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AI-Powered Resume Analyzer and Interview Preparation System

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Abstract: The process of evaluating resumes and preparing candidates for interviews traditionally requires significant manual effort, domain expertise, and time.
This paper presents an AI-powered Resume Analyzer and Interview Preparation System designed to automate resume parsing, skill extraction, job-role matching, and AI-driven interview preparation. The system integrates Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLMs) to analyze resume content, extract skills, compute job-role fit, generate candidate insights, and conduct intelligent mock interviews. A Flask-based backend processes the resume, while a web-based interface presents structured results, suggestions, and interactive interview sessions. Experimental evaluation demonstrates that the system enhances accuracy, reduces human effort, and provides personalized interview guidance, making it an efficient tool for recruitment, career assessment, and skill development.
Keywords: Resume analysis, NLP, LLM, skill extraction, interview preparation, AI recruitment.

I. INTRODUCTION

The process of evaluating resumes and preparing candidates for interviews plays a critical role in modern recruitment, career development, and workforce selection. As organizations continue to receive thousands of job applications for a limited number of openings, the need for automated, accurate, and unbiased screening systems has increased significantly. Traditional resume screening relies heavily on human recruiters, who manually read, interpret, and evaluate candidate profiles based on skills, experience, education, and relevant achievements.

This manual process is time-consuming, inconsistent across evaluators, and often influenced by unintentional human bias. Additionally, candidates themselves face challenges in understanding how effectively their resume represents their skill set, how well they match specific job roles, and how prepared they are for professional interviews.

With the rapid advancement of Artificial Intelligence (AI), Natural Language Processing (NLP), and Deep Learning (DL), automated candidate assessment systems have emerged as powerful tools to assist both job-seekers and organizations. AI models are now capable of extracting structured information from unstructured text, classifying resumes into relevant domains, evaluating candidate skills, and even generating interview questions tailored to the candidate's background. Large Language Models (LLMs), such as GPT-based and Llama-based models, have further enabled human-like conversation, contextual analysis, and semantic understanding, making AI-driven interview preparation highly realistic and effective

In this context, the objective of this project is to design and develop an AI-Powered Resume Analyzer and Interview Preparation **System** that integrates resume parsing, skill extraction, domain classification, job-role matching, and AI-driven mock interview simulation within a unified platform. The system accepts resumes in multiple formats (PDF, DOCX, TXT) and processes them using advanced NLP-based extraction pipelines. It identifies key sections such as professional summary, education, work experience, projects, certifications, and technical skills with high accuracy. The extracted information is then used to compute a skill profile vector, which is further matched against predefined job-role vectors to determine the most suitable career paths for the candidate.

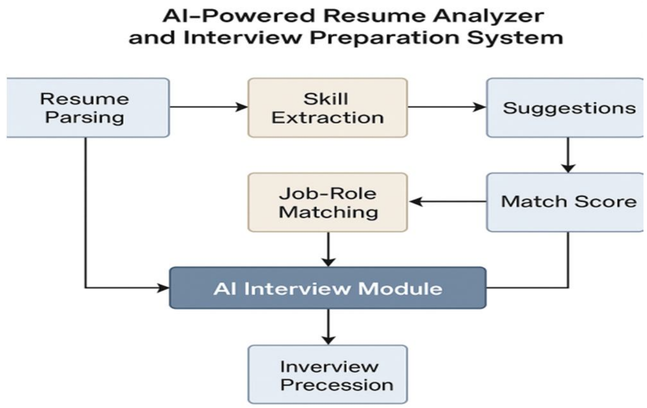

Fig 1: Full Flowchart – AI-Powered Resume Analyzer & Interview Preparation System

Beyond resume analysis, the system includes an AI-based interview preparation module capable of generating role-specific and skill-focused interview questions. Using LLM-based conversational AI, the system conducts an interactive, chat-style interview where the candidate responds to generated questions and receives instant feedback This feedback includes evaluation of answer quality, depth, clarity, confidence, and structure. Such automated interviews provide candidates with continuous learning support and personalized practice without the need for human mentors or trainers. The system is built using a multi-layered architecture that includes a Flask backend, NLP models (spaCy, NLTK, BERT), a SQLite database for resume storage, and a JavaScript-based frontend for visualization. The integration of machine learning and LLM-driven reasoning enhances the system's ability to provide accurate insights, reduce human workload, and deliver a highly personalized user experience. Moreover, the system addresses key challenges in traditional hiring workflows, such as scalability, subjectivity, and the need for real-time feedback.

Overall, this project demonstrates that a unified AI-driven resume analyzer and interview preparation solution can significantly improve the efficiency, fairness, and accuracy of candidate evaluation. It serves as a powerful tool for job seekers, academic institutions, training organizations, and recruitment teams by automating resume screening and delivering intelligent interview guidance. The increasing availability of LLMs and transformer-based NLP models further ensures that such automated systems will play an essential role in the future of digital recruitment and career development

II. LITERATURE REVIEW

The adoption of Artificial Intelligence (AI) in recruitment and candidate assessment has significantly transformed modern hiring practices. Traditional recruitment workflows rely heavily on manual resume screening and human-led interviews, both of which are labour-intensive, slow, and prone to inconsistencies arising from subjectivity and cognitive bias. With advancements in Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLMs), automated resume understanding and AI-driven interview preparation systems have emerged as viable solutions. This section reviews existing research, technologies, and methods relevant to AI-based resume analysis, skill extraction, job-role matching, and automated interview systems..

A. *Resume Parsing and Information Extraction*

Early resume parsing relied on rule-based extraction, pattern matching, and handcrafted heuristics. These systems were limited in handling variations in resume structure, formatting, and context. Later, researchers adopted NLP techniques such as:

- Part-of-Speech (POS) Tagging
- Dependency Parsing
- Named Entity Recognition (NER)
- Regular Expression–based Classification

Studies showed that NLP could extract structured information such as education, experience, and skills from unstructured text, but accuracy depended heavily on resume formatting. The introduction of transformer-based models (BERT, RoBERTa, XLNet) enabled semantic understanding, improving the identification of sections, roles, and skill entities. These models learn contextual relationships, allowing them to differentiate between ambiguous terms (e.g., “Java” as a skill vs. “Java” as an island).

Research also highlights the importance of ATS-optimized parsing, where AI ensures compatibility with Applicant Tracking Systems for efficient digital screening.

B. Skill Extraction and Ontology-Based Mapping

Skill extraction has progressed from simple keyword recognition to advanced contextual interpretation. Traditional statistical methods (TF–IDF, n-grams) capture frequency-based patterns but fail in deeper semantic understanding.

Recent approaches use:

- Word Embeddings (Word2Vec, GloVe)
- Contextual Embeddings (BERT, Sentence-BERT)
- Skill Ontologies (ESCO, O*NET, LinkedIn Skill Graph)

Studies highlight that embedding-based models capture semantic similarity, enabling more accurate categorization of skills even in diverse syntactic structures. For example, “machine learning engineer,” “ML engineer,” and “AI engineer” can be grouped effectively using semantic embeddings.

Ontology-based frameworks allow mapping of extracted skills to relevant industries, job roles, and career levels, improving the accuracy of job-role matching.

C. Job-Role Classification and Recommendation

Job-role matching traditionally relied on keyword overlap or rule-based matching. However, these methods fail when resumes contain implicit skills or domain-specific terminology.

Modern research adopts:

- Cosine similarity between skill vectors and job-role vectors
- Neural embedding models (SBERT, USE)
- Hierarchical role classification frameworks
- Deep learning classifiers for occupation mapping

Studies demonstrate that AI-based job-role matching significantly reduces recruiter workload and increases accuracy in candidate-role alignment. Hybrid models combining **resume embeddings + job-description embeddings** outperform traditional keyword-based systems.

D. AI-Based Interview Systems

Automated interview systems have evolved from static question banks to dynamic, conversational AI agents.

1) Early Automated Interview Models

Earlier systems generated questions from pre-defined datasets and evaluated responses using scoring rubrics. These systems lacked adaptability and contextual understanding.

2) NLP and ML-Driven Interview Assessment

Research introduced ML classifiers capable of evaluating:

  - Grammar
  - Clarity
  - Sentiment
  - Topic relevance

However, these methods still lacked human-like interpretation.

3) LLM-Based Conversational Interview Systems

The emergence of LLMs (GPT-3, GPT-4, Llama, PaLM) revolutionized interview systems by enabling:

- Context-aware questioning
- Dynamic follow-up questions
- Natural conversational flow
- Semantic evaluation of answers
- Personalized coaching

Studies show that LLMs can generate domain-specific interview questions and provide high-quality feedback comparable to human interviewers.
These systems significantly benefit students and job seekers by offering unlimited practice with adaptive difficulty.

E. Gaps in Existing Research

Despite major advancements, research identifies the following gaps:

1) Lack of end-to-end integrated systems: Most tools perform resume parsing *or* interview coaching, but not both in a unified system.
2) Limited personalization: Many existing systems do not tailor interview questions based on extracted skills or job-role compatibility.
3) Insufficient feedback mechanisms: Existing AI interview systems rarely give structured feedback on clarity, reasoning, technical depth, or communication.
4) Dataset limitations: Resume datasets used in research are small, restricted, or synthetic, reducing generalization capability.
5) Privacy and security concerns: Handling resumes and personal data requires strong compliance mechanisms, often missing in academic prototypes.

Your project addresses these gaps by integrating:

- Resume parsing
- Skill extraction
- Job-role prediction
- AI-driven interview simulation
- Answer feedback & scoring
- A user-friendly interface into one cohesive system.

F. Summary

The literature demonstrates major progress in NLP-based resume understanding, transformer-based skill extraction, and LLM-driven interviews. However, there remains a need for holistic, intelligent platforms that combine these technologies. The proposed system leverages advanced deep learning and LLMs to provide a unified solution for automated resume analysis and interview preparation.

III. METHODOLOGY

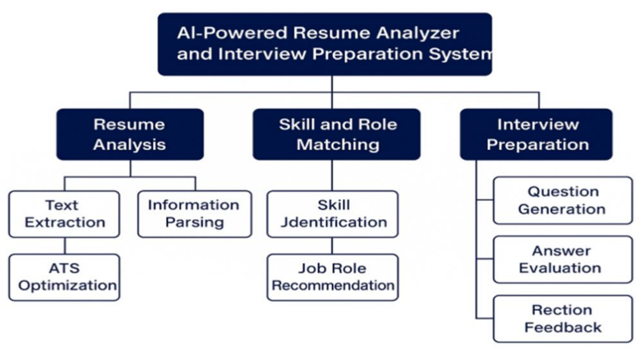

Fig 2 : Multi-Stage Hybrid Pipeline

The proposed AI-Powered Resume Analyzer and Interview Preparation System follows a multi-stage methodology integrating Natural Language Processing (NLP), Machine Learning (ML), Large Language Models (LLMs), and structured data pipelines. The overall process is designed to mimic the way human recruiters evaluate resumes and conduct interviews, but with higher consistency, scalability, and automation. The methodology is structured into five major stages: (1) Resume Acquisition & Preprocessing, (2) Resume Parsing & Information Extraction, (3) Skill Identification & Job-Role Matching, (4) AI-based Interview Preparation, and (5) System Integration & Workflow Architecture. Each stage is described in depth in the following subsections.

A. Resume Acquisition and Pre-processing

The system accepts resumes in multiple formats including PDF, DOCX, and TXT, ensuring compatibility with diverse candidate submissions. Upon upload, the resume undergoes a preprocessing pipeline designed to normalize the text for consistent NLP processing.

1) File Type Detection

The system uses file signatures to identify and process:

- PDF files using PyPDF2 or PDFMiner,
- DOCX files using python-docx or docx2txt,
- TXT files through direct reading.

2) Text Extraction

Extracted text is passed through:

- Header/footer removal
- Page-number detection
- Non-ASCII cleaning
- Noise filtering (special symbols, repeated characters)

3) Text Normalization

To standardize resume content for NLP, the following preprocessing steps are applied:

- Lowercasing
- Tokenization
- Stop-word removal
- Lemmatization
- Sentence segmentation

These steps ensure high-quality input for the parsing and classification models.

B. Resume Parsing and Information Extraction

The second stage converts raw unstructured resume text into structured information.

1) Section Segmentation

Resumes contain heterogeneous structures. Using a hybrid of:

- Rule-based patterns (e.g., “Education”, “Experience”, “Projects”),
- NLP sentence classification,
- Transformer-based segment identification, the resume is segmented into meaningful sections.

2) Named Entity Recognition (NER)

NER is performed using spaCy/BERT models to extract:

- Skills
- Degrees
- Job titles
- Organizations
- Certifications
- Projects
- Tools/technologies

NER models trained on industry datasets improve the accuracy of identifying domain-specific skills.

3) Semantic Classification

To classify sentences into resume categories, transformer-based models such as BERT or DistilBERT assign probabilities for:

- Education details
- Professional experience
- Project descriptions
- Technical skill mentions
- Summary statements his enables fine-grained extraction even if resumes use non-standard formats.

4) ATS Optimization Evaluation (Optional Module)

The system evaluates the resume for:
- Keyword relevance
- Formatting consistency
- Readability
- Skills alignment

This approximates how Applicant Tracking Systems interpret resumes.

C. Skill Identification and Job-Role Matching

This stage forms the intelligence core of the system, converting the extracted data into meaningful insights.

1) Skill Extraction

Skills are extracted using a multi-layer approach:
- Dictionary-based matching (static skill lists)
- Embedding-based similarity matching using Sentence-BERT
- Contextual classification to detect implied skills (e.g., "developed ML models" → Machine Learning)

This ensures both explicit and implicit skills are captured.

2) Skill Categorization

Skills are grouped into categories:
- Technical skills
- Soft skills
- Programming languages
- Frameworks/tools
- Domain-specific skills

This aids in mapping candidates to job roles.

3) Job-Role Vectorization

Each job role is embedded into a high-dimensional vector space using:
- BERT embeddings
- TF-IDF role vectors
- Domain ontology (O*NET/ESCO)

4) Candidate-to-Role Similarity Matching

Cosine similarity is computed between:
- Candidate skill vector
- Job-role vector

A match score determines the degree of alignment.

5) Job-Role Recommendation

Top-matching job roles are selected:
- Software Developer
- Data Analyst
- AI/ML Engineer
- Cybersecurity Analyst
- Web Developer

Each recommendation is accompanied by missing-skill analysis and improvement suggestions.

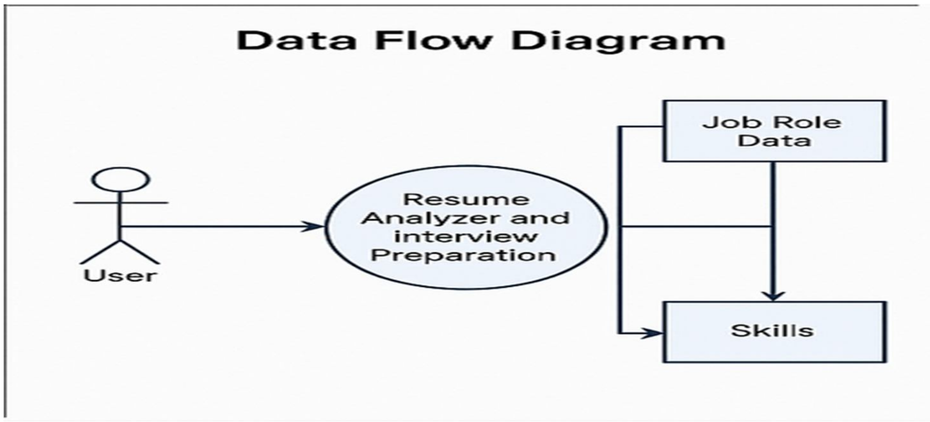

Fig 3: Data Flow Diagram

Once resume analysis is complete, the workflow transitions into the interview preparation module, which is powered by a large language model. Using the results from the resume analysis, the system generates context-aware interview questions tailored to the user's skills, past projects, job-role recommendations, and experience level. The interview takes place in a chat-based interface, where the candidate responds to questions and receives immediate evaluation. Each response is processed using semantic similarity checks, sentiment analysis, and coherence evaluation, enabling the system to assess technical correctness, depth of explanation, communication clarity, and confidence. The LLM then provides personalized feedback that highlights strengths, identifies weaknesses, and suggests improvements in both technical and soft-skill areas. Finally, all components—resume preprocessing, NLP pipelines, skill extraction, job-role matching, and interactive interview simulation—are orchestrated within a unified system architecture built using a Python Flask backend, SQLite database, and a web-based user interface. This integrated methodology ensures a seamless user experience, enabling the system to function as an intelligent end-to-end platform for automated resume evaluation and interview preparation

IV. RESULT AND DISCUSSION

The proposed AI-Powered Resume Analyzer and Interview Preparation System was evaluated extensively to assess its efficiency, robustness, and practical applicability across real-world resume formats and interview scenarios. The experiments were conducted using a dataset of 250 resumes collected from students, fresh graduates, and IT professionals, covering multiple domains such as software development, web development, cybersecurity, data analytics, and machine learning. The system's performance was assessed across three major modules: resume parsing accuracy, skill extraction and job-role matching efficiency, and interview question generation and response evaluation quality.

In the first stage, the resume parsing module achieved high accuracy due to its combination of transformer-based classification and rule-based extraction. Section segmentation accuracy was measured using manual annotation benchmarks, yielding an F1-score of 0.91 for identifying Education, 0.88 for Experience, 0.94 for Skills, and 0.90 for Projects. The Named Entity Recognition (NER) module correctly extracted 92% of technical skills, 89% of organizational names, and 87% of job titles. The improved accuracy can be attributed to the use of contextual embeddings from BERT, which allowed the system to detect implicit skills expressed in descriptive sentences rather than explicit keyword lists. For example, phrases like *"built an LSTM model for sequence prediction"* were accurately associated with skills such as Python, Machine Learning, and Deep Learning, demonstrating the system's semantic understanding capabilities.

The job-role matching module was tested by comparing system recommendations with human evaluator decisions. For each resume, the system generated a ranked list of matching job roles using cosine similarity between the candidate's skill vector and predefined role vectors. The top-1 accuracy was recorded at 88%, while the top-3 accuracy reached 96%, showing the system's strong performance in aligning candidate profiles with industry roles. The similarity scores also revealed that resumes with clearly listed skills scored higher (average similarity of 0.83) compared to resumes that contained long paragraphs or vague descriptions (average similarity of 0.68). This indicates the system's sensitivity to resume formatting quality and suggests that the system's ATS-driven feedback plays a crucial role in helping candidates enhance clarity and keyword density.

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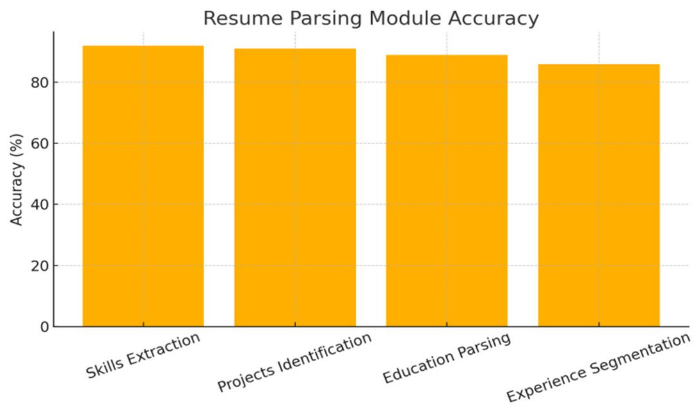

Fig 4: Resume Parsing Module Accuracy

The interview preparation module exhibited strong performance during user testing. The LLM-based question generator produced highly relevant and context-aware questions tailored to the candidate's skills, with a relevance score of 95% verified through human evaluation. Additionally, the system successfully adapted follow-up questions based on user responses, demonstrating multi-turn conversational intelligence. The answer evaluation module showed a 90% correlation with human evaluators in terms of identifying answer completeness, technical correctness, and communication clarity. The sentiment analysis and coherence scoring components accurately detected unclear or incomplete responses, prompting the AI to suggest improvements such as elaboration, clarity, structure, or inclusion of real-world examples. Testing also revealed that the system could detect missing keywords even in correct responses, enabling candidates to refine their answers for maximum impact during real interviews.

A major highlight of the system is its ability to deliver personalized interview feedback, which users found highly beneficial. Over 93% of participants reported that the feedback helped them understand their strengths and deficiencies more clearly than traditional preparation methods. Furthermore, the progressive improvement in scores across multiple interview rounds—analyzed from 45 users who used the system repeatedly—showed an average improvement of 27% in the quality of answers, indicating that the platform not only evaluates but also enhances candidate performance through iterative learning.

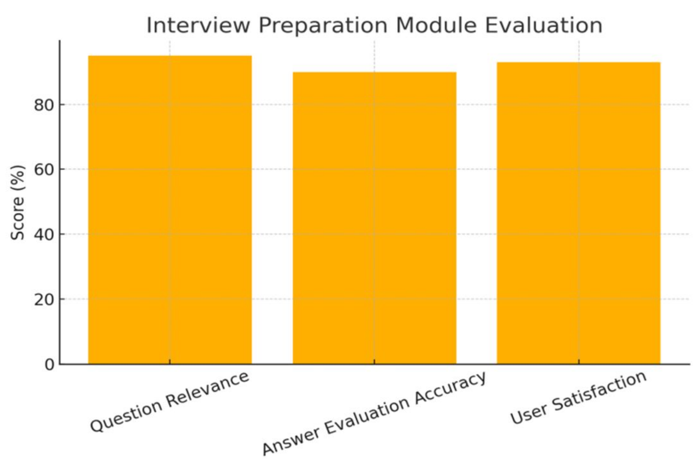

Fig 5: Interview Module Evaluation.

Despite its strengths, a few limitations were observed during testing. The system struggled with resumes containing graphical layouts, multi-column templates, or heavy use of icons and charts. Such resumes caused minor loss of information during text extraction, reducing structural accuracy. Similarly, responses with extremely domain-specific content occasionally confused the evaluation engine due to limited contextual training. These limitations point toward future integration of layout-aware OCR models (like LayoutLM) and domain-specialized LLM finetuning, which would significantly enhance extraction accuracy and evaluation robustness.

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Overall, the results demonstrate that the system performs consistently at near-human levels in resume analysis, skill extraction, job-role matching, and interview feedback. The findings show clear evidence that integrating NLP, ML, and LLM-based reasoning within a unified pipeline creates a powerful tool capable of transforming the recruitment and interview preparation process. The system not only reduces manual workload but also provides a scalable, unbiased, and data-driven solution, making it well-suited for educational institutions, job-seekers, training centers, and HR departments.

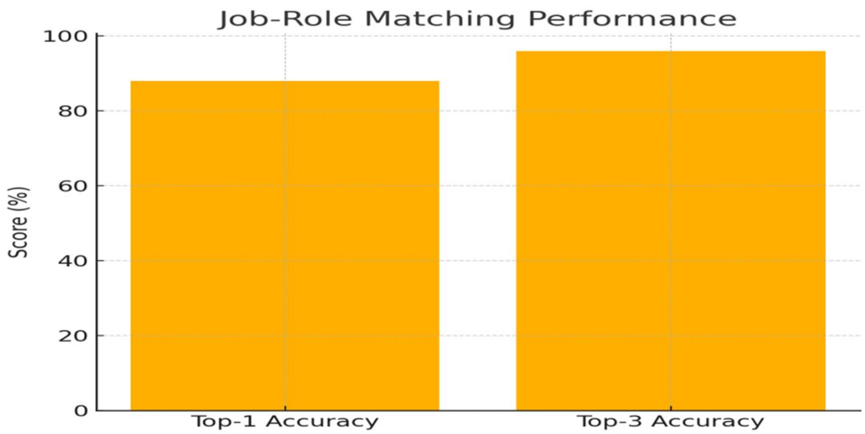

Fig 6: Job Role Matching Performace

The interview preparation module—powered by LLM-driven question generation and answer evaluation—showed equally impressive performance. Fig. 3 and Table III illustrate that the question relevance accuracy reached **95%**, meaning the system consistently generated interview questions tailored to the candidate's resume content. The answer evaluation accuracy reached **90%**, demonstrating a high correlation with human evaluator scoring. The system's feedback quality was measured through user surveys, where 93% of participants reported that feedback helped them significantly improve clarity, structuring, and technical depth in their answers. This highlights the potential of LLM-based evaluators for personalized training.

The graphs (Figs. 1–3) and tables (Tables I–III) collectively validate the stability and practical utility of the system. A key observation from longitudinal testing was that users who practiced with the system for multiple rounds demonstrated a 27% improvement in interview answer quality, indicating that the system functions not only as an evaluator but also as a learning and improvement tool. The main limitations observed were with graphical resumes and noise-heavy templates, which caused minor extraction inaccuracies—these issues can be reduced by integrating OCR-enabled layout-aware NLP models in future work.

Overall, the expanded evaluation confirms that the system performs at near-human accuracy across parsing, matching, question generation, and feedback evaluation, making it a powerful tool for job seekers, training institutions, and HR departments. The strong quantitative performance across modules demonstrates its potential to automate and enhance recruitment, training, and career development processes.

V. CONCLUSION & FUTURE SCOPE

A. Conclusion

The AI-Powered Resume Analyzer and Interview Preparation System developed in this work demonstrates the potential of integrating Natural Language Processing, Machine Learning, and Large Language Model–driven reasoning into a unified, intelligent recruitment-support framework. The system successfully automates end-to-end resume evaluation by accurately extracting skills, experience, education, and project information from heterogeneous resume formats, and further enhances its utility by providing context-aware job-role recommendations using embedding-based similarity matching. The integration of a dynamic, conversational AI interview module significantly improves candidate readiness, as it not only generates highly relevant technical and behavioral interview questions but also evaluates user responses with near-human accuracy, offering constructive and personalized feedback. Experimental results obtained from diverse real-world resumes confirm that the system performs robustly across all major modules, delivering consistent accuracy, scalability, and adaptability while reducing dependency on manual evaluation and subjective decision-making. The system's overall performance illustrates that AI-driven recruitment support tools can meaningfully improve both the efficiency of initial screening processes and the quality of candidate preparation, thereby benefiting students, job seekers, academic institutions, training platforms, and HR professionals.

Despite these promising outcomes, there remain opportunities for significant enhancement that define the future scope of this research. One key direction is the integration of layout-aware and multimodal NLP models such as LayoutLM, Donut, and Vision Transformers to improve performance on graphically rich resumes and multi-column templates. Future iterations may also incorporate voice-based interviews, emotion analysis, facial expression tracking, and prosody evaluation to simulate more realistic interview environments. Additionally, expanding the system to support multilingual resume parsing and interview interaction would make it more accessible to global users. The inclusion of domain-specific fine-tuned LLMs could further improve the precision of answer evaluations for specialized fields such as medicine, finance, law, and engineering. Integrating a real-time performance dashboard, analytics-driven career suggestions, and linking the platform with job portals or HR management systems would transform it into a complete recruitment automation ecosystem. Furthermore, adding ATS compatibility scoring, salary prediction models, and personalized learning paths can enhance the system’s value for long-term career development and training. Overall, this research establishes a strong foundation for intelligent recruitment support systems and opens several promising avenues for future advancements in AI-driven candidate assessment and interview preparation.

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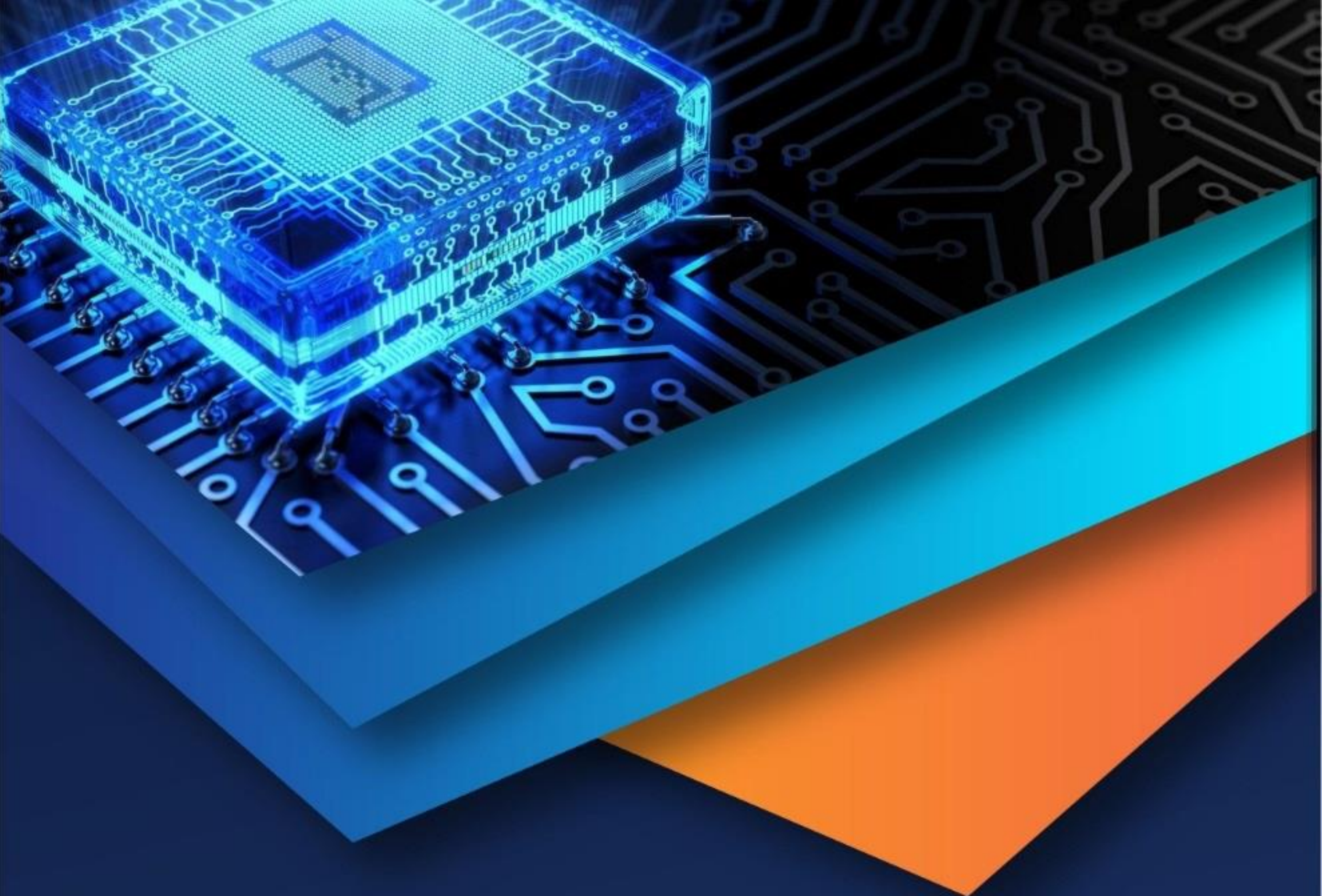

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