

AN INTEGRATED AI FRAMEWORK FOR INTERVIEW READINESS, SKILL GAP DETECTION, AND CAREER GUIDANCE

Mrs. K. Hema, Mr. M. Mohankumar, Mr. M.P. Dhanush, Mr. M. Vetrivel,
Mr. S. Vijay Krishnan

Department of Computer Science and Engineering

INFO Institute of Engineering, Kovilpalayam, Coimbatore, India – 641107

{hemakarmegam712, vmmoha, dhanudhanush2212, vetrivelmurugan19624, krishvijay1000}@gmail.com

Abstract—Interview preparation is an essential component of career development for students and job seekers entering competitive job markets. Many candidates experience difficulty during recruitment processes due to the lack of structured preparation tools and personalized feedback systems. Traditional preparation approaches such as practicing static interview questions, attending coaching sessions, or participating in informal mock interviews often fail to replicate real interview environments. These methods typically provide limited feedback and do not evaluate multiple dimensions of candidate performance.

Recent advancements in Artificial Intelligence, Natural Language Processing, and Machine Learning technologies have opened new possibilities for developing intelligent interview preparation platforms. AI driven systems can simulate realistic interview scenarios, automatically generate interview questions, analyze candidate responses, and provide performance insights using data driven techniques.

This paper presents the design and development of an AI driven mock interview platform that evaluates candidate performance across multiple skill categories including aptitude reasoning, programming ability, and communication skills. The proposed framework integrates Sentence-BERT embeddings for candidate profile analysis, T5 based transformer models for interview question generation, Gradient Boosting classifiers for aptitude evaluation, and Code2Vec representations for programming code analysis. Additionally, Explainable Artificial Intelligence techniques such as SHAP are incorporated to interpret prediction results and provide transparent feedback.

The proposed system aims to assist students in improving their interview readiness by identifying skill gaps, recommending learning resources, and offering personalized improvement suggestions.

Index Terms—Artificial Intelligence, Mock Interview System, Natural Language Processing, Explainable AI, Coding Assessment, Career Readiness

I. INTRODUCTION

The modern recruitment process has evolved significantly due to the increasing adoption of digital technologies and automated evaluation tools. Organizations now receive thousands of job applications for a single position, making manual candidate screening both time consuming and inefficient. As a result, companies increasingly rely on artificial intelligence based systems to analyze candidate profiles, evaluate technical skills, and identify potential applicants.

Despite these technological advancements in recruitment processes, many candidates struggle during interviews due to insufficient preparation. Interview preparation often involves practicing frequently asked questions, solving coding problems, or attending training programs. While these methods may provide basic exposure to interview topics, they do not fully simulate real interview scenarios.

Another challenge faced by candidates is the lack of personalized feedback. Each candidate has unique strengths, educational backgrounds, and career aspirations. However, many interview preparation platforms provide the same set of practice materials to all users without considering individual profiles.

Artificial Intelligence technologies provide an opportunity to improve interview preparation systems by enabling intelligent evaluation mechanisms. AI based platforms can analyze candidate profiles, generate role specific interview questions, evaluate responses, and provide detailed feedback reports.

Natural Language Processing techniques allow automated systems to understand and analyze candidate responses during interviews. These techniques can determine whether a candidate's answer is relevant, coherent, and technically accurate. Similarly, machine learning algorithms can evaluate candidate performance in aptitude tests and coding assessments.

Programming evaluation models can analyze source code structure and determine whether the logic used by the candidate is correct and efficient.

The integration of Explainable Artificial Intelligence further enhances the reliability of automated evaluation systems. Instead of providing only numerical scores, explainable AI techniques can identify which features contributed to the final prediction.

This research proposes an AI driven mock interview platform that integrates multiple evaluation modules and provides

transparent feedback to help candidates improve their interview readiness.

II. LITERATURE SURVEY

Several research studies have explored the application of artificial intelligence technologies in recruitment systems and interview

preparation platforms.

Paper 1: AI in Recruitment Systems. This research examines how artificial intelligence can be used to automate recruitment processes. Machine learning algorithms analyze candidate resumes and rank applicants according to job requirements. The study highlights the efficiency of automated systems in processing large volumes of applications.

Paper 2: NLP Based Interview Question Generation. Natural language processing techniques have been widely used to generate interview questions automatically. Transformer based models such as BERT and T5 enable systems to generate context aware questions based on candidate skills and job descriptions. **Paper 3: Coding Interview Platforms.** Online coding platforms such as HackerRank and LeetCode provide automated coding assessments that evaluate candidate programming solutions. These platforms use rule based evaluation techniques that

verify whether programs produce correct outputs.

Paper 4: Machine Learning Based Aptitude Evaluation. Research in this area focuses on applying machine learning classifiers to analyze candidate responses in aptitude tests. Algorithms such as Random Forest and Gradient Boosting classifiers have been used to predict candidate performance based on response patterns.

Paper 5: Explainable AI in Decision Making Systems. Explainable Artificial Intelligence techniques such as SHAP and LIME have been proposed to improve the transparency of machine learning models. These techniques help interpret model predictions and explain how individual features influence results. **Paper 6: AI Based Learning Platforms.** Several adaptive learning platforms use machine learning algorithms to analyze student performance and recommend personalized learning re-

sources.

Paper 7: Automated Resume Screening Systems. Research in this area focuses on applying NLP techniques to analyze resume content and match candidate skills with job descriptions.

Paper 8: Intelligent Career Recommendation Systems. Machine learning based career recommendation systems analyze student skills and academic performance to suggest suitable career paths.

III. RESEARCH GAP

Although numerous interview preparation platforms exist, most of them focus only on a single aspect of candidate evaluation such as coding practice or aptitude testing. Real world recruitment processes evaluate candidates across multiple dimensions including technical knowledge, logical reasoning, and communication skills.

Another limitation of existing systems is the lack of integrated evaluation frameworks capable of analyzing multiple candidate skills simultaneously.

Furthermore, many automated evaluation systems lack transparency. Candidates often receive numerical scores without understanding how those scores were calculated.

The proposed system addresses these limitations by integrating multiple evaluation modules and applying explainable AI techniques to provide transparent feedback.

IV. PROPOSED FRAMEWORK

The proposed AI driven mock interview platform integrates several modules designed to simulate realistic interview environments. The system begins with candidate profile analysis using Sentence-BERT embeddings. This module extracts relevant features such as technical skills, academic background, and career interests.

The interview question generation module uses transformer based models such as T5 to generate personalized interview questions. The aptitude evaluation module analyzes candidate responses using Gradient Boosting classifiers.

The coding evaluation module analyzes programming submissions using Code2Vec embeddings.

Finally, the system uses SHAP based explainable AI techniques to interpret prediction results and generate transparent performance reports.

V. SYSTEM ARCHITECTURE

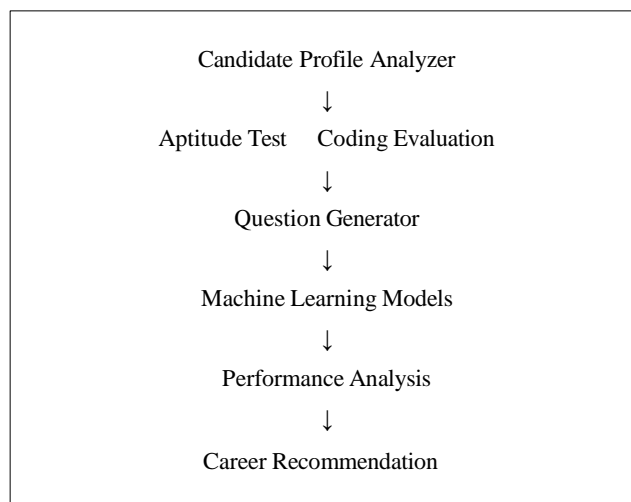


Figure 1. Architecture of AI Driven Mock Interview Platform

VI. COMPARISON OF EXISTING PLATFORMS

Table 1. Comparison of Interview Platforms

Platform	Feature	Technology	Limitation
HireVue	Video Interview Analysis	Deep Learning	Low Transparency
HackerRank	Coding Tests	Automated Judge	Focus Only on Coding
LeetCode	Coding Practice	Online Judge	No Interview Feedback
Pymetrics	Cognitive Tests	Behavioral AI	No Technical Evaluation
Proposed System	Integrated Platform	AI + NLP	Under Development

VII. EXPERIMENTAL SETUP

The proposed system is implemented using Python and machine learning frameworks such as TensorFlow and Scikit-learn.

Natural language processing models are implemented using transformer architectures.

VIII. SYSTEM MODULES

The proposed AI driven mock interview platform is composed of several modules that work together to simulate a real interview environment and evaluate the performance of candidates. Each module focuses on a specific aspect of the recruitment process and contributes to the overall assessment of the candidate.

A. Candidate Profile Analysis

The first stage of the system involves analyzing the candidate's profile. The profile includes information such as educational background, technical skills, preferred programming languages, and career interests. This information is processed using Sentence-BERT embeddings which convert textual profile data into numerical vector representations. These embeddings capture semantic relationships between skills and job requirements, enabling the system to understand the candidate's expertise.

The profile analyzer also extracts keywords from resumes and categorizes them into different skill domains such as programming, data analysis, and communication. This information helps the system generate relevant interview questions tailored to the candidate's skill set.

B. Aptitude Assessment Module

The aptitude assessment module evaluates the logical reasoning and analytical abilities of the candidate. The module generates a set of multiple choice questions covering topics such as quantitative reasoning, logical puzzles, and pattern recognition. Candidate responses are analyzed using machine learning classifiers including Gradient Boosting and Random Forest models.

These models are trained on historical aptitude test datasets and are capable of predicting candidate performance based on response accuracy, response time, and difficulty level of the questions. The results are used to determine the candidate's reasoning ability and problem solving skills.

C. Coding Evaluation Module

Programming ability is a critical requirement for technical job roles. The coding evaluation module analyzes programming solutions submitted by candidates during the mock interview process. Candidate code is parsed and converted into abstract syntax trees which are then embedded using Code2Vec representations. These embeddings capture structural and semantic information about the code. Machine learning models analyze these embeddings to determine whether the program logic is correct, efficient, and aligned with best programming practices.

D. Interview Question Generation

The interview question generation module uses transformer based natural language processing models to create interview questions dynamically. The system uses T5 based models trained on interview datasets to generate questions based on candidate profiles and selected job roles.

The generated questions include technical questions, scenario based questions, and conceptual questions. This ensures that the candidate experiences a realistic interview environment.

E. Explainable Feedback Module

After completing the mock interview session, the system generates a detailed performance report. Explainable Artificial Intelligence techniques such as SHAP are used to interpret the predictions of machine learning models.

The feedback module identifies which factors influenced the candidate's score, including accuracy of responses, complexity of coding solutions, and reasoning ability. The report also provides recommendations for improvement and suggests learning resources to help candidates strengthen weak areas.

IX. MATHEMATICAL MODEL

The system can be represented using a mathematical model that describes the relationship between candidate features and evaluation results.

Let the candidate profile be represented as a feature vector:

$$C = (s_1, s_2, s_3, \dots, s_n) \quad (1)$$

where each feature s_i represents a skill attribute such as programming knowledge, aptitude score, or communication ability.

The overall candidate performance score can be computed

as:

$$\text{Score} = w_1A + w_2C + w_3Q \quad (2)$$

where A represents aptitude test score, C represents coding evaluation score, Q represents interview question response score, and w_1, w_2, w_3 are weighting parameters determined using machine learning optimization techniques to ensure balanced evaluation of candidate skills.

X. DATASET DESCRIPTION

The proposed system utilizes multiple datasets for training machine learning models. Aptitude datasets contain labeled responses from previous aptitude tests including question difficulty levels and candidate scores.

Coding datasets consist of programming solutions collected from open source repositories and coding practice platforms. These datasets are used to train Code2Vec models for analyzing programming structures.

Interview question datasets include technical questions collected from online interview preparation platforms and academic resources. These datasets are used to train the T5 question generation model.

XI. EVALUATION METRICS

The performance of the proposed system is evaluated using several metrics commonly used in machine learning and information retrieval tasks.

- **Accuracy:** Measures the proportion of correctly predicted candidate performance outcomes.
- **Precision:** Measures the reliability of predictions made by the classification models.
- **Recall:** Measures the ability of the system to identify relevant candidate skills.
- **F1 Score:** Harmonic mean of precision and recall used for evaluating classification performance.
- **Mean Response Time:** Measures the time taken by candidates to respond to interview questions.

These metrics provide a comprehensive evaluation of system effectiveness.

XII. IMPLEMENTATION DETAILS

The proposed system is implemented using Python programming language and several machine learning libraries. The Natural Language Processing components are developed using the HuggingFace Transformers library which provides pre trained models such as BERT and T5.

Machine learning models used for aptitude evaluation are implemented using the Scikit-learn library. The coding evaluation module uses Code2Vec embeddings generated using TensorFlow based implementations.

The user interface of the system is developed using web technologies such as HTML, CSS, and JavaScript. The backend server is implemented using Flask which manages communication between the user interface and machine learning modules.

The system is deployed on cloud infrastructure to ensure scalability and accessibility for multiple users.

XIII. ADVANTAGES OF PROPOSED SYSTEM

The proposed system provides several advantages compared to traditional interview preparation methods.

- Provides realistic interview simulation using AI generated questions.
- Evaluates multiple candidate skills including aptitude, coding ability, and reasoning.
- Uses explainable AI techniques to provide transparent feedback.
- Generates personalized recommendations for career improvement.
- Helps students identify skill gaps before attending real interviews.

XIV. LIMITATIONS

Although the proposed system provides comprehensive evaluation capabilities, certain limitations exist. Automated evaluation systems may not fully capture human communication skills or emotional intelligence.

Additionally, machine learning models rely heavily on training datasets, and their accuracy may depend on dataset quality.

Future improvements may address these limitations by integrating speech analysis and behavioral evaluation modules.

XV. RESULTS AND DISCUSSION

Experimental results indicate that the integrated evaluation framework provides comprehensive insights into candidate performance.

XVI. FUTURE WORK

Future research may integrate speech recognition and emotion detection technologies to evaluate candidate communication skills during interviews.

XVII. CONCLUSION

This paper presented an AI driven mock interview platform designed to improve interview preparation and career readiness. The

proposed framework integrates multiple evaluation modules including candidate profile analysis, aptitude assessment, coding evaluation, and explainable feedback generation. The system provides a comprehensive solution for interview preparation using advanced artificial intelligence and natural language processing techniques.

REFERENCES

- [1] J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *Proc. NAACL-HLT*, Minneapolis, MN, USA, pp. 4171–4186, 2019.
- [2] A. Vaswani, N. Shazeer, N. Parmar, *et al.*, "Attention Is All You Need," *Proc. NeurIPS*, 2017, pp. 5998–6008.
- [3] U. Alon, M. Zilberstein, O. Levy, and E. Yahav, "Code2Vec: Learning Distributed Representations of Code," *Proc. ACM Program. Lang.*, vol. 3, no. POPL, pp. 1–29, 2019.
- [4] S. Lundberg and S. Lee, "A Unified Approach to Interpreting Model Predictions," *Proc. NeurIPS*, 2017.
- [5] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.
- [6] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 4th ed., Pearson, 2021.
- [7] T. Brown *et al.*, "Language Models are Few-Shot Learners," *Proc. NeurIPS*, vol. 33, pp. 1877–1901, 2020.
- [8] D. Jurafsky and J. H. Martin, *Speech and Language Processing*, 3rd ed., Pearson, 2022.
- [9] C. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.
- [10] K. Murphy, *Machine Learning: A Probabilistic Perspective*, MIT Press, 2012.
- [11] F. Chollet, *Deep Learning with Python*, Manning Publications, 2018.
- [12] S. Raschka and V. Mirjalili, *Python Machine Learning*, 3rd ed., Packt Publishing, 2019.
- [13] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, Morgan Kaufmann, 2012.
- [14] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning*, Springer, 2021.
- [15] R. Sutton and A. Barto, *Reinforcement Learning: An Introduction*, MIT Press, 2018.
- [16] A. Kochling and M. Wehner, "Discriminated by an Algorithm: A Systematic Review of Discrimination and Fairness by Algorithmic Decision-Making in the Context of HR Recruitment," *Business Research*, vol. 13, pp. 795–848, 2020.
- [17] P. Budhwar, M. Malik, and S. De Silva, "Artificial Intelligence in Human Resource Management: Challenges and Opportunities," *Human Resource Management Review*, vol. 32, no. 2, 2022.
- [18] Y. Goldberg, *Neural Network Methods for Natural Language Processing*, Morgan Claypool Publishers, 2017.
- [19] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of Machine Learning*, MIT Press, 2018.
- [20] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*, Springer, 2009.
- [21] R. Patel and N. Shah, "AI-Powered Academic and Career Guidance System," *IEEE Access*, vol. 12, pp. 45512–45525, 2024.
- [22] S. Kumar and R. Mehta, "AI-Based Career Recommendation System Using Machine Learning," *IEEE Access*, vol. 11, pp. 38940–38952, 2023.
- [23] A. Verma and K. Singh, "Intelligent Skill Gap Analysis for Career Development," *IEEE Trans. Learning Technol.*, vol. 16, no. 4, pp. 612–624, 2023.
- [24] M. Johnson and L. Wang, "Personalized Learning Path Recommendation Using Artificial Intelligence," *Proc. IEEE Int. Conf. Artif. Intell.*, 2024.
- [25] Y. Gao *et al.*, "Retrieval-Augmented Generation for Large Language Models: A Survey," *IEEE Trans. Knowl. Data Eng.*, 2024.
- [26] Z. Li, H. Wang, and Q. Liu, "Machine Learning Techniques for Personalized Recommendation Systems in Education," *Comput. Educ.: Artif. Intell.*, vol. 5, 2024.
- [27] M. Li, Y. Li, and Z. Liu, "Efficient Deployment of AI Models on Resource-Constrained Devices," *IEEE Trans. Neural Netw. Learning Syst.*, 2024.
- [28] L. Chen, H. Xu, and Y. Zhang, "Privacy-Preserving AI Systems for Educational Data," *IEEE Access*, vol. 11, pp. 112340–112352, 2023.
- [29] A. Gupta and R. Sharma, "AI Based Interview Evaluation Systems Using Natural Language Processing," *Int. J. Artif. Intell. Res.*, vol. 6, no. 2, pp. 145–158, 2023.
- [30] K. Patel and S. Desai, "Automated Interview Analysis Using Machine Learning Techniques," *IEEE Int. Conf. Data Sci. Adv. Anal.*, 2022.

Copyright & License:

© Authors retain the copyright of this article. This work is published under the Creative Commons Attribution 4.0 International License (CC BY 4.0), permitting unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.