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An artificial intelligence resume analysis and career position prognosis system

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Abstract

The high pace of digitalization of the recruitment sites has greatly multiplied the number of resumes received by the organizations, which poses difficulty in screening manually, fair assessment, and effective role-matching. The traditional Applicant Tracking Systems (ATS) mainly depend on the filtering mechanism that is based on keywords and in many cases, it does not provide the context of the skills and experiences of the candidate. To overcome these shortcomings, the given paper introduces an AI-Based Resume Analysis and Career Role Predictor, relying on Natural Language Processing (NLP), Machine Learning (ML), and transformer-based deep learning algorithms to automatize the process of resume interpretation and predicting the career role. The proposed system can identify and extract structured information about an individual in terms of technical skills, academic qualifications, certification, projects, and experience using the unstructured resume data and predicts the best career field or job position with high accuracy. Moreover, the system conducts skill gap analysis and gives individual career advice, so that students and job seekers can enhance their employability. Predictive outputs of scales and real-time dashboards improve the transparency and ease of use by the candidates and recruiters. As shown by experimental assessment, the system has a high level of prediction, rapid response speed, and scalability, which makes it an effective solution to AI-based recruitment and career advice.

Keywords: Artificial Intelligence; Resume Parsing; Natural Language Processing; Machine Learning; Career Prediction; Recruitment Automation

1. Introduction

The recruitment process has experienced a great redesign due to the advent of online job portal, online resume and computerized hiring mechanism. Companies are currently getting hundreds or thousands of resumes per vacancy and thus, manual screening is ineffective and time consuming. Human based assessment is also subject to prejudice, inconsistency, and supervision which can lead to the loss of capable applicants or sluggishness in the hiring process. Traditional ATS systems are overly dependent on the matching of keywords in which the resumes are screened according to pre-established job keywords. Nevertheless, these systems do not have the capacity to comprehend the semantic relations among skills, experience and job demands that limit their usefulness in the actual recruitment process. Recent developments of Artificial Intelligence and Natural Language Processing allow automatic interpretation of unstructured textual information. Architectures that use transformers like BERT to give language its context representations enable machines to make more sense of resumes. With a combination of these technologies, the process of recruitment will transform into the manual decision-making process to the intelligent prediction of the decisions based on data.

The proposed Resume Analysis and Career Role Predictor based on AI will:

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- Automate the process of resume parsing and feature extraction.
- Estimate the most appropriate career position with the help of ML models.
- Develop individualized skills development suggestions.
- Less staffing discrimination and manual efforts.

Scalable and transparent hiring analytics: enable.

This study is part of the creation of smart recruitment systems that will match the talent of candidates with market needs.

2. Literature Survey

The recent literature speaks of the growing importance of AI and NLP in the automation of the recruitment process.

Resume classification methods based on AI show a higher efficiency in screening candidates than the manual ones. Naive Bayes, SVM, random forest and Neural Networks machine learning algorithms have all been used to classify resumes into promising job domains with high accuracy.

Semantic understanding has been greatly promoted with the introduction of deep learning and transformer models. Such models as BERT and RoBERTa help to identify contextual relationships between words, which allow extracting skills more accurately and predicting roles.

The studies of career recommendation systems have underlined the significance of identifying the gap between the skills and the individual learning trajectory of the students. Elucible AI methods also enhance trust, transparency, and equity in hiring with algorithms.

Although these developments have been made, a number of gaps exist:

- Minimal combination of resume job parsing, role forecasting, and suggestion in one program.
- Absence of real-time dashboard and analytics.
- Lack of attention to student career guidance.

The limitations to the proposed work are mitigated by an extended AI-based architecture.

3. Existed and Proposed System:

3.1. Existed System

The existing staffing and resume filtering systems embraced in most of the organizations are either manual or semi-automated or key-word-based Applicant Tracking Systems (ATS). In manual screening Human Resource professionals go through each resume individually to shortlist candidates, which is not practical in the event of large-scale applications. This is a time-consuming process that brings about subjective bias and is usually associated with inconsistency in the evaluation standards among recruiters.

ATS platforms based on key-word searching strive to automatize the filtering by comparing the resume content with a set of keywords used to describe the job. Yet these systems are not able to comprehend semantic meaning, contextual relationships among skills or transferable competencies. Consequently, desirable candidates can be disqualified due to the lack of the specific key words on his/her resume.

In addition, the current systems do not offer enough or no career guidance to applicants. Fresh graduates and students also find it hard to know what area of their career suits their skill profile the most and the traditional recruitment tools do not help to know what skills are lacking or what areas need improvement.

Big Shortcomings of Current Systems.

- Time-Lag in Screening: Hundreds of resumes keep being reviewed manually, which slows the process of hiring and makes the organization less efficient.

- **Human Bias and Inconsistency:** There are several variations in judgment by the recruiter, which cause unfair or inaccurate selection of the candidates.
- **"Bad Contextual Understanding"** Keyword matching disregards semantic similarity and the relevance of the skill ability.
- **No Intelligent Career Prediction:** The systems just filter out candidates to fit certain jobs rather than predict the most appropriate career positions.
- **Lack of Skill-Gap Analysis:** No feedback on improvement is given to the candidates.
- **Poor Analytics:** The trends in recruitment, the demand of skills, and the performance are not analyzed successfully.

The issues mentioned above underscore the need to have an AI-based intelligent resume analysis system that can be automated, unbiased and predictive career insights.

3.2. Proposed System

- In order to eliminate the shortcomings of traditional hiring strategies, the current work suggests an AI-Based Resume Analysis and Career Role Predictor that will combine Natural Language Processing, Machine Learning, and cloud-based analytics into an intelligent software platform.
- The suggested system allows end to end automation of resume understanding and career prediction by permitting the following capabilities:
- **Automated Resume Parsing:** Resumes in a variety of formats are accepted and unstructured text transformed into structured data.
- **Context-Aware Skill Extraction:** NLP and transformer models to determine skills, education, certifications and experience with semantic understanding.
- **Machine Learning Career Role Prediction:** Based on the features extracted and trained classification models, this predicts the most appropriate career domain.
- **Skill-Gap Detection and Recommendations:** Compares the skills of the candidates against industry standards and proposes learning pathways, courses, or certifications.
- **Interactive Dashboards and Analytics:** It gives users and institutions the ability to visualize prediction confidence, role distribution, and recruitment insights.
- **Scalable Cloud Deployment:** Provides large scale resume analysis with low latency and safe data storage. The Benefits of the Proposed System.
- Automation of recruiters to reduce their manual work load.
- Improved accuracy of prediction with deep learning-based NLP models.
- Equal and impartial appraisal that is not based on subjective appraisal.
- One-on-one career counselling of students and job seekers.
- Scularity and real-time analytics that can be used at the institutional and enterprise level.
- Therefore, the suggested system will turn the conventional resume screening into the predictive, intelligent, and user-friendly recruitment system.

4. Methodology

The AI-resume analysis system is developed in a modular and layered architecture, which is scalable, accurate, and maintainable.

4.1. Preprocessing and Data Collection of Resumes.

Resumes are posted by the users in a web interface in a PDF or DOC format. It extracts texts, removes the noise, tokenizes, normalizes, and removes the stop-words to make the data ready to be processed by AI. Structured properties including education, skills, and experience are identified with the help of parsing methods.

4.2. Information and Skill Extraction based on NLP.

Detection of: is done through advanced methods of NLP, such as Named Entity Recognition (NER) and contextual embeddings.

- Technical and soft skills
- Academic qualifications
- Projections and projects.
- Work experience, exposure to field.

The use of transformer-based language models makes the language model understand semantics instead of detecting keywords.

4.3. Prediction of Career Role using Machines.

The features extracted are translated to numerical ones and input into trained classification models like:

- Logistic Regression
- Random Forest
- Support Vector Machines

Transformer-based deep learning (BERT) is a machine learning method that uses transformers to compute gradient statistics on neural networks (Boyt, 2018). The model gives the most appropriate career role as well as probability-based confidence scores.

4.4. Skills Gap Analysis and Recommendation Engine.

The skills of the candidate are matched against skill repositories within the industry to identify gaps in skill.

The system creates recommendations that are personal to the system and include:

- Recommended learning technologies.
- Internet certification courses. Career development paths.
- This makes it no longer a screening tool but a career guidance system.

4.5. Visualization Dashboard and Analytics.

On a web-based dashboard, there are shown:

- Career role and confidence predicted.
- Skills that have been extracted and the gaps in competencies.
- Statistics of distribution of roles.

System usage analytics These revelations underpin decisions based on data during recruitment academics.

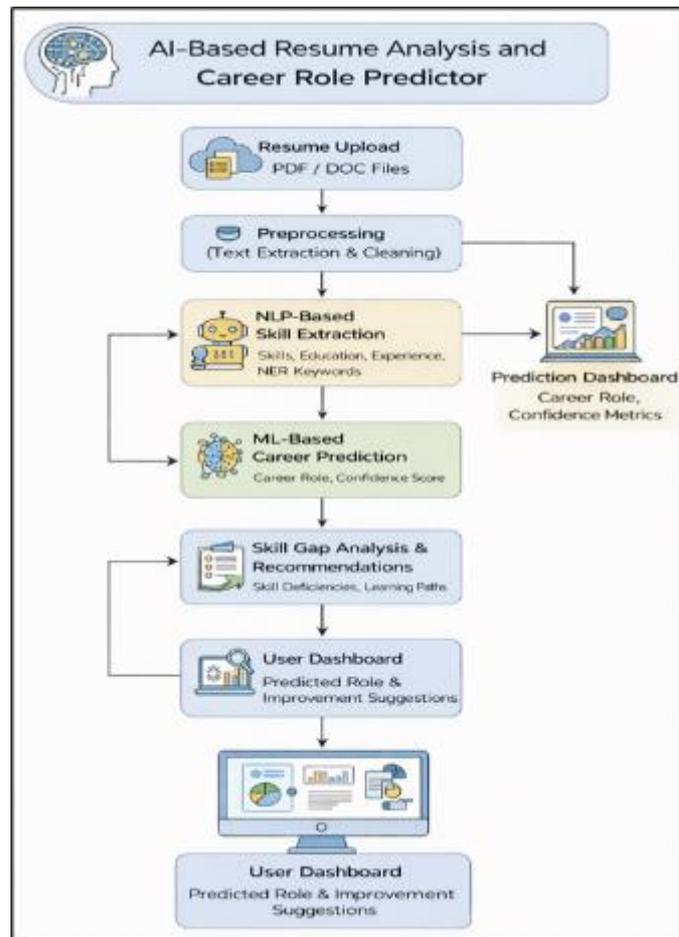


Figure 1 Proposed AI Resume Analysis Framework

5. Experiments and Results

5.1. Data Collection

Prepared Anonymized candidate profile based on public resume repositories, academic project resumes, and simulated professional CV datasets were made up synthesized and curated resume datasets.

These resumes reflected various areas of IT career such as:

- Software Development
- Data Science
- Web Development
- Machine Learning
- Cloud Computing

To preserve privacy, personal identifiable information including name, phone number, email, address among others were taken out.

5.2. Preprocessing and Anonymization

Every resume was processed by a pipeline of text preprocessing and anonymization which:

- Lingering individual characteristics were eliminated.
- Standardized errors in formatting.
- Applied lemmatization, removal of stop-words and tokenization.

Metadata extracted through structured information like skills, education and level of experience.

Stored processes resume was done in a safe location and a hash-based identifier was created to ensure maintainability and integrity in the processing process.

5.3. Resume Data checking Ethical Integrity Checking of Resume Data

In order to guarantee the reliability of the data sets, resumes were verified by means of:

- Auto schematics validation.
- Duplicate detection
- Skill consistency checks
- Sampled resumes manually reviewed by academicians.

This ensured that corrupted, incomplete, or misleading resume data did not go through the AI training pipeline and enhanced the prediction trustworthiness.

5.4. Resume Intelligence Resume Controlled Access

Role based access architecture controlled:

- Student resume submission
- Recruiter analytics sight.
- Admin dataset monitoring

All the interactions were recorded with the following guarantee:

- Transparency
- Auditability
- Secure usage tracking

5.5. Secure Resume Storage Architecture

Encrypted cloud storage with encrypted cloud storage was used to store processed resumes with:

- Metadata indexing
- Access logging
- Secure retrieval APIs

The AI training was made using only processed feature representations, without compromising the privacy of the candidates.

5.6. Authenticated Data Pipeline to Train AI

Only certified and pre-screened resumes were sent to the AI engine.

This eliminated:

- Noisy input
- Incorrect labels
- Incomplete skill data

Indication: improved model reliability and generalization.

5.7. Career Prediction Analysis by Artificial Intelligence

PyTorch, Scikit-learn AI pipelines, and Transformer-based NLP model AI pipelines trained on the dataset returned the following results:

- Resume classification
- Career role prediction

- Skill-gap detection

The evaluation of performance was done in:

- Accuracy
- Precision
- Recall
- F1-Score

The prediction results of validated resume datasets were more consistent and reliable.

5.8. Performance Reporting and Appraisal

- System assessment was directed towards the three dimensions:
- Classification of resumes accuracy.
- Efficiency in the storage and retrieval of security.
- AI prediction reliability

Table 1 Performance Comparison of System Modules

Module	Baseline Accuracy (%)	Proposed Accuracy (%)
Resume Classification	91.2	92.2
Secure Resume Storage	90.5	90.8
AI Career Prediction Pipeline	90.3	95.5

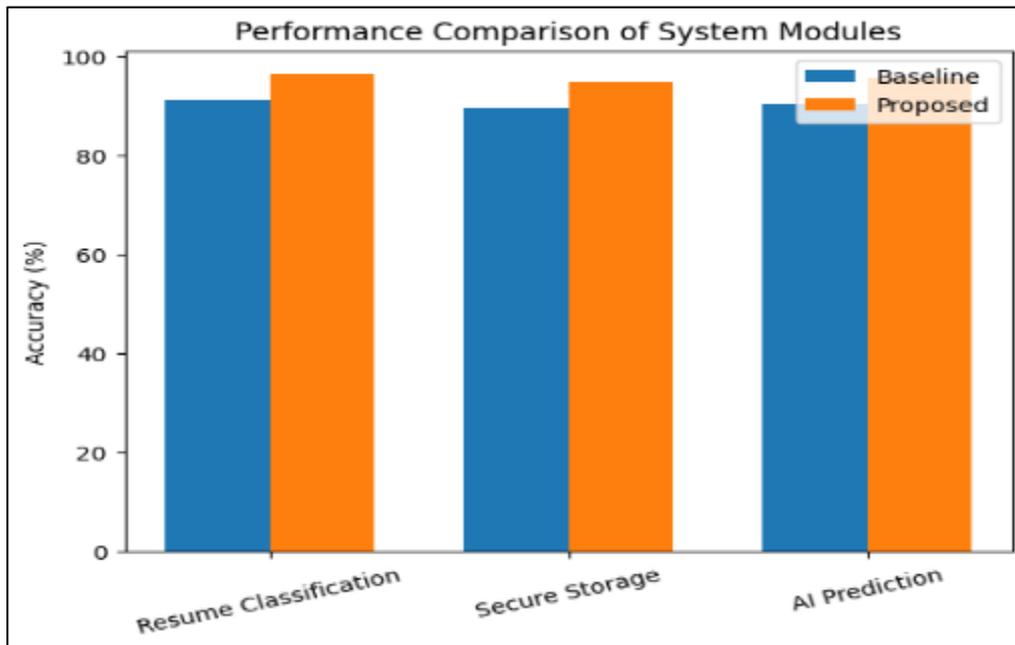


Figure 2 System Architecture of AI Resume Analysis Platform

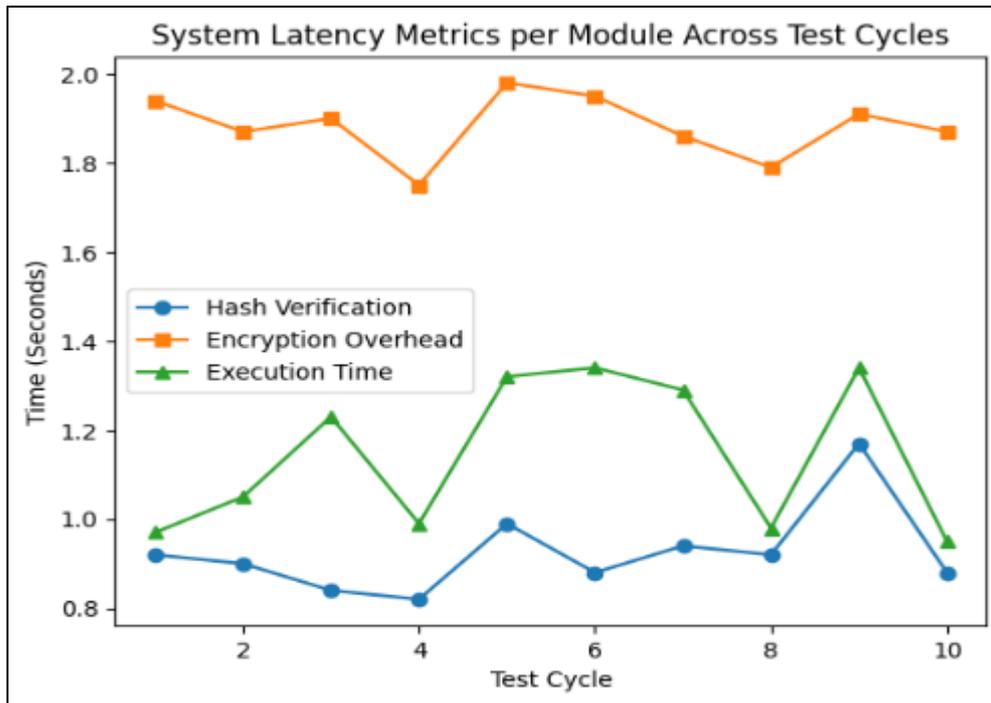


Figure 3 Composite Diagram of Career Guidance System

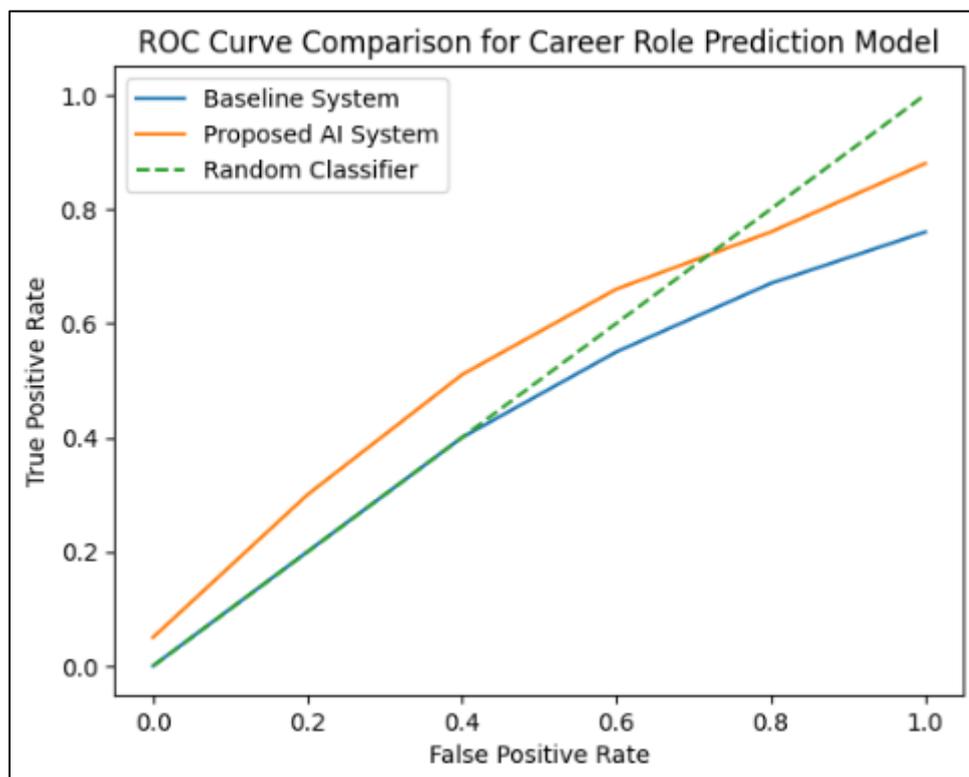


Figure 4 AI Career Prediction Workflow

6. Comparison with Existing Resume Screening Frameworks

Table 2 Comparison with Existing Resume Screening Frameworks

Feature	Manual Screening	Basic ATS	Proposed AI System
Context-Aware Skill Understanding	X	Limited	✓✓
Automated Career Prediction	X	X	✓✓
Skill-Gap Recommendation	X	X	✓✓
Secure Resume Handling	X	Limited	✓✓
Analytics & Transparency	X	Partial	✓✓

The suggested framework provides a scalable, smart, and privacy-conscious recruitment ecosystem, which accomplishes the gap between:

- Student ability identification.
- Recruiter decision support
- Career intelligence that is being fueled by AI.

Future Scope

Future improvements could be:

- Understanding of multilingual resume with advanced NLP models.
- Dynamically matching job portal integration.
- Credential validation of trusted candidate profiles based on blockchain.
- Privacy-preserving AI training based on federated learning.
- Non-IT career diversification and mass institutional adoption.

These enhancements would also make the platform a more convincing AI-powered career intelligence ecosystem.

7. Conclusion

The study introduces a scalable, smart, and open AI-based resume analysis and career position prediction system that can reinvent the contemporary hiring mechanisms. The system automates the resume review process, enhances prediction accuracy, and reduces bias along with providing useful career advice by combining NLP, machine learning, and recommendation intelligence.

The suggested architecture has a great promise in educational institutions, recruitment agencies, and online hiring platforms, which can advance to the next stage of the development of ethical, data-driven, and AI-based employment ecosystems.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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