incorporated into the spaCy NLP pipeline.
- This ruler is responsible for recognizing and labeling skills in the resume text based on the defined patterns.

Text Lowercasing and Recognition:

- Text is converted to lowercase to make the entity recognition case-insensitive.
- This step improves the accuracy of pattern matching during entity recognition.

Entity Recognition and Labeling:

- Custom patterns are used to label recognized entities as skills.
- Labels are prefixed with "SKILL|" to distinguish them from other entities.

Skill Extraction and Uniqueness:

- Extracted skills are collected into a set.
- Sets automatically ensure uniqueness and eliminate duplicates.
- This enhances the quality of the extracted skills data.

Output:

- The final output consists of the extracted skills.
- The extracted skills will be used for similarity measurement.

```
Out[15]: {'accounting',
 'business',
 'content management',
 'data management',
 'database',
 'deployment',
 'ecommerce',
 'engineering',
 'framework',
 'javascript',
 'jquery',
 'laravel',
 'medium',
 'mobile',
 'mongodb',
 'mysql',
 'node.js',
 'play',
 'project management',
 'react',
 'server',
 'software',
 'software engineering',
 'testing',
 'tower'}
```

Figure 6: Extracted Skills from the Preprocessed Text

For the role of "Back End Developer," we collected and analyzed 13 different resumes. The data from these resumes, including the applicants' emails and extracted skills, was compiled and organized in an Excel file. Table 2 presents a comprehensive overview of the 13 applicants, their corresponding emails, and the skills identified from their resumes. This data provides valuable insights into the skillsets possessed by the applicants for the Back End Developer position.

Table 2: Extracted Emails and Skills

Email	**Skills**
saifbdjp@gmail.com	html, git, troubleshooting, sql, web development, wan, mysql, css, java, database management, bootstrap, php, javascript, jquery
abir.ahmad007@gmail.com	content management, tower, data management, database, accounting, mongodb, software engineering, business, javascript, testing, project management, server, react, framework, mysql, node.js, ecommerce, jquery, laravel, mobile, play, deployment, software
numansyed675@gmail.com	web design, html, html5, communication, responsive web design, css3, communication skills, css, communication skill, java, bootstrap, php, javascript, jquer

Email	Skills
noman.fiverr@gmail.com	web design, html, excel, git, html5, communication, sql, css3, mysql, dl, css, java, leadership, bootstrap, photoshop, adobe photoshop, php, javascript, illustrator, restful api, gre, jquery, teamwork
ti862650@gmail.com	excel, communication, communication skill, gre
smalamin.piash@gmail.com	html, git, sql, css3, mysql, css, java, bootstrap, python, php, javascript, restful api, gre, jquery, github
ddipa57@gmail.com	html, git, html5, communication, sql, css3, mysql, communication skills, dl, css, communication skill, java, bootstrap, php, javascript, jquery
shaiful@shaiful.me	html, excel, git, html5, communication, sql, c++, mysql, dl, problem-solving, java, php, project management, javascript, goal-oriented, jquery, github
jahidcse18@gmail.com	html, excel, html5, sql, wan, css3, mysql, css, java, bootstrap, php, javascript, gre, jquery
smoshajib100@gmail.com	web design, html, excel, html5, web development, wan, css3, css, java, bootstrap, python, django, php
rakib9204@gmail.com	html, git, html5, sql, c++, mysql, css, java, soa, soap, php, javascript, gre, jquery
shahriarsagor50@gmail.com	jquery, html, mysql, sql, css, c++, java, php, communication, git, javascript

4.4 Similarity Measurement results

Execution of Algorithm 3, Algorithm 4 and Algorithm 5, we have found similarity scores between the resume skills and job description skills.

Resume skill= content management, tower, data management, database, accounting, mongodb, engineering, medium, software engineering, business, javascript, testing, project management, server, react, framework, mysql, node.js, ecommerce, jquery, laravel, mobile, play, deployment, software

Job Description skill= node. js, javascript, typescript, express.js, nosql, mongodb, mysql, restful api, git, nest js, api design, github, software engineering, database, project management, framework

For that sample resume we have found the following scores:

```
Cosine Similarity: 0.626
Jaccard Similarity: 0.242
Jaro-Winkler similarity: 0.685
```

In a similar way, Table 3 displays the similarity scores for the remaining applicants across this mentioned job position. The scores are calculated using three similarity measurement algorithms, allowing us to assess the alignment between each applicant's skills and the corresponding job description. Higher similarity scores indicate a stronger match between an applicant's skills and the requirements of the job, potentially making them a more suitable candidate. On the other hand, lower scores may suggest a weaker fit for the position.

Table 3: Scores and Decision of the Similarity Measure Algorithms

Email	**Cosine Similarity**	**Cosine Decision**	**Jaccard Similarity**	**Jaccard Decision**	**Jaro-Winkler Similarity**	**Jaro Winkler Decision**	**Human Decision**
saifbdjp@gmail.com	0.492	Accepted	0.071	Rejected	0.7247	Accepted	Accepted
abir.ahmad007@gmail.com	0.626	Accepted	0.242	Accepted	0.685	Accepted	Accepted
numansyed675@gmail.com	0.577	Accepted	0.034	Rejected	0.68	Accepted	Rejected
noman.fiverr@gmail.com	0.577	Accepted	0.071	Rejected	0.7061	Accepted	Accepted
ti862650@gmail.com	0	Rejected	0	Rejected	0.565	Rejected	Rejected
smalaminpiash@gmail.com	0.344	Rejected	0.065	Rejected	0.67	Accepted	Accepted
ddipa57@gmail.com	0.606	Rejected	0.133	Rejected	0.729	Accepted	Rejected
shaiful@shaiful.me	0.513	Accepted	0.108	Rejected	0.71	Accepted	Accepted
jahidcse18@gmail.com	0.628	Accepted	0.117	Rejected	0.7293	Accepted	Accepted
smoshajib100@gmail.com	0.447	Rejected	0	Rejected	0.647	Rejected	Rejected
rakib9204@gmail.com	0.466	Accepted	0.096	Rejected	0.707	Rejected	Rejected
shahriarsagor0@gmail.com	0.62	Accepted	0.038	Rejected	0.709	Accepted	Accepted
saifbdjp@gmail.com	0.492	Accepted	0.071	Rejected	0.724	Accepted	Accepted

By analyzing the data in Table 3, we gain valuable insights into the performance of the automated system in efficiently matching applicants to the appropriate job openings based on their skills and qualifications. This data represents the similarity scores for different applicants' skills in comparison to the skills mentioned in the job descriptions. The scores range from 0 to 1, where higher values indicate a higher similarity between the applicant's skills and the required skills in the job description.

Based on the data, we can observe the following:
Similarly, for "abir.ahmad007@gmail.com," the similarity scores are 0.626, 0.242, and 0.685 for the cosine, Jaccard and Jaro-winkler respectively. All three algorithms consistently accepted the applicant for the mentioned job description, as indicated by the similarity scores.

On the other hand, the applicant with the email ti862650@gmail.com was consistently rejected by all three algorithms for the job descriptions, as indicated by the similarity scores of 0. The scores suggest that there is little to no similarity between the applicant's skills and the required skills in the job description, leading to the rejection.

4.5 Threshold and Decision

After conducting multiple runs with different resumes, we determined the threshold values for each similarity measurement algorithm to achieve optimal performance in our automated job-resume matching system.

For the cosine similarity algorithm, threshold of 0.4 is set for cosine similarity, for the Jaccard similarity algorithm, threshold of 0.2 is used, and for the Jaro-Winkler similarity algorithm, threshold of 0.65 is applied.

Using these threshold values, each similarity algorithm generated a decision for each applicant, either "Accepted" or "Rejected," based on their similarity scores. Applicants with similarity scores equal to or above the respective threshold were classified as "Accepted," indicating a strong match with the job requirements. Conversely, applicants with similarity scores below the threshold were marked as "Rejected," suggesting that their skills may not closely align with the job description.

In Table 3, the columns "Cosine Decision," "Jaccard Decision," and "Jaro-Winkler Decision" display the automated decisions for each applicant based on the respective similarity measurement algorithms.

For "Cosine Decision," the applicants were categorized as "Accepted" if their cosine similarity score was equal to or greater than the threshold value of 0.4. Otherwise, they were labeled as "Rejected".

Similarly, for "Jaccard Decision," applicants with a Jaccard similarity score greater than or equal to 0.2 were considered "Accepted," while those below the threshold were marked as "Rejected."

In the case of "Jaro-Winkler Decision," applicants were classified as "Accepted" if their Jaro-Winkler similarity score exceeded the threshold value of 0.65. Otherwise, they were categorized as "Rejected."

4.6 Human Decision

In Table 3, the column "Human Decision" represents the decisions (Accepted or Rejected) made by human evaluators after manually reviewing each applicant's resume. Unlike the automated decisions generated by the similarity measurement algorithms, the human decision is based on a thorough assessment of the applicant's qualifications, skills, and overall suitability for the job position.

Since human decision-making involves subjective evaluation and contextual understanding, it is often considered more accurate and comprehensive than machine-generated decisions. Human evaluators can take into account various factors beyond just skills and qualifications, such as experience, communication skills, and cultural fit with the organization.

By including the human decision in Table 3, the research highlights the comparison between the automated decision-making process and the more nuanced judgments made by human evaluators.

4.7 Model Performance

In the evaluation of the automated system, three accuracy values are calculated, each representing the agreement between the decisions generated by the similarity measurement algorithms (cosine, Jaccard, and Jaro-Winkler) and the decisions made by human evaluators. These accuracy values serve as performance metrics for assessing how well the automated system aligns with human judgments.

Cosine Similarity: Cosine similarity measures the cosine of the angle between two vectors, which represent the frequency of words in the documents (resumes in this case). It calculates the similarity between documents based on the orientation of their word frequency vectors, irrespective of their magnitudes. In general, cosine similarity is effective in capturing the similarity of documents with different lengths and word frequencies. The relatively high accuracy value (0.75) suggests that the cosine similarity algorithm is performing well in aligning with human decisions for this specific dataset.

The accuracy of the cosine similarity algorithm is calculated by comparing the Cosine Decision column (generated by the cosine similarity algorithm) with the Human Decision column.

```
----Cosine----
Accuracy: 0.75
Confusion Matrix:
True Negatives: 1
False Positives: 2
False Negatives: 1
True Positives: 8
Precision: 0.888
Recall: 0.8
F1 Score: 0.842
```

Jaccard Similarity: Jaccard similarity calculates the intersection over the union of sets, measuring the similarity between documents based on the presence or absence of words. It is well-suited for binary data or scenarios where word frequencies are not crucial. The accuracy value of 0.33 indicates that the Jaccard similarity algorithm is moderately effective in aligning with human decisions but may exhibit some discrepancies compared to the cosine similarity.

Similarly, the accuracy of the Jaccard similarity algorithm is calculated by comparing the Jaccard Decision column with the Human Decision column.

```
----Jaccard----
Accuracy: 0.333
Confusion Matrix:
True Negatives: 3
False Positives: 0
False Negatives: 8
True Positives: 1
Precision: 0.111
Recall: 1.0
F1 Score: 0.199
```

Jaro-Winkler Similarity: Jaro-Winkler similarity is specifically designed for comparing strings with slight spelling variations or typos. It takes into account the number of common characters and the number of transpositions between strings. The accuracy value of 0.91 suggests that the Jaro-Winkler similarity algorithm is performing well in capturing similarities between strings, which can be beneficial in cases where resumes may contain minor spelling differences.

The accuracy of theJaro-Winkler similarity algorithm is calculated by comparing the Jaro-Winkler Decision column with the Human Decision column.

```
----JaroWinkler----
Accuracy: 0.916
Confusion Matrix:
True Negatives: 2
False Positives: 1
False Negatives: 0
True Positives: 9
Precision: 1.0
Recall: 0.9
F1 Score: 0.947
```

The variations in the accuracy values of the three similarity measurement algorithms (cosine, Jaccard, and Jaro-Winkler) can be attributed to their underlying methodologies and how they handle text similarity calculations.

4.8 K Means Clustering

In our research, we applied K-Means clustering to group resumes based on their similarity scores obtained from the cosine similarity measurement. Before clustering, we normalized the cosine similarity scores to ensure that they are in the range of [0, 1], where 0 represents no similarity and 1 indicates a perfect match. We then reversed the order of the normalized data so that higher similarity scores are given more weight, reflecting a better match between the applicant's skills and the job requirements.

Next, we applied K-Means clustering with a pre-defined number of clusters (k=3) to categorize the resumes into three distinct groups based on their similarity scores. The clustering process grouped resumes with similar skills into the same clusters, allowing us to gain insights into potential talent pools for specific job positions.

We assigned meaningful names to the clusters to facilitate interpretation and understanding. The clusters were named as follows:

- **"Good Match" Cluster:** This cluster represents resumes with high cosine similarity scores, indicating a strong alignment between the applicant's skills and the job requirements. These applicants are considered to be good matches for the respective job position.

- **"Average Match" Cluster:** Resumes in this cluster have moderate cosine similarity scores, signifying a reasonable overlap of skills with the job description. These applicants might possess some of the required skills but may also have some gaps.
- **"Poor Match" Cluster:** This cluster includes resumes with low cosine similarity scores, suggesting a limited correspondence between the applicant's skills and the job description. These applicants may not be well-suited for the job position based on the skills extracted from their resumes.

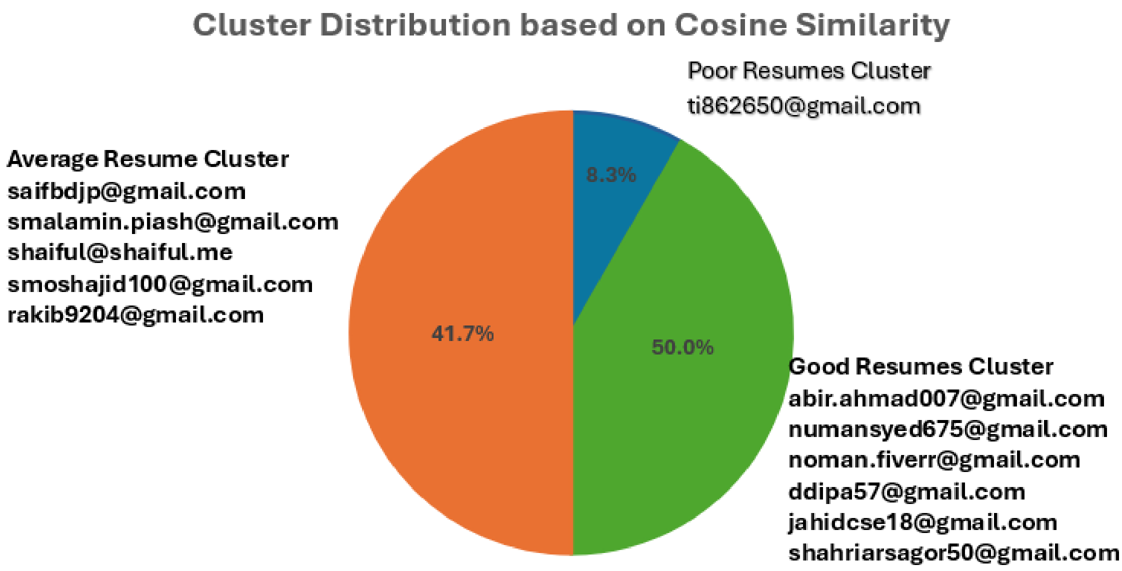


Figure 7: Clustering (Good', 'Average' and 'Poor') of Applicants Based on Cosine Similarity Scores

By visualizing the distribution of resumes in each cluster using a pie chart shows in Figure 6, we are able to gain a clear understanding of how applicants were grouped based on their similarity to the job description.

Same techniques are applied in Jaccard and Jaro-Winkler for grouping the applicants into 3 groups. Figure 7 shows the clusters using Jaccard similarity scores and Figure 8 shows the clusters using Jaro-Winkler similarity scores.

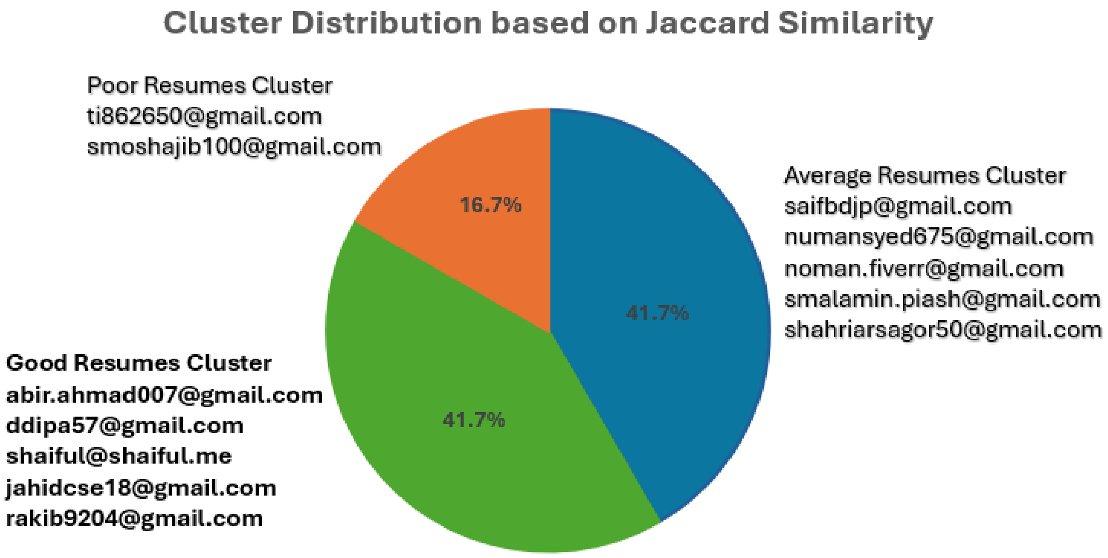


Figure 8: Clustering (Good', 'Average' and 'Poor') of Applicants Based on Jaccard Similarity Scores

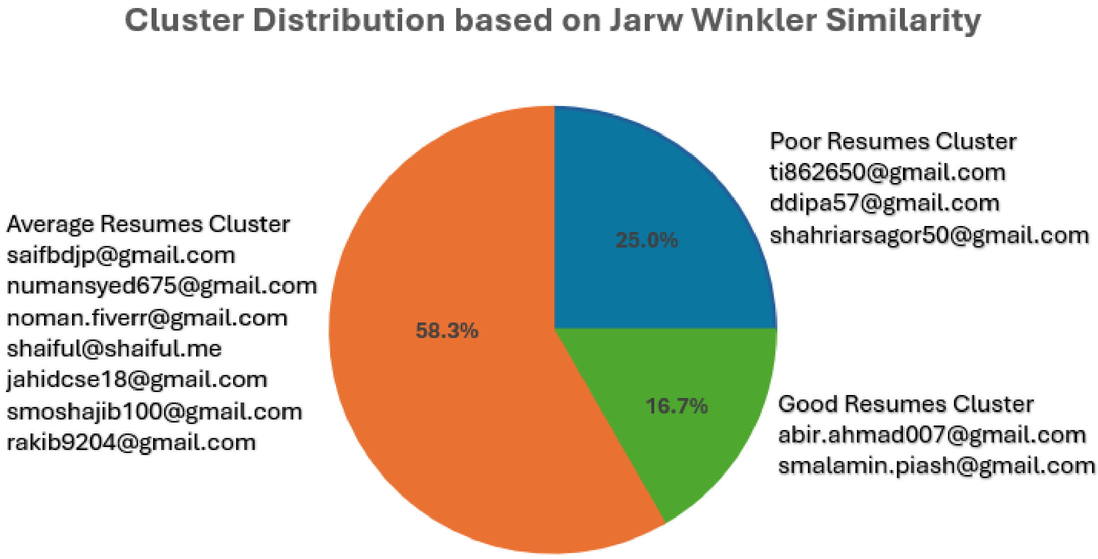


Figure 9: Clustering (Good', 'Average' and 'Poor') of Applicants Based on Jaro Winkler Similarity Scores

4.9 Comparative Analysis

This section provides analysis of the job descriptions and resumes for nine additional job positions, following the format and methodology used for the BackEnd Developer job.

The results reveal variations in similarity scores, machine decisions, and human evaluations across different job roles. The insights gained from this analysis offer valuable understanding of how the machine's accuracy varies for various job positions and resumes. The results provide insights into the variations in similarity scores between job descriptions and resumes, highlighting how different jobs and individual resumes contribute to the accuracy of the machine decisions.

We can easily understand how similar scores vary between different job descriptions and resumes, as well as the accuracy of the machine decisions for each job position. The overall analysis provides a comprehensive overview of the research findings and their significance.

4.9.1 Front-End Developer

Table 4: Required Job Skills for Front-End Developer

Job Description's Required Skills
HTML, CSS, JavaScript, jQuery, Bootstrap, Web Design, Web Development, CSS3

Table 5: Applicants' Emails and Skills for Front-End Developer Position

Email	**Skills**
saifbdjp@gmail.com	jquery, html, mysql, sql, css, web development, database management, wan, bootstrap, java, php, troubleshooting, git, javascript
abir.ahmad007@gmail.com	mongodb, jquery, mysql, sql, project management, java, php, git, javascript, branding
arpitakabir8@gmail.com	html, mysql, sql, css, web development, web design, excel, dl, bootstrap, java, php, gre
numansyed675@gmail.com	jquery, css3, html, css, responsive web design, web design, communication skill, bootstrap, java, html5, php, communication, communication skills, javascript
noman.fiverr@gmail.com	jquery, css3, html, adobe photoshop, mysql, sql, css, web design, excel, dl, leadership, bootstrap, illustrator, java, html5, teamwork, php, restful api, communication, git, javascript, gre, photoshop
ti862650@gmail.com	communication skill, excel, communication, gre
smalamin.piash@gmail.com	jquery, css3, html, mysql, sql, css, github, python, bootstrap, java, php, restful api, git, javascript, gre
ddipa57@gmail.com	jquery, css3, html, mysql, sql, css, communication skill, dl, bootstrap, java, html5, php, communication, communication skills, git, javascript
shaiful@shaiful.me	jquery, html, problem-solving, mysql, sql, github, c++, project management, excel, dl, java, html5, goal-oriented, php, communication, git, javascript
jahidcse18@gmail.com	jquery, css3, html, mysql, sql, css, wan, excel, bootstrap, java, html5, php, javascript, gre
smoshajib100@gmail.com	css3, html, css, web development, python, web design, django, wan, excel, bootstrap, java, html5, php
rakib9204@gmail.com	jquery, html, mysql, sql, soa, css, c++, java, html5, php, soap, git, javascript, gre
shahriarsagor50@gmail.com	jquery, html, mysql, sql, css, c++, java, php, communication, git, javascript

Table 6: Similarity Scores and Decisions for Front-End Developer Applicants

Email	**Cosine Similarity**	**Cosine Decision**	**Jaccard Similarity**	**Jaccard Decision**	**Jaro-Winkler Similarity**	**Jaro Winkler Decision**	**Human Decision**

saifbdjp@gmail.com	0.632	Accepted	0.375	Accepted	0.695	Accepted	Accepted
abir.ahmad007@gmail.com	0.426	Accepted	0.125	Rejected	0.65	Accepted	Accepted
arpitakabir8@gmail.com	0.75	Accepted	0.333	Accepted	0.839	Accepted	Accepted
numansyed675@gmail.com	0.671	Accepted	0.466	Accepted	0.68	Accepted	Accepted
noman.fiverr@gmail.com	0.512	Accepted	0.291	Accepted	0.647	Rejected	Accepted
ti862650@gmail.com	0	Rejected	0	Rejected	0.514	Rejected	Rejected
smalaminpiash@gmail.com	0.612	Accepted	0.352	Accepted	0.683	Accepted	Accepted
ddipa57@gmail.com	0.5	Accepted	0.333	Accepted	0.621	Rejected	Rejected
shaiful@shaiful.me	0.397	Rejected	0.136	Rejected	0.652	Accepted	Rejected
jahidcse18@gmail.com	0.654	Accepted	0.375	Accepted	0.694	Accepted	Accepted
smoshajib100@gmail.com	0.766	Accepted	0.4	Accepted	0.701	Accepted	Accepted
rakib9204@gmail.com	0.554	Accepted	0.222	Rejected	0.663	Accepted	Accepted
shahriarsagor0@gmail.com	0.632	Accepted	0.266	Accepted	0.645	Rejected	Accepted

Performance:

```
----Cosine----
Accuracy: 0.923
Confusion Matrix:
True Negatives: 2
False Positives: 1
False Negatives: 0
True Positives: 10
Precision: 1.0
Recall: 0.909
F1 Score: 0.952
----------------------------------------
----Jaccard----
Accuracy: 0.769
Confusion Matrix:
True Negatives: 2
False Positives: 1
False Negatives: 2
True Positives: 8
Precision: 0.8
Recall: 0.888
F1 Score: 0.842
----------------------------------------
----JaroWinkler----
Accuracy: 0.769
Confusion Matrix:
True Negatives: 2
False Positives: 1
False Negatives: 2
True Positives: 8
Precision: 0.8
Recall: 0.888
F1 Score: 0.842
```

4.9.2 Graphics Designer

Table 7: Required Job Skills for Graphics Designer

Job Description Skills
'Illustrator, Photoshoot, Photo editing, Video making, Video Editing, Design concepts, Creativity, Social media

proficiency, Communication skill, Idea sharing, Graphics design, Photoshop

Table 8: Applicants' Emails and Skills for Graphics Designer Position

Email	**Skills**
kaocherahmedtarek@gmail.com	adobe indesign, adobe photoshop, typography, dl, illustrator, adobe illustrator, git, illustration, photoshop
fkhan151@bba.uiu.ac.bd	creativity, adobe photoshop, planning, interpersonal skills, dl, communication, git, illustration, photoshop
anikameem9@gmail.com	deep learning, html, problem-solving, adobe photoshop, mysql, sql, css, web development, python, machine learning, django, dl, bootstrap, illustrator, java, teamwork, adobe illustrator, php, forecasting, communication, git, javascript, photoshop
apumazumder.ak10@gmail.com	mysql, sql, c++, communication skill, wan, project management, documentation, excel, dl, leadership, illustrator, graphics design, communication, git, gre, photoshop
shanchay777@gmail.com	jquery, css3, html, adobe photoshop, mysql, ui/ux design, sql, data analysis, css, responsive web design, python, web design, interpersonal skills, communication skill, wan, email marketing, documentation, excel, dl, bootstrap, illustrator, java, graphics design, data visualization, html5, adobe illustrator, seo, communication, communication skills, git, javascript, gre, photoshop
mijanhawlader746@gmail.com	creativity, planning, video editing, leadership, illustrator, graphics design, communication, illustration, photoshop
contact@motakabbir.com	creativity, design concepts, time management, dl, leadership, teamwork, communication, git, team management
santo9585@gmail.com	mongodb, css3, html, css, web development, github, router, web design, express.js, documentation, dl, bootstrap, illustrator, java, graphics design, html5, node.js, communication, git, javascript, photoshop
mdsajibbiswas92@gmail.com	adobe indesign, adobe photoshop, typography, dl, leadership, illustrator, adobe illustrator, git, illustration, photoshop
ssultanaorpi@gmail.com	html, css, wan, java, html5, gre
saif.shouvik@gmail.com	adobe indesign, jquery, css3, html, adobe photoshop, css, web development, copywriting, web design, c++, communication skill, django, excel, illustrator, java, html5, load balancing, adobe illustrator, php, seo, communication, javascript, photoshop

Table 9: Similarity Scores and Decisions for Graphics Designer Developer Applicants

Email	**Cosine Similarity**	**Cosine Decision**	**Jaccard Similarity**	**Jaccard Decision**	**Jaro-Winkler Similarity**	**Jaro Winkler Decision**	**Human Decision**
kaocherahmedtaek@gmail.com	0.603	Accepted	0.105	Rejected	0.66	Accepted	Accepted
fkhan151@bba.uiu.ac.bd	0.64	Accepted	0.105	Rejected	0.683	Accepted	Accepted
anikameem9@gmail.com	0.474	Accepted	0.06	Rejected	0.713	Accepted	Accepted
apumazumderak10@gmail.com	0.596	Accepted	0.166	Rejected	0.707	Accepted	Accepted
shanchay777@gmail.com	0.645	Accepted	0.097	Rejected	0.683	Accepted	Accepted
mijanhawlader746@gmail.com	0.804	Accepted	0.312	Accepted	0.694	Accepted	Accepted
contact@motakabbir.com	0.505	Accepted	0.105	Rejected	0.663	Accepted	Accepted
santo9585@gmail.com	0.5	Accepted	0.1	Rejected	0.726	Accepted	Accepted
mdsajibbiswas92@gmail.com	0.589	Accepted	0.1	Rejected	0.663	Accepted	Accepted
ssultanaorpi@gmail.com	0	Rejected	0	Rejected	0.52	Rejected	Rejected
saif.shouvik@gmail.com	0.485	Accepted	0.093	Rejected	0.731	Accepted	Accepted

Performance:

```
----Cosine----
Accuracy: 1.0
Confusion Matrix:
True Negatives: 1
False Positives: 0
False Negatives: 0
True Positives: 10
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
----------------------------------------
----Jaccard----
Accuracy: 0.181
Confusion Matrix:
True Negatives: 1
False Positives: 0
False Negatives: 9
True Positives: 1
Precision: 0.1
Recall: 1.0
F1 Score: 0.181
----------------------------------------
----JaroWinkler----
Accuracy: 1.0
Confusion Matrix:
True Negatives: 1
False Positives: 0
False Negatives: 0
True Positives: 10
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
```

4.9.3 Python Developer

Table 10: Required Job Skills for Python Developer

Job Description Skills
NoSQL, MySQL, Postgresql, MongoDB, Python, Django, Flask, Tkinter, Kivy, ORM (Object Relational Mapper), JavaScript, HTML5, CSS3, API based architectures, SOA, Micro-Services Node.js,JavaScript,Typescript,Express.js,NoSQL,MongoDB,MySQL,RESTful API,Git,Nest Js,API design,GitHub

Table 11: Applicants' Emails and Skills for Python Developer Position

Email	Skills
ameerulislam@gmail.com	interpersonal skills, java, sql, gre, postgresql, git, php, project management, deep learning, mysql, python, leadership, github, troubleshooting, dl, html, css, machine learning, web development, javascript, graphics design
abdullah.nordicab.se@gmail.com	agile methodology, java, sql, c++, git, mysql, python, github, html, css, communication, javascript
jabed.akcc@gmail.com	flask, mongodb, java, sql, gre, postgresql, git, organizational skills, mysql, jquery, budgeting, bts, excel, python, github, data analysis, cash flow analysis, django, html, css, communication, web development, javascript
shaikotbhuiya@gmail.com	bootstrap, flask, mongodb, java, sql, gre, postgresql, git, mysql, python, github, django, html, css, javascript, node.js, typescript
omarcsejust@gmail.com	bootstrap, flask, mongodb, java, sql, gre, postgresql, git, php, project management, mysql, jquery, restful api, python, github, data analysis, django, html, debugging, communication, communication skills, communication skill, web development, javascript, java ee, nosql, problem-solving

Email	Skills
saifull668@gmail.com	java, sql, gre, c++, postgresql, git, php, adaptability, project management, mysql, planning, data visualization, transmission, excel, python, github, data analysis, django, dl, communication, decision-making, machine learning, wan
shalmanpappu@gmail.com	bootstrap, java, sql, gre, seo, c++, git, php, mysql, python, github, django, dl, html, css, javascript
mdtanvirahmed74@gmail.com	photoshop, git, adobe illustrator, illustrator, excel, adobe photoshop, graphics design
jm.tarif55@gmail.com	flask, java, sql, c++, git, php, teamwork, mysql, python, leadership, github, django, dl, html, time management, css, communication, communication skill, javascript
mntushar25@gmail.com	bootstrap, java, sql, documentation, gre, c++, postgresql, git, project management, mysql, reporting, restful api, excel, python, django, html, css, communication, communication skills, communication skill, javascript
16511042@student.bup.edu.bd	java, sql, c++, git, php, organizational skills, mysql, excel, python, html, css, communication, machine learning, javascript, wan

Table 12: Similarity Scores and Decisions for Python Developer Applicants

Email	Cosine Similarity	Cosine Decision	Jaccard Similarity	Jaccard Decision	Jaro-Winkler Similarity	Jaro Winkler Decision	Human Decision
ameerulislam@gmail.com	0.371	Rejected	0.121	Rejected	0.714	Accepted	Rejected
abdullah.ordicab.se@gmail.com	0.5	Accepted	0.12	Rejected	0.642	Rejected	Rejected
jabed.akcc@gmail.com	0.483	Accepted	0.218	Rejected	0.728	Accepted	Rejected
shaikotbhuiya@gmail.com	0.623	Accepted	0.269	Accepted	0.712	Accepted	Accepted
omarcsejust@gmail.com	0.457	Accepted	0.228	Rejected	0.704	Accepted	Accepted
saifull668@gmail.com	0.371	Rejected	0.114	Rejected	0.692	Accepted	Rejected
shalmanpappu@gmail.com	0.516	Accepted	0.142	Rejected	0.646	Rejected	Accepted
mdtanvirahmed74@gmail.com	0	Rejected	0	Rejected	0.634	Rejected	Rejected
jm.tarif55@gmail.com	0.476	Accepted	0.166	Rejected	0.717	Accepted	Accepted
mntushar25@gmail.com	0.447	Accepted	0.156	Rejected	0.702	Accepted	Accepted
16511042@student.bup.edu.bd	0.433	Accepted	0.13	Rejected	0.646	Rejected	Rejected

Performance:

```
----Cosine----
Accuracy: 0.818
Confusion Matrix:
True Negatives: 3
False Positives: 2
False Negatives: 0
True Positives: 6
Precision: 1.0
Recall: 0.75
F1 Score: 0.857
----------------------------------------
----Jaccard----
Accuracy: 0.545
Confusion Matrix:
True Negatives: 5
False Positives: 0
False Negatives: 5
True Positives: 1
```

```
Precision: 0.166
Recall: 1.0
F1 Score: 0.285
----------------------------------------
----JaroWinkler----
Accuracy: 0.636
Confusion Matrix:
True Negatives: 2
False Positives: 3
False Negatives: 1
True Positives: 5
Precision: 0.833
Recall: 0.625
F1 Score: 0.714
```

4.9.4 Sales Executive

Table 13: Required Job Skills for Sales Executive

Job Description Skills
Sales Presentations, Product Knowledge, Relationship Building, Sales Strategy, Sales Target, Relationship Management, Market Expansion, Revenue Collection, Sales Strategy, Customer Support, Stakeholder Engagement, Report Generation, Planning, Coordination

Table 14: Applicants' Emails and Skills for Sales Executive Position

Email	Skills
sheakriad96@gmail.com	coordination, documentation, negotiation, planning, excel, leadership, data analysis, performance management, dl, time management, communication
majorlazer775@gmail.com	java, seo, c++, negotiation, data visualization, excel, html, communication
afsana26-1369@diu.edu.bd	coordination, gre, customer support, report generation, planning, relationship management, revenue collection, excel, market expansion, sales target, relationship building, dl, stakeholder engagement, relationship management, communication, communication skill, wan, sales strategy, product knowledge
arnobnazir2000@gmail.com	communication, communication skill
iasifemon@gmail.com	marketing campaigns, gre, negotiation, excel, leadership, time management, prospecting, communication
fahadbinmahfuj@gmail.com	market research, seo, git, content marketing, social media marketing, dl, html, css, communication, creativity, google analytics
fahmidaafroj4068@gmail.com	photoshop, git, adobe illustrator, planning, illustrator, reporting, excel, social media marketing, dl, communication, graphics design
orishafareen24@gmail.com	gre, photoshop, php, excel, html, adobe photoshop, web development
manojsannashi@gmail.com	coordination, training and development, market research, documentation, gre, git, project management, forecasting, negotiation, planning, relationship management, sales target, relationship management, communication, analytical skills, creativity
mugdtourlovers@gmail.com	excel, wan
tahsins713@gmail.com	gre, excel, dl, communication, communication skills, communication skill, wan

Table 15: Similarity Scores and Decisions for Sales Executive Applicants

Email	Cosine Similarity	Cosine Decision	Jaccard Similarity	Jaccard Decision	Jaro-Winkler Similarity	Jaro Winkler Decision	Human Decision

sheakriad96@gmail.com	0.577	Accepted	0.09	Rejected	0.663	Accepted	Accepted
majorlazer775@gmail.com	0	Rejected	0	Rejected	0.565	Rejected	Rejected
afsana26-1369@diu.edu.bd	0.809	Accepted	0.6	Accepted	0.778	Accepted	Accepted
arnobnazir2000@gmail.com	0	Rejected	0	Rejected	0.52	Rejected	Rejected
iasifemon@gmail.com	0.316	Rejected	0	Rejected	0.624	Rejected	Rejected
fahadbinahfuj12@gmail.com	0.235	Rejected	0	Rejected	0.633	Rejected	Rejected
fahmidaafroj40@gmail.com	0.242	Rejected	0.043	Rejected	0.662	Accepted	Rejected
orishafareen24@gmail.com	0	Rejected	0	Rejected	0.546	Rejected	Rejected
manojsannashi@gmail.com	0.53	Accepted	0.16	Rejected	0.727	Accepted	Accepted
mugdhbdtour@gmail.com	0	Rejected	0	Rejected	0.53	Rejected	Rejected
tahsins713@gmail.com	0	Rejected	0	Rejected	0.572901	Rejected	Rejected

Performance:

```
----Cosine----
Accuracy: 1.0
Confusion Matrix:
True Negatives: 8
False Positives: 0
False Negatives: 0
True Positives: 3
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
----------------------------------------
----Jaccard----
Accuracy: 0.818
Confusion Matrix:
True Negatives: 8
False Positives: 0
False Negatives: 2
True Positives: 1
Precision: 0.333
Recall: 1.0
F1 Score: 0.5
----------------------------------------
----JaroWinkler----
Accuracy: 0.909
Confusion Matrix:
True Negatives: 7
False Positives: 1
False Negatives: 0
True Positives: 3
Precision: 1.0
Recall: 0.75
F1 Score: 0.857
```

4.9.5 Java Developer

Table 16: Required Job Skills for Java Developer

Job Description Skills
Java EE, Enterprise JavaBeans (EJB), Java Persistence API (JPA), SQL – Postgre, Oracle, Angular, Vaadin, Enterprise

JavaBeans (EJB), Java Persistence API (JPA), JBoss EAP, SOAP, REST web services, Jenkins, Oracle DB, Maven, Java

Table 17: Applicants' Emails and Skills for Java Developer Position

Email	**Skills**
akib@gmail.com	java, sql, git, php, mysql, jquery, html, css, javascript
arifa07aust@gmail.com	gre, planning, reporting, communication
kmshoibal@gmail.com	java, sql, gre, git, mysql, python, github
rezaul.bappy1@gmail.com	java, sql, documentation, gre, c++, planning, reporting, communication, wan
khaledtanim@gmail.com	java, sql, gre, c++, photoshop, git, project management, router, mysql, planning, illustrator, excel, python, leadership, github, troubleshooting, dl, html, time management, css, web development, creativity
mahfujaakterdu@gmail.com	soa, documentation, gre, seo, jenkins, soap, communication, configuration management, configuration management
iftekhar.pony22@gmail.com	documentation, c++, data mining, network security, communication, wan
mehedees@live.com	css3, bootstrap, java, sql, seo, c++, git, html5, php, mysql, jquery, data mining, social media marketing, network security, python, github, django, html, css, machine learning, web development
nadimkaysar1@outlook.com	reporting, communication
neelapriya12@gmail.com	java, technical documentation, sql, database management, documentation, gre, git, php, project management, mysql, risk management, reporting, tx, dl, html, css, communication
suvro167@gmail.com	java, sql, gre, php, mysql, transmission, html, css, communication, web development, javascript
saudmm37@gmail.com	gre, adaptability, presentation skills, router, excel, time management, communication, decision-making, wan
shahid.csedu@yahoo.com	java, git, project management, planning, excel, dl, communication, communication skills, communication skill
shihabzhasan2013@gmail.com	java, sql, gre, web design, project management, organizational skills, jquery, planning, responsive web design, excel, leadership, dl, html, css, communication, javascript, creativity
kmshoibal@gmail.com	java, sql, gre, git, sql – postgre, mysql, vaadin, enterprise javabeans (ejb), python, github, java persistence api (jpa), oracle, angular, java ee

Table 18: Similarity Scores and Decisions for Java Developer Applicants

Email	**Cosine Similarity**	**Cosine Decision**	**Jaccard Similarity**	**Jaccard Decision**	**Jaro-Winkler Similarity**	**Jaro Winkler Decision**	**Human Decision**
akib@gmail.com	0.404	Accepted	0.045	Rejected	0.533	Rejected	Accepted
arifa07aust@gmail.com	0	Rejected	0	Rejected	0.519	Rejected	Rejected
kmshoibal@gmail.com	0.458	Accepted	0.05	Rejected	0.517	Rejected	Accepted
rezaul.bappy1@gmail.com	0.428	Accepted	0.045	Rejected	0.556	Rejected	Accepted
khaledtanim@gmail.com	0.277	Rejected	0.028	Rejected	0.615	Rejected	Rejected
mahfujaakterdu@gmail.com	0.365	Rejected	0.1	Rejected	0.525	Rejected	Rejected
iftekhar.pony22@gmail.com	0	Rejected	0	Rejected	0.494	Rejected	Rejected
mehedees@live.com	0.277	Rejected	0.029	Rejected	0.606	Rejected	Rejected
nadimkaysar1@outlook.com	0	Rejected	0	Rejected	0.502	Rejected	Rejected

neelapriya12@gmail.com	0.225	Rejected	0.033	Rejected	0.593	Rejected	Rejected
suvro167@gmail.com	0.408	Accepted	0.041	Rejected	0.588	Rejected	Rejected
saudmm37@gmail.com	0	Rejected	0	Rejected	0.567	Rejected	Rejected
shahid.csedu@yahoo.com	0.235	Rejected	0.045	Rejected	0.559	Rejected	Rejected
shihabzhasan213@mail.com	0.323	Rejected	0.033	Rejected	0.637	Rejected	Rejected
kmshoibal@gmail.com	0.848	Accepted	0.285	Accepted	0.667	Accepted	Accepted

Performance:

```
----Cosine----
Accuracy: 0.933
Confusion Matrix:
True Negatives: 10
False Positives: 1
False Negatives: 0
True Positives: 4
Precision: 1.0
Recall: 0.8
F1 Score: 0.888
----------------------------------------
----Jaccard----
Accuracy: 0.8
Confusion Matrix:
True Negatives: 11
False Positives: 0
False Negatives: 3
True Positives: 1
Precision: 0.25
Recall: 1.0
F1 Score: 0.4
----------------------------------------
----JaroWinkler----
Accuracy: 0.8
Confusion Matrix:
True Negatives: 11
False Positives: 0
False Negatives: 3
True Positives: 1
Precision: 0.25
Recall: 1.0
F1 Score: 0.4
```

4.9.6 Network Engineer

Table 19: Required Job Skills for Network Engineer

Job Description Skills
Data Centre, WAN, Network Technologies, Cisco, Palo Alto, Fortinet, Juniper Firewalls, Cisco Wireless Solutions, Cisco, IOS, Nexus, Router, Switches, MPLS, EGP, IGP, VPN (L2 and L3), GRE, IPsec, L2TP VPN tunneling protocol, CCNP, SCOR, CCNP, ENCOR, CCNA, JNCIA, JNCIP

Table 20: Applicants' Emails and Skills for Network Engineer Position

Email	Skills

Email	Skills
ztasnim35@gmail.com	html, data analysis, time management, excel, communication, dl, css, python, c++, teamwork, github, java, web development, git
afsana261369@diu.edu.bd	capacity planning, report generation, l2tp vpn tunneling protocol, firewalls, troubleshooting, juniper junos, load balancing, communication skill, relationship management, excel, vlans, capacity planning, communication, dl, comptia network+, documentation, product knowledge, palo alto, relationship management, stakeholder engagement, ipsec, relationship building, network documentation, network monitoring, planning, sales strategy, coordination, routing and switching, network security, customer support, sales target, cisco ios, fortinet, revenue collection, gre, market expansion, mpls, wan
arnobnazir2000@gmail.com	communication skill, communication
iasifemon@gmail.com	leadership, time management, excel, communication, prospecting, marketing campaigns, negotiation, gre
Tashrif34@gmail.com	switches, routers, capacity planning, l2tp vpn tunneling protocol, firewalls, troubleshooting, juniper junos, load balancing, vlans, capacity planning, comptia network+, documentation, palo alto, router, ipsec, network documentation, network monitoring, planning, routing and switching, network security, cisco ios, fortinet, gre, mpls, wan
saif.shouvik@gmail.com	switches, encor, l2tp vpn tunneling protocol, vpn (l2 and l3), html5, firewalls, html, cisco wireless solutions, load balancing, igp, communication skill, web design, css3, excel, scor, communication, css, javascript, adobe illustrator, palo alto, router, ipsec, photoshop, seo, c++, egp, nexus, juniper firewalls, adobe indesign, java, web development, adobe photoshop, copywriting, jquery, fortinet, django, illustrator, gre, mpls, php
fahadbinmahfuj12@gmail.com	html, google analytics, communication, dl, market research, css, seo, creativity, social media marketing, git, content marketing
fahmidaafroj4068@gmail.com	graphics design, excel, communication, dl, adobe illustrator, photoshop, planning, social media marketing, reporting, git, illustrator
orishafareen2@gmail.com	html, excel, photoshop, web development, adobe photoshop, gre, php
Manojsanna4shi@gmail.com	relationship management, communication, project management, market research, documentation, relationship management, analytical skills, creativity, planning, training and development, coordination, negotiation, sales target, git, gre, forecasting

Table 21: Similarity Scores and Decisions for Network Engineer Applicants

Email	**Cosine Similarity**	**Cosine Decision**	**Jaccard Similarity**	**Jaccard Decision**	**Jaro-Winkler Similarity**	**Jaro Winkler Decision**	**Human Decision**
ztasnim35@gmail.com	0.25	Rejected	0	Rejected	0.577	Rejected	Rejected
afsana26-1369@diu.edu.bd	0.436	Accepted	0.127	Rejected	0.663	Accepted	Accepted
arnobnazir2000@gmail.com	0	Rejected	0	Rejected	0.518	Rejected	Rejected
iasifemon@gmail.com	0.316	Rejected	0.031	Rejected	0.586	Rejected	Rejected
Tashrif34@gmail.com	0.579	Accepted	0.225	Rejected	0.691	Accepted	Accepted
saif.shouvik@gmail.com	0.6	Accepted	0.326	Accepted	0.705	Accepted	Accepted
fahadbinmahfuj12@gmail.com	0	Rejected	0	Rejected	0.605	Rejected	Rejected
fahmidaafroj4068@gmail.com	0	Rejected	0	Rejected	0.628	Rejected	Rejected
orishafareen24@gmail.com	0.301	Rejected	0.032	Rejected	0.536	Rejected	Rejected

manojsannashi@gmail.com	0.25	Rejected	0.025	Rejected	0.641	Rejected	Rejected

Performance:

```
----Cosine----
Accuracy: 1.0
Confusion Matrix:
True Negatives: 7
False Positives: 0
False Negatives: 0
True Positives: 3
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
----------------------------------------
----Jaccard----
Accuracy: 0.8
Confusion Matrix:
True Negatives: 7
False Positives: 0
False Negatives: 2
True Positives: 1
Precision: 0.333
Recall: 1.0
F1 Score: 0.5
----------------------------------------
----JaroWinkler----
Accuracy: 1.0
Confusion Matrix:
True Negatives: 7
False Positives: 0
False Negatives: 0
True Positives: 3
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
```

4.9.7 Data Scientist

Table 22: Required Job Skills for Data Scientist

Job Description Skills
Machine Learning, Data Mining, Model Optimization, R, Python, Communication Skills, Decision Making, Deep learning, Data Analysis, Data Science

Table 23: Applicants' Emails and Skills for Data Scientist Position

Email	Skills
moumitakabir13@gmail.com	deep learning, html, machine learning, scor, sql, python, c++, data science, java, git, gre, php
aislamantu@gmail.com	mysql, html5, html, css3, excel, communication, sql, documentation, css, reporting, bootstrap, git, gre
abdullah.sanam@konasl.com	mysql, communication, project management, sql, soap, soa, java, reporting, adaptability, git, gre
aalimkuet@gmail.com	html, communication, sql, css, javascript, python, github, java, reporting, bootstrap, jquery, git
rifatrabbi024@gmail.com	leadership, html, excel, communication, css, javascript, c++, github, java, web development, git, gre

Email	Skills
razibhasan634@gmail.com	restful api, mysql, html5, html, css3, postgresql, communication, nosql, dl, sql, css, javascript, github, java, bootstrap, jquery, git, gre, wan, php
soumikkanti1995@gmail.com	communication skills, communication skill, excel, communication, project management, sql, problem-solving, python, planning, java, git
mahmuda.anika@gmail.com	communication skills, mysql, html, communication skill, communication, project management, sql, css, javascript, photoshop, c++, routing and switching, teamwork, customer support, java, web development, adobe photoshop, database management, wan, php
saumenroy323@gmail.com	html, machine learning, react.js, communication, dl, css, javascript, python, c++, github, java, jquery, django, git
kowshiksaha78@gmail.com	mysql, html, troubleshooting, sql, documentation, css, routing and switching, java, bootstrap, gre
hossaintanjila20@gmail.com	critical thinking, web design, communication, problem-solving, creativity, planning, teamwork, customer support, git, wan
ztasnim35@gmail.com	html, data analysis, time management, excel, communication, dl, css, python, c++, teamwork, github, java, web development, git

Table 24: Similarity Scores and Decisions for Data Scientist Developer Applicants

Email	Cosine Similarity	Cosine Decision	Jaccard Similarity	Jaccard Decision	Jaro-Winkler Similarity	Jaro Winkler Decision	Human Decision
moumitakabir13@gmail.com	0.666	Accepted	0.222	Rejected	0.641	Rejected	Accepted
aislamantu@gmail.com	0.277	Rejected	0	Rejected	0.637	Rejected	Rejected
abdullah.sanam@konasl.com	0.288	Rejected	0	Rejected	0.658	Accepted	Rejected
aalimkuet@gmail.com	0.408	Accepted	0.047	Rejected	0.602	Rejected	Rejected
rifatrabbi024@gmail.com	0.288	Rejected	0	Rejected	0.625	Rejected	Rejected
razibhasan634@gmail.com	0.218	Rejected	0	Rejected	0.627	Rejected	Rejected
soumikkanti195@gmail.com	0.629	Accepted	0.105	Rejected	0.686	Accepted	Accepted
mahmuda.anika@gmail.com	0.458	Accepted	0.034	Rejected	0.693	Accepted	Rejected
saumenroy323@gmail.com	0.487	Accepted	0.09	Rejected	0.636	Rejected	Rejected
kowshiksaha78@gmail.com	0	Rejected	0	Rejected	0.625	Rejected	Rejected
hossaintanjila20@gmail.com	0.267	Rejected	0	Rejected	0.678	Accepted	Rejected
ztasnim35@gmail.com	0.433	Accepted	0.09	Rejected	0.679	Accepted	Accepted

Performance:

```
----Cosine----
Accuracy: 0.75
Confusion Matrix:
True Negatives: 6
False Positives: 3
False Negatives: 0
True Positives: 3
Precision: 1.0
Recall: 0.5
F1 Score: 0.666
----------------------------------------
----Jaccard----
Accuracy: 0.75
Confusion Matrix:
True Negatives: 9
False Positives: 0
```

```
False Negatives: 3
True Positives: 0
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
----------------------------------------
----JaroWinkler----
Accuracy: 0.666
Confusion Matrix:
True Negatives: 6
False Positives: 3
False Negatives: 1
True Positives: 2
Precision: 0.666
Recall: 0.4
F1 Score: 0.5
```

4.9.8 Finance Manager

Table 25: Required Job Skills for Finance Manager

Job Description Skills
Budgeting, Forecasting, Balance Sheet Management, Profit and Loss (P&L) Analysis, Cash Flow Management, Receivables Portfolio Management, Working Capital Management, Financial Reporting, Financial Analysis, Financial Budgeting, Financial Forecasting, Financial Results Analysis, Financial Recommendations, Financial Control, Management Reporting, Financial Viability Analysis, Working Capital Investment Analysis, EBITDA Management, Accounting, Administration, Operations Management, Financial Software, Financial Statements Preparation, Financial Data Accuracy, Debt Covenant Compliance, Payment Review, Financial Decision Making, Cash Flow Planning, Asset Management, Banking Relationships, Strategic Alliances, Financial Insight, Financial Modeling, Audit Compliance

Table 26: Applicants' Emails and Skills for Finance Manager Position

Email	Skills
mithilaalishila007@gmail.com	leadership, ui, excel, communication, dl, photoshop, seo, git
kmshoibal@gmail.com	mysql, ui, logs, java ee, java persistence api (jpa), oracle, angular, enterprise javabeans (ejb), sql, python, github, java, vaadin, git, gre, sql – postgre
soumikkanti1995@gmail.com	communication skills, ui, communication skill, excel, communication, project management, sql, problem-solving, python, planning, java, git
rezaul.bappy1@gmail.com	ui, communication, sql, documentation, c++, planning, java, reporting, gre, wan
khaledtanim@gmail.com	leadership, mysql, ui, html, troubleshooting, time management, excel, project management, dl, sql, ux, css, router, python, photoshop, c++, creativity, planning, github, java, web development, git, illustrator, gre
mahfujaakterdu@gmail.com	configuration management, ui, communication, soap, documentation, jenkins, soa, seo, configuration management, gre
moumitakabir13@gmail.com	deep learning, ui, html, machine learning, scor, sql, python, c++, data science, java, git, gre, php
iftekhar.pony22@gmail.com	ui, communication, ux, documentation, c++, network security, data mining, wan
mahmuda.anika@gmail.com	communication skills, mysql, ui, html, communication skill, communication, project management, sql, ux, css, javascript, photoshop, c++, routing and switching, teamwork, customer support, java, web development, adobe photoshop, database management, wan, php
saumenroy323@gmail.com	ui, html, machine learning, react.js, communication, dl, css, javascript, python, c++, github, java, jquery, django, git
Zaman29@gmail.com	financial modeling, financial planning, leadership, communication skills, ui, ratio analysis, communication skill, financial reporting, data analysis, excel, communication, cost

Email	Skills
	analysis, budgeting, analytical skills, planning, decision-making, reporting, gre, forecasting
Alif89@gmail.com	financial modeling, financial planning, leadership, communication skills, ui, ratio analysis, communication skill, financial reporting, data analysis, excel, communication, investment analysis, cost analysis, budgeting, analytical skills, planning, decision-making, reporting, gre, forecasting
sayman@gmail.com	financial modeling, financial planning, leadership, financial statement analysis, risk assessment, ui, financial reporting, excel, communication, dl, investment analysis, market research, mergers and acquisitions analysis, budgeting, planning, decision-making, reporting, presentation skills, gre, forecasting, risk management

Table 27: Similarity Scores and Decisions for Finance Manager Applicants

Email	Cosine Similarity	Cosine Decision	Jaccard Similarity	Jaccard Decision	Jaro-Winkler Similarity	Jaro Winkler Decision	Human Decision
mithilaalishila007@gmail.com	0	Rejected	0	Rejected	0.515	Rejected	Rejected
kmshoibal@gmail.com	0	Rejected	0	Rejected	0.529	Rejected	Rejected
soumikkanti1995@gmail.com	0.237	Rejected	0	Rejected	0.551	Rejected	Rejected
rezaul.bappy1@gmail.com	0.447	Accepted	0	Rejected	0.523	Rejected	Rejected
khaledtanim@gmail.com	0.398	Rejected	0	Rejected	0.56	Rejected	Rejected
mahfujaakterdu@gmail.com	0.5	Accepted	0	Rejected	0.545	Rejected	Accepted
moumitakabir13@gmail.com	0.242	Rejected	0	Rejected	0.528	Rejected	Rejected
iftekhar.pony22@gmail.com	0.333	Rejected	0	Rejected	0.523	Rejected	Rejected
mahmuda.anika@gmail.com	0.333	Rejected	0	Rejected	0.581	Rejected	Rejected
saumenroy323@gmail.com	0	Rejected	0	Rejected	0.517	Rejected	Rejected
Zaman29@gmail.com	0.632	Accepted	0.08	Rejected	0.613	Rejected	Accepted
Alif89@gmail.com	0.637	Accepted	0.078	Rejected	0.618	Rejected	Accepted
sayman@gmail.com	0.703	Accepted	0.076	Rejected	0.637	Rejected	Accepted

Performance:

```
----Cosine----
Accuracy: 0.923
Confusion Matrix:
True Negatives: 8
False Positives: 1
False Negatives: 0
True Positives: 4
Precision: 1.0
Recall: 0.8
F1 Score: 0.888
----------------------------------------
----Jaccard----
Accuracy: 0.692
Confusion Matrix:
True Negatives: 9
False Positives: 0
False Negatives: 4
True Positives: 0
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
```

```
----------------------------------------
----JaroWinkler----
Accuracy: 0.692
Confusion Matrix:
True Negatives: 9
False Positives: 0
False Negatives: 4
True Positives: 0
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
```

4.9.9 UX/UI Designer

Table 28: Required Job Skills for UX/UI Designer

Job Description Skills
Sketch, Figma, Adobe XD, Photoshop, User-centered design, Illustrations, Logos, Layouts, Mobile design, Responsive design, Accessibility principles, User research, User interface (UI) design, InVision, Wireframes, Prototypes, HTML, CSS,, JavaScript, Communication skills, Teamwork

Table 29: Applicants' Emails and Skills for UX/UI Designer Position

Email	**Skills**
kaocherahmedtarek@gmail.com	typography, ui, logs, illustration, dl, adobe illustrator, photoshop, adobe indesign, adobe photoshop, git, illustrator
fkhan151@bba.uiu.ac.bd	ui, illustration, communication, dl, photoshop, creativity, planning, adobe photoshop, interpersonal skills, git
anikameem9@gmail.com	deep learning, mysql, ui, html, machine learning, communication, dl, sql, problem-solving, css, javascript, adobe illustrator, python, photoshop, teamwork, java, web development, bootstrap, adobe photoshop, django, git, illustrator, forecasting, php
apumazumder.ak10@gmail.com	leadership, mysql, ui, graphics design, communication skill, excel, communication, project management, dl, sql, documentation, photoshop, c++, git, illustrator, gre, wan
bakar@gmail.com	responsive design, ui, user interface (ui) design, mobile design, adobe xd, communication skill, user research, accessibility principles, sketch, illustration, wireframes, excel, communication, illustrations, invision, photoshop, figma, user-centered design, prototypes, layouts, gre
smalamin.piash@gmail.com	restful api, mysql, ui, html, css3, sql, css, javascript, python, github, java, bootstrap, jquery, git, gre, php
shanchay777@gmail.com	communication skills, mysql, ui, ui/ux design, html5, html, adobe xd, responsive web design, graphics design, communication skill, web design, css3, data analysis, excel, communication, dl, sql, ux, documentation, css, javascript, data visualization
mijanhawlader746@gmail.com	leadership, graphics design, illustration, communication, photoshop, creativity, planning, video editing, illustrator
contact@motakabbir.com	leadership, ui, design concepts, time management, communication, team management, dl, ux, creativity, teamwork, git
smoshajib100@gmail.com	html5, html, web design, css3, excel, css, python, java, web development, bootstrap, django, wan, php
santo9585@gmail.com	mongodb, node.js, html5, html, graphics design, web design, css3, communication, dl, documentation, css, javascript, router, photoshop, express.js, github, java, web development, bootstrap, git, illustrator
mdsajibbiswas92@gmail.com	leadership, typography, ui, illustration, dl, adobe illustrator, photoshop, adobe indesign, adobe photoshop, git, illustrator, layouts
ssultanaorpi@gmail.com	ui, html5, html, sketch, ux, css, figma, java, gre, wan

Table 30: Similarity Scores and Decisions for UX/UI Designer Applicants

Email	**Cosine**	**Cosine**	**Jaccard**	**Jaccard**	**Jaro-**	**Jaro**	**Human**

	Similarity	Decision	Similarity	Decision	Winkler Similarity	Winkler Decision	Decision
kaocherahmedtarek@gmail.com	0.707	Accepted	0.031	Rejected	0.637	Rejected	Accepted
fkhan151@bba.uiu.ac.bd	0.717	Accepted	0.032	Rejected	0.633	Rejected	Accepted
anikameem9@gmail.com	0.573	Accepted	0.121	Rejected	0.697	Accepted	Accepted
apumazumder.ak10@gmail.com	0.4	Accepted	0.026	Rejected	0.658	Accepted	Accepted
bakar@gmail.com	0.943	Accepted	0.535	Accepted	0.78	Accepted	Accepted
smalamin.piash@gmail.com	0.485	Accepted	0.085	Rejected	0.594	Rejected	Rejected
shanchay777@gmail.com	0.689	Accepted	0.134	Rejected	0.735	Accepted	Accepted
mijanhawlader746@gmail.com	0.426	Accepted	0.033	Rejected	0.646	Rejected	Rejected
contact@motakabbir.com	0.401	Accepted	0.031	Rejected	0.61	Rejected	Rejected
smoshajib100@gmail.com	0.342	Rejected	0.06	Rejected	0.583	Rejected	Rejected
santo9585@gmail.com	0.501	Accepted	0.102	Rejected	0.685	Accepted	Accepted
saif.shouvik@gmail.com	0.378	Rejected	0.101	Rejected	0.757	Accepted	Rejected
mdsajibbiswas92@gmail.com	0.7	Accepted	0.062	Rejected	0.651	Accepted	Accepted
ssultanaorpi@gmail.com	0.7071	Accepted	0.142	Rejected	0.536	Rejected	Rejected

Performance:

```
----Cosine----
Accuracy: 0.714
Confusion Matrix:
True Negatives: 2
False Positives: 4
False Negatives: 0
True Positives: 8
Precision: 1.0
Recall: 0.666
F1 Score: 0.8
----------------------------------------
----Jaccard----
Accuracy: 0.5
Confusion Matrix:
True Negatives: 6
False Positives: 0
False Negatives: 7
True Positives: 1
Precision: 0.125
Recall: 1.0
F1 Score: 0.222
----------------------------------------
----JaroWinkler----
Accuracy: 0.785
Confusion Matrix:
True Negatives: 5
False Positives: 1
False Negatives: 2
True Positives: 6
Precision: 0.75
Recall: 0.857
```

F1 Score: 0.799

4.10 Overall Model Performance

4.10.1 Cosine Similarity Performance

Accuracy: 0.877

Precision: 0.983

Recall: 0.808

F1 Score: 0.887

Confusion Matrix:

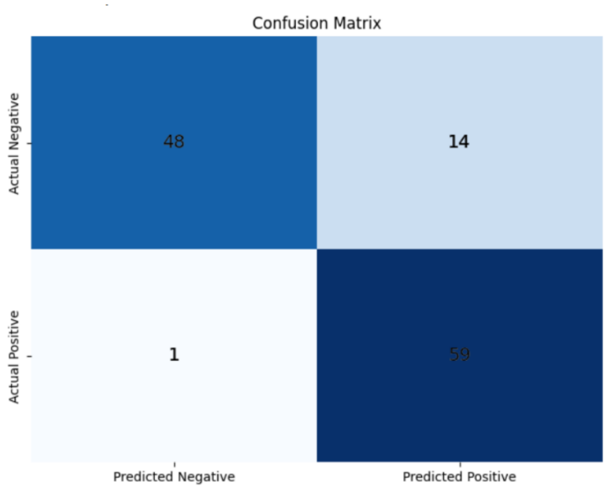


Figure 10: Confusion Matrix for Cosine Similarity

True Negatives (TN): 48 Resumes were correctly predicted as Rejected.

False Positives (FP): 14 incorrectly predicted as Accepted actually Rejected.

False Negatives (FN): 1 Resumes was incorrectly predicted as Rejected when it was actually Accepted.

True Positives (TP): 59 Resumes were correctly predicted as Accepted.

4.10.2 Jaccard Performance

Jaccard Accuracy: 0.623

Precision: 0.25

Recall: 0.937

F1 Score: 0.395

Confusion Matrix

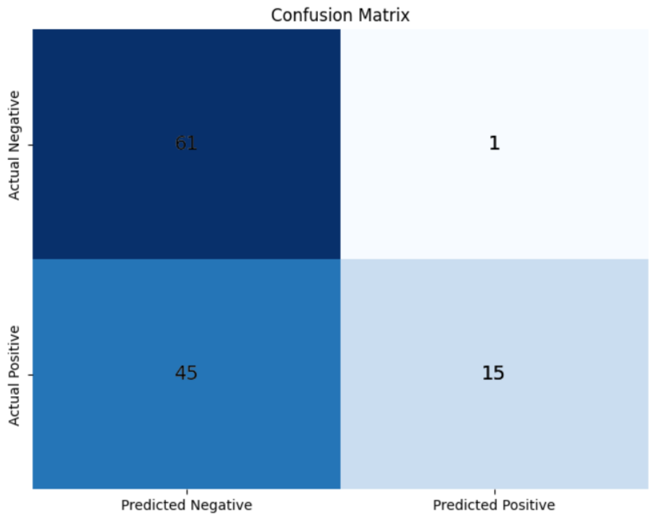


Figure 11: Confusion Matrix for Jaccard Similarity

True Negatives: 61

False Positives: 1

False Negatives: 45

True Positives: 15

4.10.3 Jaro Winkler Performance

JaroWinkler Accuracy: 0.811

Precision: 0.783

Recall: 0.824

F1 Score: 0.803

Confusion Matrix:

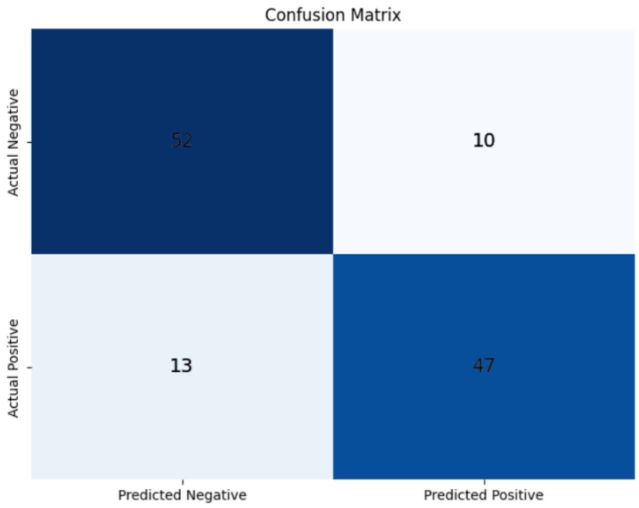


Figure 12: Confusion Matrix for Jaro Winkler Similarity

True Negatives: 52

False Positives: 10

False Negatives: 13

True Positives: 47

4.11 Overall Observation

Comparing the three algorithms (Cosine Similarity, Jaccard Similarity, and Jaro-Winkler Distance) in key points:

Cosine Similarity:

Strengths:

- High overall accuracy (0.877).
- Excellent precision (0.983), indicating reliable positive predictions.
- Well-balanced F1 Score (0.887).

Weaknesses:

- Relatively lower recall (0.808), suggesting room for improvement in capturing positive instances.

Jaccard Similarity:

Strengths:

- High recall (0.938), effectively capturing actual positive instances.

Weaknesses:

- Lower accuracy (0.623) compared to Cosine Similarity.
- Low precision (0.25), indicating a high rate of false positives.
- Relatively lower F1 Score (0.395), highlighting a trade-off between precision and recall.

Jaro-Winkler Distance:

Strengths:

- High accuracy (0.811) with balanced precision (0.783) and recall (0.825).
- Robust F1 Score (0.803), indicating well-balanced performance.

Weaknesses:

- Slightly lower accuracy compared to Cosine Similarity.

The choice between algorithms depends on specific use case requirements and priorities. If precision is critical, Cosine Similarity may be preferable. If capturing as many positive instances as possible is crucial, Jaccard Similarity might be favored. Jaro-Winkler Distance provides a balanced option suitable for various scenarios.

4.12 Non-Technical Job Candidate Assessment: Low Performance Analysis

In this study, the focus lies on assessing the suitability of technical job roles for skill extraction and similarity scoring against job descriptions. This approach may not be as effective for positions like customer service, general labor, delivery and courier services, entry-level administrative roles etc., which typically do not demand specialized skills. Consequently, achieving a high similarity score in these instances becomes challenging.

To illustrate this point, I have chosen to examine a non-technical job, specifically the customer service role (Table 31). Utilizing several resumes, I evaluated their similarity with the corresponding job description.

Table 31: Required Job Skills for Customer Representative

Job Description Skills
Communication, Problem-solving, Interpersonal, Organizational, Sales, Attention to detail, Product/service knowledge, Customer focus

Applicants often do not explicitly mention common skills such as communication, problem-solving, interpersonal abilities, organizational skills, etc., in their resumes for several reasons:

Assumed Competency: Many applicants assume that these skills are so fundamental that they are implied and understood by employers. They may believe that explicitly stating these skills would be redundant.

Space Limitations: Resumes typically have limited space, and applicants prioritize including experiences, achievements, and qualifications that differentiate them from other candidates. As a result, they may omit mentioning basic skills to make room for more pertinent information.

Focus on Achievements: Applicants often emphasize their accomplishments and results rather than listing out generic skills. They may prefer to showcase how they utilized these skills to achieve specific outcomes rather than simply stating that they possess them.

Assessment through Experience: Employers often expect candidates to possess these basic skills, and they may infer competency in them based on the candidate's work experience, achievements, and the overall presentation of their resume.

Keyword Optimization: In some cases, applicants may focus more on incorporating keywords related to specific job requirements or industry-specific terminology to increase the chances of their resumes being picked up by systems or during manual reviews.

When utilizing skill extraction methods, the process becomes inherently challenging if applicants do not explicitly list essential skills like communication, problem-solving, interpersonal abilities, and others on their resumes. Since our system relies on the skills presented within resumes to determine similarity with job descriptions, the absence of crucial skills can result in markedly lower similarity scores. As a consequence, resumes lacking these key skills may be automatically disregarded by the system. Table 32 presents a comprehensive overview of the 10 applicants, their corresponding emails, and the skills identified from their resumes.

Table 32: Applicants' Emails and Skills for Customer Representative Position

Email	Description
jm.tarif55@gmail.com	flask, java, sql, c++, git, php, teamwork, mysql, python, leadership, github, django, dl, html, time management, css, communication, communication skill, javascript
mntushar25@gmail.com	documentation, postgresql, javascript, mysql, software, support, database, bootstrap, ajax, django, python, server, project management, git, design
arnobnazir2000@gmail.com	certificate, marketing, business
iasifemon@gmail.com	certificate, support, software, commerce, mobile, marketing, business
fahadbinmahfuj12@gmail.com	certificate, snippet, search engine, analytics, material, monitoring, business, google, collaboration, hubspot, advertising, google analytics, marketing, broadcasting, wordpress
fahmidaafroj4068@gmail.com	schedule, certificate, adobe illustrator, software, google, operating system, business administration, windows, marketing, business
orishafareen24@gmail.com	certificate, adobe photoshop, business administration, languages
manojsannashi@gmail.com	business process, documentation, customer relationship management, collaboration, monitoring, information management, business intelligence, project management, marketing, business
mugdho.bdtourlovers@gmail.com	accounting, business, operating system, business administration
tahsins713@gmail.com	mobile, certificate, business

Table 33 displays the similarity scores for the remaining applicants across this mentioned job position:

Table 33: Similarity Scores and Decisions for Customer Representative Applicants

Email	**Cosine Similarity**	**Cosine Decision**	**Jaccard Similarity**	**Jaccard Decision**	**Jaro-Winkler Similarity**	**Jaro Winkler Decision**	**Human Decision**
jm.tarif55@gmail.com	0.22	Rejected	0	Rejected	0.61	Rejected	Accepted
mntushar25@gmail.com	0	Rejected	0	Rejected	0.69	Accepted	Accepted
arnobnazir2000@gmail.com	0	Rejected	0	Rejected	0.58	Rejected	Accepted
iasifemon@gmail.com	0	Rejected	0	Rejected	0.62	Rejected	Accepted
fahadbinmahfuj12@gmail.com	0	Rejected	0	Rejected	0.76	Accepted	Accepted
fahmidaafroj4068@gmail.com	0	Rejected	0	Rejected	0.71	Accepted	Accepted
orishafareen24@gmail.com	0	Rejected	0	Rejected	0.64	Rejected	Accepted
manojsannashi@gmail.com	0.18	Rejected	0	Rejected	0.72	Accepted	Accepted
mugdho.bdtourlovers@gmail.com	0	Rejected	0	Rejected	0.61	Rejected	Rejected
tahsins713@gmail.com	0	Rejected	0	Rejected	0.55	Rejected	Rejected

```
----Cosine----
Accuracy: 0.2
Confusion Matrix:
True Negatives: 2
False Positives: 0
False Negatives: 8
True Positives: 0
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
----------------------------------------

----Jaccard----
Accuracy: 0.2
Confusion Matrix:
True Negatives: 2
False Positives: 0
False Negatives: 8
True Positives: 0
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
----------------------------------------
----JaroWinkler----
Accuracy: 0.6
Confusion Matrix:
True Negatives: 2
False Positives: 0
False Negatives: 4
True Positives: 4
Precision: 0.5
Recall: 1.0
F1 Score: 0.66
```

These performance metrics indicate low accuracy across various similarity measurement methods (Cosine, Jaccard, JaroWinkler) for assessing non-technical job candidates. In each case, the accuracy is 0.2 or 20%, which means the models are not effectively distinguishing between suitable and unsuitable candidates.

The confusion matrices reveal that the models are misclassifying a significant portion of candidates, with all true positives and negatives being very low or zero. This suggests that the models struggle to correctly identify candidates who are suitable for the job, leading to poor precision, recall, and F1 scores.

4.13 Accuracy: National vs. International Perspectives

The landscape of hiring for back-end developer positions varies significantly between national and international companies. In this scenario, we examine the below distinct job descriptions and candidate pools for a national company versus an international company.

4.13.1 National Company

Job Description: A local company is in search of a proficient back-end developer to oversee the maintenance and optimization of their website. The ideal candidate should possess strong proficiency in a specific programming language like Python or Java, along with experience in database management, familiarity with local payment gateways and regulations, and expertise in web development frameworks such as Django or Spring. Additionally, knowledge of version control systems, best security practices, problem-solving abilities, excellent communication skills, attention to detail, and a commitment to continuous learning are essential.

Candidate Pool: Most candidates (Table 2) applying to the national company are local developers with experience in similar domains. They are familiar with local payment gateways and regulations and have a good understanding of the local market.

4.13.2 International Company

Job Description: An international tech company is seeking a back-end developer to contribute to their global platform catering to users across multiple countries. The role necessitates proficiency in multiple programming languages, encompassing versatile skills adaptable to the diverse needs of a global user base. Candidates should exhibit experience in managing large-scale databases, ensuring data integrity and scalability on an international scale. Furthermore, familiarity with international data privacy regulations, exemplified by knowledge of standards such as GDPR, is imperative for safeguarding user data and compliance with global legal requirements. This multifaceted position requires a candidate capable of navigating the complexities of an international environment while upholding the highest standards of technical proficiency and regulatory compliance.

Candidate Pool: Candidates (Table 2) applying to the international company come from diverse backgrounds and may have experience working on global platforms. They possess multilingual skills and may have experience dealing with international data privacy regulations.

4.13.3 Findings

Considering the above scenario, we can come up with the below observations:

- In this above example, the skill extraction process from resumes would involve identifying technical skills such as proficiency in programming languages, experience with database management, and familiarity with relevant regulations.
- For the national company, the skill extraction process may focus on specific technical skills required for the local context, such as knowledge of local payment gateways and regulations.
- Conversely, for the international company, the skill extraction process may need to consider a broader range of technical skills, including proficiency in multiple programming languages and experience with international data privacy regulations.
- The accuracy of predicting candidate suitability for each company may be influenced by how well the extracted skills align with the specific job requirements and the unique characteristics of the candidate pool.
- It's noteworthy that the accuracy of skill extraction is not inherently tied to the company's national or international status. The accuracy remains consistent

regardless of the company's location, as the process solely involves extracting skills from resumes without considering the company's background.

4.14 KMeans Clustering

Resumes are categorized into clusters ("good," "average," and "poor") based on similarity scores obtained from similarity measurement algorithms. This clustering method offers insights into potential talent pools for specific positions, empowering recruiters to identify candidates more effectively by assessing the alignment of resumes with job requirements. The approach streamlines the recruitment process, enabling targeted candidate evaluations based on the degree of similarity to the job description.

4.14.1 Cosine Similarity

Figure 13 illustrates the distribution of applicants across three clusters based on their similarity scores using Cosine Similarity. The clusters are labeled as "Good," "Average," and "Poor." The clustering was performed using K-means algorithm, with higher similarity scores representing "good" applicants, intermediate scores as "average," and lower scores as "poor." The distribution indicates that a majority of applicants fall into the "Average" category, followed by "Good" and "Poor" categories. A total of 122 resumes are clustered into three groups shown in Figure 14.

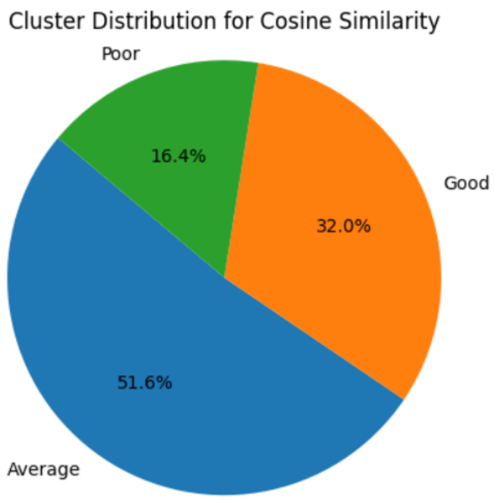


Figure 13: Cluster Distribution for Jaccard Similarity

```
Clustered Data:
                          Email    Cosine  Cluster
0           saifbdjp@gmail.com  0.492366  average
1      abir.ahmad007@gmail.com  0.754997     good
2       numansyed675@gmail.com  0.577350     good
3       noman.fiverr@gmail.com  0.577350     good
4           ti862650@gmail.com  0.000000     poor
..                         ...       ...      ...
117     smoshajib100@gmail.com  0.342997  average
118        santo9585@gmail.com  0.501486  average
119     saif.shouvik@gmail.com  0.378620  average
120  mdsajibbiswas92@gmail.com  0.700000     good
121     ssultanaorpi@gmail.com  0.707107     good

[122 rows x 3 columns]
```

Figure 14: Clustering Candidates Based on Cosine Similarity Scores

4.14.2 Jaccard Similarity

Figure 15 shows how applicants are grouped into three clusters ("Good," "Average," and "Poor") based on their similarity scores using Jaccard Similarity. Higher scores represent "good" applicants, while lower scores denote "poor" ones. The majority of applicants fall into the "Poor" category. In total, 122 resumes are clustered across the three groups, as shown in Figure 16.

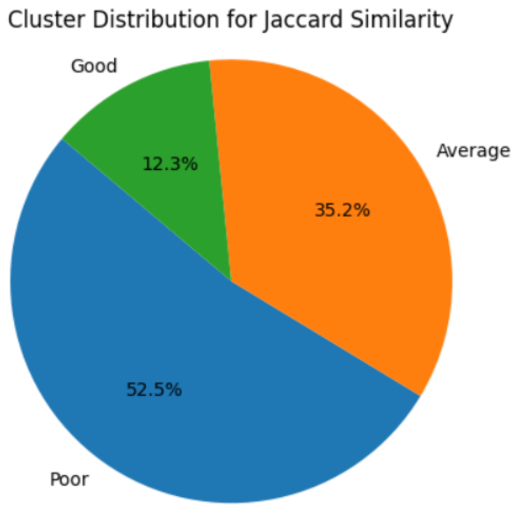


Figure 15: Cluster Distribution for Jaccard Similarity

```
Clustered Data:
                          Email   Jaccard  Cluster
0            saifbdjp@gmail.com  0.071429     poor
1       abir.ahmad007@gmail.com  0.205882  average
2        numansyed675@gmail.com  0.034483     poor
3        noman.fiverr@gmail.com  0.071429     poor
4            ti862650@gmail.com  0.000000     poor
..                          ...       ...      ...
117     smoshajib100@gmail.com  0.060606     poor
118        santo9585@gmail.com  0.102564  average
119     saif.shouvik@gmail.com  0.101695  average
120  mdsajibbiswas92@gmail.com  0.062500     poor
121      ssultanaorpi@gmail.com  0.142857  average

[122 rows x 3 columns]
```

Figure 16: Clustering Candidates Based on Jaccard Similarity Scores

4.14.3 Jarw Winkler Similarity

Figure 17 depicts applicants categorized into three clusters ("Good," "Average," and "Poor") based on their similarity scores using Jaro Winkler. The clustering, performed with the K-means algorithm, shows most applicants in the "Average" category, followed by "Good" and "Poor" categories. A total of 122 resumes are clustered, as seen in Figure 18.

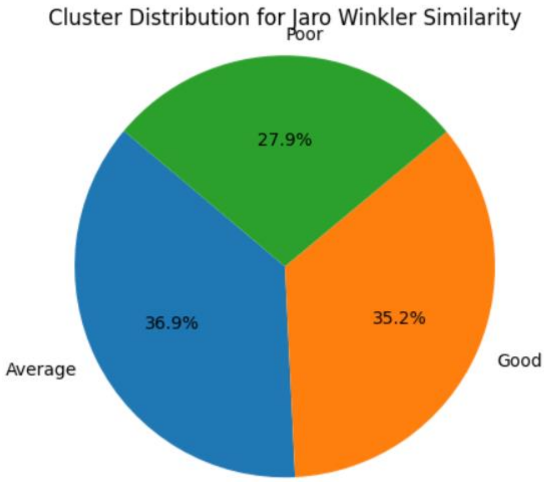


Figure 17: Cluster Distribution for Jaro Winkler Similarity

```
Clustered Data:
                          Email  Jaro Winkler  Cluster
0            saifbdjp@gmail.com      0.724769     good
1       abir.ahmad007@gmail.com      0.715033     good
2        numansyed675@gmail.com      0.680586     good
3        noman.fiverr@gmail.com      0.706163     good
4            ti862650@gmail.com      0.565821     poor
..                          ...           ...      ...
117      smoshajib100@gmail.com      0.583597     poor
118         santo9585@gmail.com      0.685462     good
119      saif.shouvik@gmail.com      0.757829     good
120  mdsajibbiswas92@gmail.com      0.651024  average
121      ssultanaorpi@gmail.com      0.536888     poor

[122 rows x 3 columns]
```

Figure 18: Clustering Candidates Based on Jaccard Similarity Scores

Chapter 5

Conclusion and Future Works

5.1 Summary

In conclusion, the study highlights the effectiveness of the proposed automated system in assessing job descriptions and resumes using similarity measurement algorithms. The alignment between machine-generated decisions and human judgments indicates the system's reliability in approximating human assessment. By leveraging NLP techniques and clustering, the research provides valuable insights into potential talent pools for specific positions, facilitating more effective candidate selection. The combination of machine and human decisions enhances the talent acquisition process, streamlining recruitment efforts, and ensuring better matches between candidates and job requirements.

5.2 Limitations

1. The research focuses solely on skills in job descriptions, while job requirements often encompass multiple factors (e.g., skills, experience, educational qualifications), limiting the system's scope.
2. The sample size of 10 job descriptions and 20 resumes per job might restrict the generalizability of the findings; a larger sample could yield more robust results.
3. The study's applicability to all job positions or industries may be limited, as different industries may have unique requirements and skill sets.
4. Threshold determination for similarity measures can be challenging, and the choice of threshold values may need frequent updates to adapt to the dynamic job market.
5. Non-technical job resumes may pose challenges for accurate evaluation and matching within the automated system. Keyword extraction could be difficult, potentially leading to less precise skill and qualification identification, and overlooking qualified candidates with unique skill sets that do not conform to conventional keyword patterns.

5.3 Future Work

1. Further research and development of advanced NLP techniques can improve the accuracy of skills extraction from resumes, enabling the system to handle specialized job roles and non-technical job descriptions more effectively.
2. Expanding the automated system to consider multiple factors in job descriptions, such as experience and educational qualifications, can provide a more comprehensive evaluation of candidate suitability.
3. Developing dynamic threshold determination methods that can adapt to the evolving job market can enhance the system's performance in making binary decisions based on similarity scores.
4. Tailoring the automated system for specific industries or job sectors can lead to more precise matching, considering the unique requirements and skill sets of each domain.
5. Exploring hybrid approaches that combine different similarity measurement algorithms and clustering techniques can potentially yield more accurate and nuanced candidate assessments.
6. Conducting experiments on larger and more diverse datasets will provide a more comprehensive assessment of the system's performance and generalizability.

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