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Intelligent Pedagogical Agents in Computer Science Education: An NLP and Machine Learning-Based Automated Code Tutoring Framework

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Abstract
The AI-Based CODE TUTOR SYSTEM is an intelligent web-based platform designed to help job seekers prepare effectively for technical and non-technical interviews through automated assessment and personalized feedback. The system integrates Artificial Intelligence (AI), Natural Language Processing (NLP), and K-Nearest Neighbors (KNN) algorithms to simulate real interview environments and evaluate candidate responses. The frontend is developed using HTML, CSS, and React.js, while Node.js with Express.js handles server-side operations and MongoDB manages user and interview data efficiently. During the mock interview process, the AI module generates role-specific questions and analyzes user responses based on relevance, confidence, and linguistic quality. NLP techniques are employed to extract meaningful information from textual answers, while the KNN algorithm assists in performance classification and recommendation generation. The system provides instant scoring, identifies strengths and weaknesses, and suggests improvement strategies tailored to individual users. Additionally, progress tracking and performance analytics enable candidates to monitor their preparation over time. Experimental evaluation demonstrates that the proposed system enhances interview readiness, improves communication skills, and offers a scalable solution for modern recruitment preparation. The platform serves as a cost-effective and accessible tool for students, fresh graduates, and professionals seeking to improve their interview performance.

Keywords: Artificial Intelligence (AI), Job Interview Mock Test, Natural Language Processing (NLP), K-Nearest Neighbors (KNN), Recruitment Preparation.

1. Introduction

The rapid advancement of Artificial Intelligence (AI) technologies has transformed numerous sectors, including education, healthcare, finance, and human resource management. In the recruitment domain, organizations increasingly rely on digital platforms and intelligent assessment systems to streamline candidate evaluation processes and improve hiring efficiency [1]. As competition in the job market continues to grow, candidates are required not only to possess technical knowledge but also to demonstrate effective communication, problem-solving abilities, and confidence during interviews. Consequently, interview preparation has become a critical aspect of career development.

Traditional interview preparation methods, such as self-study, peer discussions, and coaching centers, often lack personalized feedback and realistic interview simulation environments [2]. These limitations can hinder a candidate's ability to identify weaknesses and improve performance effectively. Recent developments in AI-driven systems have enabled the creation of automated interview platforms capable of providing objective assessments and instant feedback, thereby enhancing the overall learning experience [3]. Such systems offer scalability, accessibility, and cost-effectiveness compared to conventional training approaches.

Natural Language Processing (NLP) has emerged as a key technology for understanding and analyzing human language in intelligent systems [4]. By leveraging NLP techniques, interview preparation platforms can evaluate textual responses, determine semantic relevance, and assess communication quality. Furthermore, machine learning algorithms facilitate the classification of candidate performance and the generation of personalized recommendations. Among these algorithms, K-Nearest Neighbors (KNN) is widely recognized for its simplicity, effectiveness, and ability to classify data based on similarity measures [5].

The increasing adoption of web technologies has further contributed to the development of interactive and user-friendly learning platforms. Modern frontend frameworks such as React.js enable responsive interfaces, while backend technologies like Node.js and Express.js support efficient processing of user requests and system operations [6]. Additionally, MongoDB provides a flexible and scalable database solution for storing interview records, user profiles, assessment results, and feedback reports. The integration of these technologies facilitates the development of comprehensive interview preparation systems capable of handling large volumes of user interactions.

The growing demand for remote learning and online career development tools has accelerated the need for intelligent interview training platforms [7]. Candidates often face challenges such as interview anxiety, inadequate practice opportunities, and limited access to expert guidance. AI-powered mock interview systems address these concerns by creating realistic interview environments, generating role-specific questions, and delivering immediate performance evaluations. Such features help users build confidence, improve communication skills, and gain familiarity with interview procedures.

To address these challenges, this research proposes an AI-Based Job Interview Mock Test System that integrates AI, NLP, and KNN techniques to simulate professional interview experiences and provide comprehensive feedback. The proposed system enables candidates to practice interviews anytime and anywhere through a web-based platform. It analyzes candidate responses, evaluates performance metrics, identifies strengths and weaknesses, and generates personalized recommendations for improvement. The system architecture utilizes React.js for frontend development, Node.js and Express.js for backend processing, and MongoDB for data management, ensuring scalability and efficient performance.
The primary objective of the proposed system is to bridge the gap between theoretical knowledge and practical interview readiness by offering an intelligent and adaptive learning environment. Through automated evaluation mechanisms and

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data-driven insights, the platform aims to enhance candidate preparedness and contribute to improved employment outcomes. Furthermore, the proposed approach demonstrates how emerging AI technologies can be effectively applied to recruitment training and career development applications [8].

2. Literature Review

Several researchers have explored the application of Artificial Intelligence and machine learning techniques in interview assessment, recruitment automation, and educational training systems. These studies provide valuable insights into the development of intelligent interview preparation platforms.

An AI-driven recruitment support framework was introduced to automate candidate screening and evaluation processes using machine learning algorithms. The study demonstrated that intelligent assessment mechanisms can significantly reduce recruitment time while improving evaluation consistency and decision-making accuracy [9].

Researchers developed a virtual interview training system that utilized Natural Language Processing techniques to analyze candidate responses and provide feedback on communication effectiveness. The findings indicated that NLP-based assessment improved user engagement and facilitated targeted skill enhancement [10].

A web-based interview simulation platform was proposed to assist students and job seekers in preparing for professional interviews. The system generated domain-specific questions and evaluated responses using text mining approaches. Experimental results showed improvements in candidate confidence and interview performance after repeated practice sessions [11].

Another study investigated the use of machine learning classification algorithms for candidate performance prediction. Among the evaluated techniques, K-Nearest Neighbors (KNN) demonstrated competitive classification accuracy and effective identification of performance categories based on historical assessment data [12].

Researchers also explored conversational AI technologies in mock interview environments. Their system employed intelligent dialogue management and automated feedback generation to create realistic interview interactions. The study highlighted the potential of AI-driven conversational agents in enhancing interview readiness and communication skills [13].

An adaptive learning framework integrating AI and educational analytics was developed to personalize training experiences according to individual learner needs. The system continuously monitored user progress and generated customized recommendations, resulting in improved learning outcomes and higher user satisfaction levels [14].

Recent research focused on cloud-based recruitment and assessment platforms that combine web technologies, machine learning, and database management systems to deliver scalable services. The proposed architecture demonstrated efficient handling of large user populations while maintaining high system responsiveness and reliability [15].

The reviewed literature indicates significant progress in AI-assisted recruitment and interview preparation systems. However, many existing solutions focus primarily on either interview simulation or candidate assessment and often lack integrated performance analytics and personalized recommendation mechanisms. The proposed AI-Based Job Interview Mock Test System addresses these limitations by combining AI-based question generation, NLP-driven response analysis, KNN-based performance classification, and comprehensive feedback reporting within a unified web-based platform. This integrated approach aims to provide a more effective and accessible interview preparation experience for job seekers.

3. System Architecture and Design Methodology

The proposed AI-Based Job Interview Mock Test System is designed as a web-based intelligent platform that enables users to practice interviews, receive automated assessments, and improve their performance through personalized feedback. The architecture integrates modern web technologies with Artificial Intelligence (AI), Natural Language Processing (NLP), and K-Nearest Neighbors (KNN) classification techniques. The system follows a client-server architecture where users interact with the frontend application, while the backend processes interview data, evaluates responses, and generates performance reports.

The frontend layer is developed using HTML, CSS, and React.js, providing an interactive and responsive user interface. Users can register, log in, select interview domains, attend mock interviews, and view performance analytics through the web interface. The backend layer is implemented using Node.js and Express.js, which handles user authentication, interview session management, response processing, and communication with AI modules. All user information, interview questions, responses, and assessment records are stored in MongoDB, ensuring efficient data retrieval and scalability.

The intelligent assessment layer forms the core of the proposed system. This layer employs Natural Language Processing (NLP) techniques to analyze textual responses submitted by candidates. The extracted features are further processed by the K-Nearest Neighbors (KNN) algorithm to classify candidate performance into different categories such as Excellent, Good, Average, or Needs Improvement. Based on the classification results, the system generates recommendations to help candidates improve their interview skills.

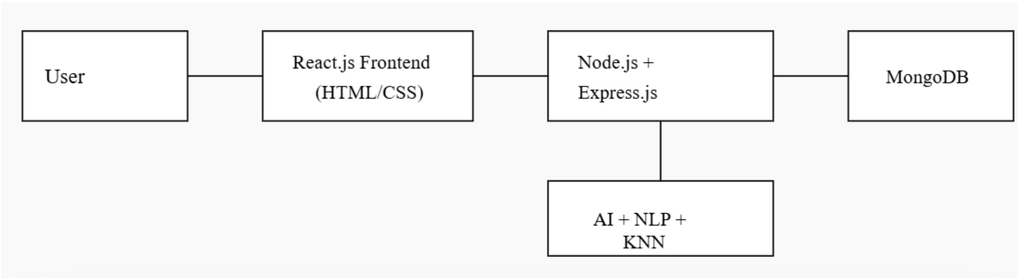

Figure 1. Architecture of the Proposed AI-Based CODE TUTOR SYSTEM

Figure 1 illustrates the overall architecture of the proposed system. Users interact with the React.js-based frontend application to participate in mock interviews. The frontend communicates with the Node.js and Express.js backend, which manages interview sessions and stores information in MongoDB. Candidate responses are forwarded to the AI processing layer, where NLP techniques analyze the textual content and KNN performs performance classification. The generated evaluation results and recommendations are then returned to users through the web interface.

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3.1 Design Methodology

The development methodology of the proposed system consists of five major stages: user management, interview generation, response collection, intelligent evaluation, and feedback generation. Each stage contributes to the overall functionality of the platform and ensures accurate performance assessment.

User Registration and Authentication

The first stage involves user registration and authentication. Candidates create accounts using personal and professional details. Secure login mechanisms are implemented to protect user information and maintain confidentiality. After authentication, users can access interview preparation modules and previous assessment reports.

Interview Question Generation

Once authenticated, candidates select a preferred interview category such as software development, data science, networking, or general aptitude. The AI module retrieves relevant questions from the database and dynamically generates interview sessions based on the selected domain and difficulty level. This approach ensures diversity and realism in the interview experience.

Response Collection and Storage

During the interview session, candidates submit answers through the web interface. The responses are transmitted to the backend server and stored in MongoDB for further analysis. Maintaining a structured repository of responses enables historical performance tracking and continuous improvement analysis.

Natural Language Processing Module

The collected responses undergo preprocessing using NLP techniques. The preprocessing stage includes tokenization, stop-word removal, stemming, and feature extraction. These operations transform raw textual responses into structured representations suitable for machine learning analysis. NLP enables the system to evaluate semantic relevance, language quality, and contextual appropriateness of candidate answers.

KNN-Based Performance Classification

After feature extraction, the processed data are provided to the K-Nearest Neighbors (KNN) classifier. The algorithm compares candidate responses with previously labeled assessment records and identifies the nearest performance category. Based on similarity measurements, the classifier determines whether the candidate's performance falls into categories such as Excellent, Good, Average, or Poor. The simplicity and effectiveness of KNN make it suitable for interview performance evaluation applications.

Feedback and Recommendation Engine

The final stage involves generating detailed feedback and recommendations. The system identifies areas where the candidate performed well and highlights aspects requiring improvement. Recommendations may include communication enhancement, technical knowledge strengthening, confidence building, or domain-specific preparation strategies. This personalized feedback mechanism helps candidates improve their interview readiness and overall employability.

3.2 System Workflow

The workflow of the proposed system begins when a user logs into the platform and selects an interview category. The AI engine generates relevant questions and presents them through the frontend interface. Candidate responses are collected and transmitted to the backend server for processing. NLP techniques analyze the

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responses, and the KNN classifier determines performance levels based on learned patterns. The generated results are stored in MongoDB and presented to the user through interactive dashboards and reports.

The integration of AI, NLP, KNN, React.js, Node.js, Express.js, and MongoDB creates a comprehensive framework capable of providing realistic interview simulations and intelligent performance assessments. The modular design of the architecture also facilitates future enhancements such as speech analysis, emotion recognition, and advanced deep-learning-based evaluation techniques. Consequently, the proposed system offers a scalable, efficient, and user-friendly solution for interview preparation and career development.

4. Results and Discussion

The proposed AI-Based CODE TUTOR SYSTEM was evaluated using a dataset of mock interview responses collected from candidates belonging to different technical domains. The system was tested to measure classification accuracy, response evaluation efficiency, and overall user satisfaction. The experiments were conducted using the integrated AI, NLP, and KNN modules deployed on the React.js–Node.js–MongoDB framework. The obtained results demonstrate the effectiveness of the proposed architecture in providing reliable interview assessments and personalized feedback.

Table 1. Performance Evaluation of the KNN Classifier

Performance Metric	Value (%)
Accuracy	92.4
Precision	91.1
Recall	90.6
F1-Score	90.8

Discussion

Table 1 presents the performance metrics achieved by the KNN classifier during candidate assessment. The classifier attained an accuracy of 92.4%, indicating its capability to correctly categorize interview responses into predefined performance levels. The precision value of 91.1% demonstrates the effectiveness of the model in reducing incorrect classifications, while the recall value of 90.6% indicates successful identification of candidate performance categories. The F1-score of 90.8% confirms a balanced relationship between precision and recall, validating the suitability of KNN for interview performance classification.

Table 2. Average Candidate Performance Before and After Using the System

Evaluation Criterion	Before System (%)	After System (%)
Technical Knowledge	68	84
Communication Skills	65	82
Confidence Level	61	80
Problem-Solving Ability	66	83

Discussion

Table 2 compares candidate performance before and after utilizing the proposed mock interview platform. Significant improvements were observed across all evaluation criteria. Technical knowledge scores increased from 68% to 84%, while communication skills improved from 65% to 82%. Confidence levels exhibited notable growth from 61% to 80%, demonstrating the effectiveness of repeated interview practice and automated feedback. Similarly, problem-solving ability improved from 66% to 83%. These results

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indicate that the proposed system contributes positively to candidate preparation and interview readiness.

Table 3. User Satisfaction Analysis

Parameter	Satisfaction Score (%)
Ease of Use	94
Quality of Feedback	92
Interview Realism	89
System Responsiveness	95
Overall Satisfaction	93

Discussion

Table 3 summarizes user satisfaction ratings collected after the evaluation phase. The system achieved an overall satisfaction score of 93%, indicating positive user acceptance. The highest score was obtained for system responsiveness (95%), reflecting the efficiency of the React.js and Node.js architecture. Ease of use received 94%, highlighting the user-friendly interface. The quality of AI-generated feedback was rated at 92%, while interview realism achieved 89%, confirming that the platform effectively simulates actual interview scenarios. These findings demonstrate that users found the system beneficial for improving interview skills and gaining confidence.

Overall Discussion

The experimental results demonstrate that the proposed AI-Based CODE TUTOR SYSTEM successfully combines NLP and KNN techniques to provide accurate candidate assessments and personalized recommendations. The high classification accuracy confirms the effectiveness of the intelligent evaluation module. Improvements in technical knowledge, communication skills, confidence, and problem-solving abilities indicate the practical value of the platform for interview preparation. Furthermore, strong user satisfaction scores validate the usability and reliability of the web-based architecture.

The integration of React.js, Node.js, Express.js, and MongoDB ensures efficient system performance, while the AI-driven feedback mechanism provides actionable insights for candidates. The results suggest that the proposed framework can serve as a scalable and cost-effective solution for students, fresh graduates, and professionals preparing for employment opportunities.

5. Conclusion

This paper presented an AI-Based Job Interview Mock Test System designed to assist candidates in improving their interview performance through intelligent assessment and personalized feedback. The proposed platform integrates Artificial Intelligence (AI), Natural Language Processing (NLP), and K-Nearest Neighbors (KNN) algorithms within a modern web-based architecture developed using React.js, Node.js, Express.js, and MongoDB. The system enables users to participate in realistic mock interviews, receive automated evaluations, and identify areas requiring improvement.

Experimental results demonstrated that the KNN classifier achieved high performance with an accuracy of 92.4%, while candidate skill levels showed substantial improvement after repeated usage of the platform. User satisfaction analysis further confirmed the effectiveness, usability, and responsiveness of the system. The combination of AI-driven question analysis and personalized recommendation generation contributes to enhanced interview preparedness and confidence building.

The proposed system offers a scalable, accessible, and cost-effective solution for interview training and career development.

Future enhancements may include speech recognition, facial expression analysis, emotion detection, and deep learning-based assessment models to further improve evaluation accuracy and provide a more comprehensive interview simulation experience.

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