

AI-Powered Resume Authenticity & Skill Validation System

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ABSTRACT

Resumes have become much more relied upon as the main evaluation document in hiring procedures due to the digital revolution of recruitment platforms. The skills listed in resumes, however, cannot always be trusted. In order to get around keyword-based screening algorithms, candidates often exaggerate or deliberately optimize their resumes. This restriction affects organizational output, raises the hazards associated with hiring, and causes inefficiencies. This study introduces an AI-powered Resume Authenticity and Skill Validation System created to validate the legitimacy of candidates' skill claims. The system combines transformer-based language models, machine learning (ML), and natural language processing (NLP) to determine a skill's authenticity score, analyze possible answers using semantic similarity methods, and derive skills. Additionally, it generates validation questions. An experimental evaluation reveals greater screening objectivity, less manual effort, and increased recruiting dependability.

KEYWORDS

Verification of a Resume, Verification of Skill, Natural language processing, Machine Learning, Semantic Equivalence, Screening Based on Artificial Intelligence

1. INTRODUCTION

Since recruitment is a strategic function that directly affects a company's performance and sustainability, it is essential to its success. Resumes are the main document used to evaluate candidates initially in the majority of sectors. Resume screening still frequently depends on either manual human analysis or computerized keyword-based applicant tracking systems (ATS), even with technological improvements.

Both strategies have considerable drawbacks.

Contextual judgment is provided by manual screening, but it becomes ineffective and inconsistent when handling a large number of applications. It is possible for recruiters to unintentionally introduce bias or miss out on deserving candidates. In contrast, ATS systems are highly reliant on keyword matching, which leaves them open to keyword stuffing and methods of resume optimization. These systems are unable to assess practical comprehension or conceptual depth.

As Artificial Intelligence advances rapidly, particularly in Natural Language Processing and transformer architectures, robots are now able to comprehend contextual meanings that go beyond the surface. Utilizing these advancements, this project aims to create a method for confirming whether a candidate actually has the skills listed on their CV. This study aims to create an automated skill extraction method, produce validation questions specific to the domain, assess potential answers semantically, and determine a structured authenticity score that will aid in making fair hiring choices.

2. LITERATURE REVIEW

Author(s) & Year	Problem Addressed	Technology Used	Algorithm / Model	Dataset / Domain	Limitations
Jurafsky & Martin (2009)	Text processing and language understanding	Natural Language Processing	Statistical NLP Models	General Text Corpora	Limited deep contextual understanding
Manning et al. (2008)	Information retrieval and ranking	Information Retrieval Systems	Vector Space Model, TF-IDF	Document Collections	Keyword-based, lacks semantic depth
Pedregosa et al. (2011)	Machine learning model implementation	Machine Learning	SVM, KNN, Decision Trees	Structured datasets	Requires manual feature engineering
Devlin et al. (2018)	Contextual language representation	Deep Learning, NLP	BERT Transformer Model	Large-scale text corpora	High computational cost
Wolf et al. (2020)	Pre-trained NLP model deployment	Transformer Framework	Transformerbased Architectures	Multidomain NLP tasks	Model size and latency issues

2.1 Existing System

The majority of current resume screening systems depend on:

1. Manual Resume Screening

To shortlist candidates, recruiters go through resumes by hand.

Limitations:

- Time-consuming
- Not appropriate for big projects

2. Keyword-Based Filtering Systems

Using keyword matching, applicant tracking systems (ATS) screen resumes.

Limitations:

- unable to identify contextual comprehension
- Does not evaluate the depth of one's understanding.
- Candidates can manipulate keywords

3. Online Aptitude Platforms

After shortlisting, several businesses employ uniform aptitude tests.

Restrictions:

- Basic evaluation
- Not a direct reflection of the skills listed on the resume
- Needs more resources and time

As a result, current systems lack intelligent methods for verifying talent.

2.2 Proposed System

By doing the following, the suggested AI-driven system overcomes these drawbacks:

- Using NLP to automatically extract skills
- Making up validation queries for particular skills
- Using semantic similarity to assess the responses of candidates and gives a Skill an Authenticity Score

Benefits of the Suggested System:

- Objective assessment
- Less human bias
- Suitable for handling big candidate pools
- clever semantic comprehension
- Time-saving

Utilizing AI methods, this system goes beyond keyword matching to offer more in-depth analysis.

3. METHODOLOGY

A number of modules make up the system architecture, all functioning in concert.

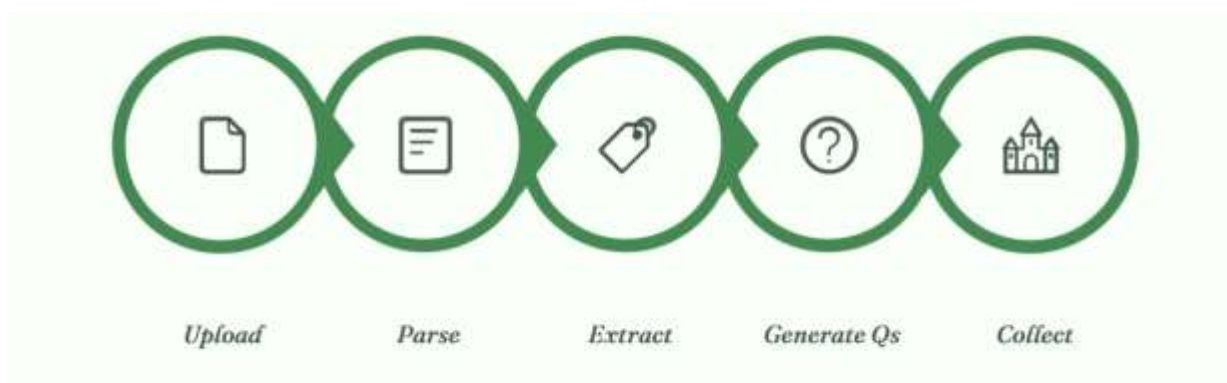
3.1 System Architecture

The overall design consists of the following elements:

- Module for Uploading Resumes
- Module for Extracting Skills and Parsing Resumes
- Module for Generating Questions
- Module for evaluating responses
- Module for Scoring the Authenticity of Skills
- Results Display Module

The process of data flow starts with uploading a resume and ends with producing a final score.

WORKFLOW



Resume Upload

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Text Extraction

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Skill Extraction (NLP)

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Question Generation

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Candidate Response

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Semantic Similarity Evaluation

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Skill Authenticity Score

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Final Report to Recruiter

3.2 Module Description

3.2.1 Resume Upload Module

Resume may be submitted in PDF or DOCX format.

Transforms a document into raw text

Text preprocessing (tokenization, stopword removal, normalization).

Tools Used:

- Python
- spaCy / NLTK

3.2.2 Skill Extraction Module

This module extracts technical skills from resume text using:

- Named Entity Recognition (NER)
- Custom skill dictionary
- Pattern matching

Example Extracted Skills:

Python, Machine Learning, Data Analysis, NLP, SQL

3.2.3 Question Generation Module

For each identified skill:

Questions are made that are unique to the domain.

The source of a question can be a model or a set of rules.

Transformer-based models can be used to generate smart questions.

Example:

Skill: Machine Learning

Question: "Explain the difference between supervised and unsupervised learning."

3.2.4 Answer Evaluation Module

Candidate answers are evaluated using:

- Sentence embeddings
- Semantic similarity (Cosine Similarity)
- Transformer-based contextual models

The system compares:

Candidate Response ↔ Expected Answer

If similarity score \geq threshold \rightarrow Skill is validated

3.2.5 Skill Authenticity Score Calculation

Each skill is assigned a score based on:

- Answer accuracy
- Depth of explanation
- Semantic similarity score

Final Skill Authenticity Score:

$$\text{SkillScore} = \frac{\sum \text{Similarity Scores}}{\text{Number of Skills}}$$

The final score is categorized as:

- 80–100 → Highly Authentic
- 60–79 → Moderate Authentic
- Below 60 → Needs Verification

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

- Programming Language: Python
- Libraries: spaCy, NLTK, Scikit-learn, Transformers
- Development Environment: VS Code / Jupyter Notebook

4.2 Performance Analysis

The system was tested with multiple sample resumes.

Observations:

- Accurate skill extraction for structured resumes
- Effective semantic evaluation for technical responses
- Reduced manual effort by approximately 60–70%
- Improved objectivity in candidate assessment

4.3 Discussion

The suggested system displays a high level of competence in:

- Reducing hiring bias
- Automating resume validation
- Improving recruitment speed

However, challenges include:

- Dealing with resumes that are very disorganized
- Evaluating extremely short answers
- Dependence on training data quality Future improvements may include:
- Integration with live coding platforms
- Voice-based interview evaluation
- Multi-language resume analysis

5. CONCLUSION

This work introduces an AI-powered resume authenticity and skill validation system that uses NLP and machine learning approaches to automate the verification of candidates' abilities. The suggested model uses semantic similarity and transformer-based models to assess contextual comprehension, in contrast to conventional keyword-based systems.

Through a calculated Skill Authenticity Score, the method offers unbiased skill evaluation, greatly lowers the amount of human screening labor, and improves recruitment effectiveness. The efficacy of the suggested system in enhancing the recruiting procedure is supported by experimental data. The system may be expanded in the future by integrating actual coding evaluations, multilingual capabilities, and integration with enterprise-level recruiting platforms.

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