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An AI-Based Applicant Tracking System for Resume Analysis and Skill Gap Prediction Using NLP Techniques

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Abstract- The rapid growth of online recruitment platforms has increased the number of job applications received by organizations, making manual resume screening time-consuming and inefficient. Traditional recruitment methods often rely on keyword matching and manual evaluation, which may lead to inaccurate candidate selection and human bias. This research proposes an AI-Based Applicant Tracking System (ATS) for Resume Analysis and Skill Gap Prediction using Natural Language Processing (NLP) techniques. The system uses TF-IDF vectorization and cosine similarity algorithms to compare resumes with job descriptions and calculate candidate compatibility scores. A skill gap prediction module identifies missing skills required for specific job roles. The proposed system also includes a dashboard analytics module that displays recruitment metrics such as total resumes analyzed, highest match score, average compatibility score, and candidate ranking. In addition, the HOT-Fit model is used to evaluate the system from human, organizational, and technological perspectives. The proposed framework improves recruitment efficiency, reduces manual effort, supports transparent hiring decisions, and enhances candidate-job matching accuracy through AI-driven analysis.

Keywords- Applicant Tracking System (ATS), Natural Language Processing (NLP), Resume Analysis, TF-IDF, Cosine Similarity, Skill Gap Prediction.

I. INTRODUCTION

1.1 Background of Study

Recruitment is an important process in organizations because selecting suitable candidates directly affects productivity and growth. Traditional resume screening is time-consuming and often affected by human bias. Applicant Tracking Systems (ATS) use Artificial Intelligence (AI) and Natural Language Processing (NLP) to automate resume analysis and candidate matching. However, many existing ATS systems rely only on keyword matching and lack skill gap analysis and recruitment analytics. This study proposes an AI-Based ATS Resume Analysis and Skill Gap Prediction System to improve recruitment accuracy, efficiency, and transparency. Applicant Tracking Systems (ATS) use Artificial Intelligence (AI) and Natural Language Processing (NLP) to automate resume analysis and candidate matching [1][4]. However, many existing ATS systems rely only on keyword matching and lack skill gap analysis and recruitment analytics [5][6].

1.2 Problem Statement

Traditional recruitment systems rely heavily on manual screening and keyword-based filtering methods. These approaches are inefficient and may lead to inaccurate candidate selection. Many ATS systems struggle to process unstructured resume formats and cannot effectively identify missing skills required for job roles.

Additionally, existing systems often lack transparency and do not provide recruitment analytics or evaluation frameworks to assess system effectiveness. As a result, organizations require an intelligent recruitment system capable of automating resume analysis, predicting skill gaps, and improving hiring decisions.

1.3 Motivation

The increasing adoption of AI technologies in recruitment motivates the development of intelligent ATS systems capable of improving hiring efficiency and reducing manual effort. Organizations require systems that not only automate resume screening but also provide meaningful insights into candidate strengths, weaknesses, and compatibility.

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The motivation behind this study is to build an AI-driven ATS system that can accurately analyze resumes, identify missing skills, and support recruiters through dashboard analytics and system evaluation models.

1.4 Objectives of Study
The objective of this study is to develop an AI-based Applicant Tracking System for automated resume analysis, skill gap prediction, recruitment analytics, and accurate candidate-job matching using NLP techniques

Objective 1: To develop an AI-based Applicant Tracking System for automated resume analysis.
Objective 2: To calculate similarity scores between resumes and job descriptions using TF-IDF and cosine similarity algorithms.
Objective 3: To identify missing skills using a skill gap prediction module.
Objective 4: To visualize recruitment analytics using dashboard metrics.
Objective 5: To evaluate system effectiveness using the HOT-Fit model.

1.5 Contributions of the paper
This paper contributes to the field of AI-based recruitment systems in several ways:

- Development of an intelligent ATS resume analysis system.
- Integration of TF-IDF and cosine similarity for resume-job matching.
- Implementation of skill gap prediction for candidate improvement.
- Development of a dashboard analytics module for recruitment monitoring.
- Application of the HOT-Fit model for evaluating system performance.
- Improvement of recruitment transparency and efficiency through AI-based decision-making.

1.6 Organisation of the Paper
Section 1 presents the literature review related to ATS systems, NLP techniques, and resume analysis.
Section 2 explains the proposed methodology and system architecture.
Section 3 discusses expected results and evaluation strategies.
Section 4 highlights applications and use cases of the proposed system.
Section 5 concludes the paper and discusses future work.

II. LITERATURE REVIEW

The use of Artificial Intelligence and Natural Language Processing in recruitment systems has increased significantly in recent years. Researchers have proposed multiple techniques for automating resume screening, candidate ranking, and job recommendation.

Several studies have used machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, TF-IDF, and cosine similarity for analyzing resumes and matching them with job descriptions. Recent advancements in deep learning and transformer-based architectures such as BERT have further improved semantic understanding in recruitment systems.

However, many existing ATS systems still rely on keyword matching and fail to identify missing skills or provide meaningful analytics. Most systems also lack standardized evaluation models. Researchers have proposed multiple techniques for automating resume screening, candidate ranking, and job recommendation [1][2].

Several studies have used machine learning algorithms such as Support Vector Machines (SVM), TF-IDF, and cosine similarity for analyzing resumes and matching them with job descriptions [3][5][6].

Recent advancements in deep learning and transformer-based architectures such as BERT have further improved semantic understanding in recruitment systems [8][9].

Even though AI-based recruitment systems have improved resume screening and candidate matching, many existing ATS platforms still face several problems. Most systems mainly depend on keyword matching and cannot fully understand the actual meaning of resumes and job descriptions. Some

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systems also fail to identify missing skills required for a job role. In addition, many ATS platforms do not provide proper recruitment analytics or transparent decision-making processes.

Author & Year	Method / Technique	Limitation
Gharat (2024)	NER, TF-IDF, Cosine Similarity	Difficulty handling complex resumes
Sharma et al. (2023)	Collaborative Filtering, ML Models	Scalability issues
Kashif & Parimal Kumar (2024)	NLP, Tokenization, Regex	Poor support for unstructured resumes
Sowjanya et al. (2023	TF-IDF, Cosine Similarity, KNN	Depends on training data quality
Jivtode et al. (2023)	SVM, NLP	Requires large datasets
Lokesh et al. (2022)	Machine Learning Approaches	Limited semantic understanding
Roy et al. (2020)	NLP, Classification Models	Requires continuous training
Reza & Zaman (2022)	NLP, Text Classification	Limited contextual analysis
Brindashree & Pushphavath	NER, Machine Learning	Limited real-time analytics
Deepa et al. (2025)	Deep Learning, Resume Parsing	High computational cost

Table 1: Comparative Analysis of Existing ATS and Resume Analysis Techniques

i. Gharat (2024) – Recommendation for Jobs and Resume Analyzer Using NLP
The main objective of this study was to develop a resume analyzer and job recommendation system using NLP techniques.
Methods used in this study included Named Entity Recognition (NER), TF-IDF vectorization, and cosine similarity algorithms.

As a result, the proposed system improved resume-job matching accuracy and reduced manual effort.

The study concluded that NLP-based recruitment systems improve automation but require better handling of complex resume formats.

ii. Sharma et al. (2023) – Enhancing Job Recommendation Systems Using Machine Learning
The objective of this study was to improve job recommendation systems using machine learning algorithms.

Methods included collaborative filtering, content-based filtering, and machine learning classification models.

The results showed improved candidate-job matching and personalized recommendations.

The study concluded that machine learning improves recruitment systems but scalability remains a challenge.

iii. Kashif and Parimal Kumar (2024) – Resume Parser Using NLP
The main objective of this study was to build a resume parser capable of extracting structured information.

The study used NLP techniques such as tokenization, regex, and text preprocessing.

The system successfully extracted education, skills, and experience information from resumes.

The study concluded that NLP-based resume parsing improves recruitment automation but requires support for unstructured resumes.

iv. Sowjanya et al. (2023) – Smart Resume Analyzer
The objective of this study was to develop a smart resume analyzer for candidate ranking.

Methods used included TF-IDF, cosine similarity, and KNN algorithms.

The proposed model achieved improved ranking precision and resume analysis.

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The study concluded that machine learning improves resume screening but depends heavily on training data quality.

v. Jivtode et al. (2023) – Resume Analysis Using Machine Learning and NLP
The objective of this study was to automate resume screening using machine learning and NLP techniques. The researchers used SVM classifiers and text preprocessing methods to classify resumes. The results demonstrated improved screening speed and classification accuracy. The study concluded that machine learning enhances resume analysis but requires large datasets for better performance. The objective of this study was to automate resume screening using machine learning and NLP techniques. The researchers used SVM classifiers and text preprocessing methods to classify resumes. The results demonstrated improved screening speed and classification accuracy. The study concluded that machine learning enhances resume analysis but requires large datasets for better performance.

vi. Lokesh et al. (2022) – Resume Screening and Recommendation System Using Machine Learning
This study aimed to automate candidate screening and recommendation using machine learning approaches. The system analyzed resumes and ranked candidates according to job requirements. The results showed reduced manual effort and improved recruitment efficiency. The study concluded that machine learning can improve hiring systems but lacks advanced semantic understanding.

vii. Roy et al. (2020) – Machine Learning Approach for Resume Recommendation Systems
The main objective of this study was to automate candidate recommendation using machine learning techniques. Classification models and NLP approaches were applied for analyzing resumes and recommending suitable candidates. The study achieved better recommendation performance and reduced recruitment workload. The study concluded that AI-driven systems improve recruitment but require continuous model training.

viii. Reza and Zaman (2022) – Analyzing CV/Resume Using NLP and Machine Learning
The study focused on analyzing resumes using NLP and machine learning techniques. Methods included text classification, feature extraction, and resume parsing. The results improved resume analysis and candidate classification accuracy. The study concluded that combining NLP with machine learning improves ATS performance.

ix. Brindashree and Pushphavath – HR Analytics: Resume Parsing Using NER and Candidate Hiring Prediction
The objective of this study was to develop an HR analytics system for resume parsing and hiring prediction. Named Entity Recognition (NER) and machine learning algorithms were used to analyze candidate data. The results showed effective extraction of candidate information and prediction accuracy. The study concluded that AI-based HR analytics can improve recruitment quality.

x. Deepa et al. (2025) – Automated Resume Parsing: A Review of Techniques, Challenges and Future Directions
This study reviewed different resume parsing techniques including rule-based, machine learning, and deep learning approaches. The researchers analyzed parsing accuracy, challenges, and future improvements in ATS systems. The study found that deep learning models provide higher accuracy compared to traditional approaches. The study concluded that future ATS systems should focus on improving semantic understanding, reducing bias, and integrating advanced AI models.

2.2 Comparative Analysis of Existing Methods
Researchers have proposed several techniques for resume analysis and candidate matching. Traditional ATS systems mainly use keyword-based filtering approaches. Modern systems apply NLP and machine learning algorithms to improve matching accuracy.
Some studies focus on text extraction and classification, while others emphasize recommendation systems and candidate ranking. However, few systems integrate skill gap analysis, dashboard analytics, and evaluation frameworks together.

2.3 Critical Review

AI-based recruitment systems have improved resume analysis and candidate-job matching using machine learning and NLP techniques. Earlier ATS systems mainly relied on keyword-based filtering, which often produced inaccurate results due to lack of contextual understanding. Modern techniques such as TF-IDF, cosine similarity, NER, and BERT have improved semantic analysis and matching accuracy.
However, existing ATS systems still face several challenges, including poor handling of unstructured resumes, lack of skill gap analysis, limited recruitment analytics, and low transparency in decision-making. Most systems also do not use evaluation frameworks such as the HOT-Fit model. Therefore, there is a need for an intelligent ATS framework that combines resume analysis, skill gap prediction, analytics, and evaluation in a unified system. Modern techniques such as TF-IDF, cosine similarity, NER, and BERT have improved semantic analysis and matching accuracy [1][4][8].

However, existing ATS systems still face several challenges, including poor handling of unstructured resumes, lack of skill gap analysis, and limited recruitment analytics [5][6][10].

2.4 Identified Research Gaps
Existing research in AI-based recruitment systems has primarily focused on automating resume screening and candidate-job matching using machine learning and NLP techniques. However, several important research gaps remain unresolved.

One major gap is the overdependence on keyword-based matching approaches. Many ATS systems still rely on exact keyword matching, which limits semantic understanding and fails to capture contextual meaning between resumes and job descriptions. As a result, suitable candidates may be rejected even if they possess relevant skills and experience.

Another significant gap is the lack of skill gap prediction mechanisms. Most existing systems only calculate compatibility scores and shortlist candidates without identifying missing skills or suggesting areas for improvement. Candidates therefore receive limited feedback regarding their suitability for a job role.

Handling unstructured and complex resume formats is also a major challenge. Many ATS systems struggle to process resumes containing tables, graphics, multiple columns, or non-standard layouts. This affects the accuracy of information extraction and candidate evaluation.

Additionally, existing systems provide limited recruitment analytics and visualization features. Recruiters often lack access to meaningful metrics such as average match scores, candidate rankings, and recruitment performance statistics, which are important for data-driven hiring decisions.

Another important research gap is the absence of standardized evaluation frameworks. Most ATS studies focus only on algorithmic performance metrics such as accuracy and precision but do not evaluate system usability, organizational impact, or user satisfaction. Very few systems integrate evaluation models such as the HOT-Fit framework to assess overall system effectiveness.

Furthermore, many current ATS systems lack transparency and explainability. Recruiters and candidates are often unable to understand how AI algorithms make decisions, which reduces trust in automated hiring systems.

To address these gaps, this research proposes an integrated AI-based ATS system that combines NLP-driven resume analysis, skill gap prediction, dashboard analytics, and HOT-Fit evaluation in a unified framework. The proposed system aims to improve recruitment transparency, efficiency, and accuracy while supporting data-driven hiring decisions. Many ATS systems still rely on exact keyword matching, which limits semantic understanding between resumes and job descriptions [1][3].

Most systems only calculate compatibility scores and do not identify missing skills or provide recommendations for improvement [5][6].

III. PROPOSED METHODOLOGY

The proposed methodology focuses on developing an AI-Based Applicant Tracking System (ATS) capable of automating resume analysis, candidate-job matching, skill gap prediction, and recruitment analytics. The system integrates Artificial Intelligence (AI), Natural Language Processing (NLP), and machine learning techniques to improve recruitment efficiency and reduce manual screening effort.

The proposed framework begins with collecting candidate resumes and job descriptions as input data. These documents are processed using NLP techniques such as tokenization, lowercasing, stopword removal, and text preprocessing to improve text quality and prepare the data for analysis.

After preprocessing, the system applies the TF-IDF (Term Frequency–Inverse Document Frequency) vectorization technique to convert textual information into numerical vectors. TF-IDF helps identify important keywords, technical skills, qualifications, and experience mentioned in resumes and job descriptions.

The generated vectors are then compared using the cosine similarity algorithm to calculate the similarity score between candidate resumes and job requirements. The similarity score determines how closely a candidate matches a specific job role. Candidates with higher scores are considered more suitable for recruitment.

The system also includes a skill gap prediction module that identifies missing skills by comparing required job skills with the skills available in the candidate's resume. This feature helps recruiters evaluate candidate readiness and provides candidates with recommendations for skill improvement.

In addition, the proposed system integrates a dashboard analytics module that visualizes recruitment metrics such as total resumes analyzed, highest match score, lowest match score, average compatibility score, and candidate rankings. These analytics support data-driven hiring decisions and improve recruitment transparency.
To evaluate system effectiveness, the proposed framework uses the HOT-Fit model, which measures performance based on Human, Organizational, and Technological factors. This evaluation ensures that the system is not only technically efficient but also usable and beneficial for recruiters and organizations.
Overall, the proposed methodology combines NLP, machine learning, analytics, and evaluation techniques to create an intelligent recruitment framework capable of improving candidate selection accuracy, reducing recruitment workload, and supporting modern hiring processes.

The proposed framework uses TF-IDF vectorization and cosine similarity algorithms for resume-job matching [1][5].

The system also integrates skill gap prediction and dashboard analytics to improve recruitment transparency and decision-making [6][7].

3.1 System Overview
The proposed system consists of the following modules:

- Resume Input Module
- NLP Text Processing Modulex
- TF-IDF Feature Extraction
- Cosine Similarity Matching
- Skill Gap Prediction Module
- Dashboard Analytics Module
- HOT-Fit Evaluation Module

The system processes resumes and job descriptions using NLP techniques and calculates similarity scores between them.

3.2 Framework Architecture
This section contains the major parts required for the suggested framework

3.2.1 Data Collection
The system collects:

- Job descriptions
- Candidate resumes
- Skills and qualification details
- Recruitment analytics data

3.2.2 Data Preprocessing
The preprocessing stage performs:

- Lowercasing text

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- Tokenization
- Stopword removal
- Removal of special characters

These steps improve the quality of textual data.

3.2.3 Feature Extraction
Feature extraction is one of the most important stages in the proposed ATS system because it converts unstructured textual data into a machine-readable format. In this process, resumes and job descriptions are transformed into numerical vectors using the TF-IDF (Term Frequency–Inverse Document Frequency) technique. TF-IDF assigns higher weights to important words that frequently appear in a document but are less common across all documents. This helps the system identify significant skills, technologies, qualifications, and keywords relevant to recruitment.

Before feature extraction, text preprocessing techniques such as tokenization, stopword removal, lowercasing, and removal of special characters are applied to improve text quality. The extracted features represent the semantic importance of words in resumes and job descriptions, enabling efficient comparison and analysis. By converting textual information into numerical vectors, the system improves the accuracy of candidate-job matching and supports intelligent resume analysis.

TF-IDF:

$$TF\text{-}IDF(t,d) = TF(t,d) \times \log\left(\frac{N}{DF(t)}\right)$$

Figure 1: TF-IDF Formula for Feature Extraction in Resume Analysis

3.2.4 Resume Matching
Resume matching is the core functionality of the proposed ATS system. After feature extraction, the system compares the TF-IDF vectors of resumes and job descriptions using the cosine similarity algorithm. Cosine similarity measures the angle between two vectors and calculates how closely the resume content matches the job requirements.
A higher similarity score indicates a stronger match between candidate skills and job expectations, while a lower score suggests weaker compatibility. This approach enables automated candidate ranking and reduces dependency on manual resume screening. Unlike traditional keyword-based systems, cosine similarity considers the importance and frequency of terms, leading to more accurate and context-aware matching results.

Cosine Similarity Formula

$$Similarity(A,B) = \frac{A \cdot B}{||A|| \times ||B||}$$

Figure 2: Cosine Similarity Formula for Resume and Job Description Matching

3.2.5 Skill Gap Prediction
The skill gap prediction module is designed to identify missing skills by comparing candidate resumes with job descriptions. This module analyzes the required skills mentioned in the job description and compares them with the skills available in the candidate's resume.

If certain required skills are not found in the resume, the system highlights them as missing skills. This provides valuable feedback to candidates by helping them understand which competencies need improvement for a particular job role.

Unlike traditional ATS systems that only focus on candidate selection, the proposed framework adds an intelligent recommendation layer through skill gap analysis.a

Research Gaps	Methodology Used	Proposed Solutions
Keyword-based matching lacks semantic understanding	TF-IDF and Cosine Similarity	Improved resume-job matching
No skill gap prediction	NLP Skill Analysis	Missing skill identification
Manual resume screening	AI-Based ATS	Automated candidate ranking
Lack of recruitment analytics	Dashboard Analytics	Real-time hiring insights
No evaluation framework	HOT-Fit Model	System performance evaluation

Table 2: Research Gaps, Methodology Used, and Proposed Solutions for the AI-Based ATS System

3.3 Workflow Diagram

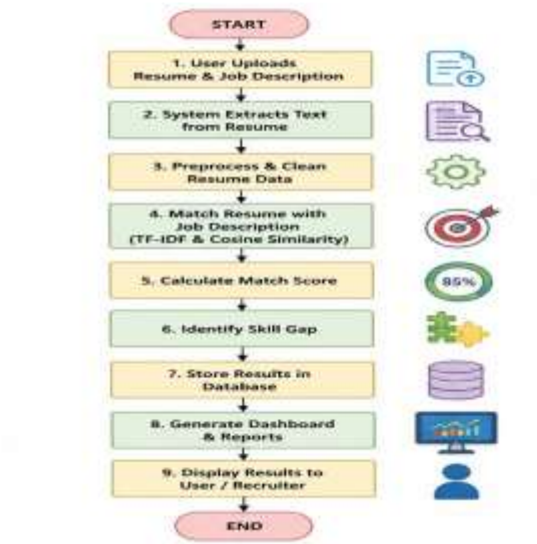

Figure 3: System Architecture of AI-Based ATS Resume Analysis and Skill Gap Prediction System

3.4 Algorithm Used

3.4.1 TF-IDF

TF-IDF is used to identify important keywords and skills from resumes and job descriptions by converting text into numerical vectors.

3.4.2 Cosine Similarity

Cosine similarity calculates the similarity score between resumes and job descriptions for accurate candidate matching.

3.4.3 NLP Preprocessing

NLP preprocessing techniques such as tokenization, stopword removal, and text cleaning are used to prepare textual data for analysis.

3.4.4 Skill Gap Detection

Skill gap detection identifies missing skills by comparing candidate resumes with job requirements.

IV. EXPECTED RESULTS AND DISCUSSION

The proposed AI-Based ATS Resume Analysis and Skill Gap Prediction System is expected to significantly improve the efficiency and accuracy of modern recruitment processes. By integrating Artificial Intelligence (AI), Natural Language Processing (NLP), and recruitment analytics, the system aims to automate resume screening and provide intelligent candidate evaluation.

The implementation of TF-IDF vectorization and cosine similarity algorithms is expected to improve resume-job matching accuracy compared to traditional keyword-based systems. The system can analyze candidate resumes more effectively by understanding the importance of skills, qualifications, and experience mentioned in both resumes and job descriptions. As a result, recruiters can quickly identify suitable candidates and reduce the time spent on manual screening.

Another important expected outcome is the successful identification of missing skills through the skill gap prediction module. The system will compare candidate profiles with job requirements and highlight missing competencies. This feature is beneficial for both recruiters and candidates, as it improves candidate evaluation and provides guidance for skill improvement.

The dashboard analytics module is expected to provide meaningful recruitment insights such as total resumes analyzed, highest match score, lowest match score, average compatibility score, and candidate rankings. These analytics support data-driven hiring decisions and help organizations monitor recruitment performance more efficiently.

4.1 Expected Outcomes

i. Performance Improvements

The system is expected to improve resume-job matching accuracy through AI and NLP techniques.

ii. Robustness

The system can process multiple resume formats and identify missing skills effectively.

iii. Scalability

The framework can be extended for large-scale recruitment systems and online job platforms.

Metric	Expected Value
Accuracy	90%
Precision	88%

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Recall	87%
F1-Score	89%

Table 3: Expected Performance Metrics of the Proposed AI-Based ATS System

4.2 Comparative Evaluation Plan

The proposed system will be evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score

The results will be compared with traditional ATS systems.

4.3 Discussion

Unlike traditional recruitment systems, the proposed framework provides both candidate matching and skill gap analysis.

The integration of dashboard analytics and HOT-Fit evaluation improves transparency and recruitment decision-making.

The system reduces manual effort and supports fair candidate evaluation.

V. APPLICATIONS AND USE CASES

The proposed AI-Based ATS Resume Analysis and Skill Gap Prediction System has a wide range of applications in recruitment, human resource management, career guidance, and educational sectors. By integrating Artificial Intelligence (AI) and Natural Language Processing (NLP), the system automates resume screening, improves candidate evaluation, and supports data-driven hiring decisions.
The system can be used by organizations to manage large volumes of job applications efficiently. It helps recruiters identify suitable candidates based on skills, qualifications, and experience while reducing manual workload. The skill gap prediction module also provides valuable feedback to candidates by highlighting missing competencies required for specific job roles.

In addition to recruitment, the proposed framework can be integrated into job portals, HR analytics platforms, talent management systems, and career guidance applications. The dashboard analytics feature enables organizations to monitor recruitment performance, candidate rankings, and hiring trends in real time.

The system is flexible and scalable, making it suitable for startups, educational institutions, multinational companies, and government recruitment agencies.

AI-based recruitment systems are widely used in HR analytics, job recommendation systems, and talent management platforms [1][2][7].

5.1 Industry Use

The proposed ATS framework can be widely used in industries and corporate organizations to automate recruitment workflows and improve hiring efficiency. HR departments often receive thousands of resumes for a single job opening, making manual screening difficult and time-consuming. The proposed system helps organizations quickly analyze resumes, calculate compatibility scores, and shortlist suitable candidates.

Technology companies can use the system to identify candidates with specific technical skills such as programming languages, cloud computing, machine learning, and cybersecurity. Similarly, organizations in healthcare, finance, education, and manufacturing sectors can customize the system according to their recruitment requirements.

The dashboard analytics module supports recruiters by providing insights into candidate performance, average match scores, and recruitment statistics. This improves decision-making and reduces the time required for candidate selection.

The system can also be integrated into existing HR management software and Applicant Tracking Systems to enhance automation and recruitment transparency.

5.2 Social Impact

The proposed AI-based ATS system can create a positive social impact by improving fairness and transparency in recruitment processes. Traditional

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recruitment methods often involve human bias and inconsistent evaluation, which may lead to unfair candidate selection. By using AI-driven matching techniques, the proposed system reduces dependency on manual judgment and promotes objective candidate evaluation.

The skill gap prediction feature helps job seekers understand missing skills and improve their employability. Candidates can use this feedback to upgrade their technical and professional skills according to industry requirements.

The system also supports equal opportunities for candidates by evaluating resumes based on qualifications and skills rather than personal preferences. This contributes to more inclusive and unbiased hiring practices.

Furthermore, the automation of recruitment processes reduces workload for recruiters and improves overall recruitment efficiency, benefiting both organizations and job seekers.

5.3 Policy Relevance

AI-based recruitment systems are becoming increasingly important in modern workforce management and digital hiring policies. The proposed ATS framework supports transparent and data-driven recruitment practices, which align with organizational and government initiatives promoting fair hiring standards.

The integration of analytics and evaluation frameworks such as the HOT-Fit model can help organizations measure recruitment efficiency, system usability, and technological performance. These evaluation metrics are valuable for policy development related to AI adoption in human resource management.

The system can also support compliance with recruitment guidelines by maintaining consistent evaluation criteria for all candidates. By reducing bias and improving transparency, the proposed framework contributes to ethical AI adoption in recruitment processes.
As organizations continue adopting digital recruitment technologies, intelligent ATS systems can play a significant role in shaping future workforce policies and smart hiring strategies.

5.4 Academic Value

The proposed research contributes to academic studies in the fields of Artificial Intelligence, Natural Language Processing, Machine Learning, and HR Analytics. The integration of TF-IDF vectorization, cosine similarity, skill gap prediction, and HOT-Fit evaluation provides a multidisciplinary research framework for future studies.

This study demonstrates how NLP techniques can be applied to solve real-world recruitment challenges and improve candidate-job matching accuracy. The research also highlights the importance of combining technical algorithms with evaluation frameworks for measuring system effectiveness.

The proposed framework can serve as a reference model for future researchers working on AI-based recruitment systems, recommendation systems, resume analysis, and HR analytics platforms.

Additionally, the project provides practical implementation knowledge using Flask, SQLite, Python, HTML, CSS, and dashboard analytics, making it useful for academic projects, dissertations, and further research development.

VI. CONCLUSION

This research proposed an AI-Based ATS Resume Analysis and Skill Gap Prediction System for improving recruitment efficiency and candidate evaluation.

The system integrates NLP techniques such as TF-IDF and cosine similarity to automate resume analysis and calculate candidate-job compatibility scores.
The inclusion of skill gap prediction and dashboard analytics enhances the usefulness of the system for recruiters and candidates.

Furthermore, the HOT-Fit evaluation model helps assess system effectiveness from human, organizational, and technological perspectives.

Future work may include integrating transformer-based models such as BERT and connecting the system with real-time job portals for advanced semantic matching.

The integration of TF-IDF, cosine similarity, and NLP techniques improves candidate-job matching accuracy and recruitment efficiency [1][4][5].

Future improvements may include transformer-based models such as BERT for advanced semantic analysis [8][9].s

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