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SKILLTWIN AI – AN INTELLIGENT SYSTEM FOR SKILL EVALUATION & RECRUITMENT SUPPORT

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Abstract

The conventional methods depend only on self-reported CVs and subjective interviews, which makes it difficult for recruiters to independently assess a candidate's actual technical ability. To overcome this challenge, SkillTwinAI is proposed. It is a full-stack web platform, which combining Large Language Model (LLM)-based dynamic skill assessments, an ensemble machine learning career prediction engine, and a score-gated job application system. Candidates build verified skill profiles through AI-generated practical assessments powered by the Groq API (Llama 3.3-70B). This model earn certifications through AI-generated 8-module learning paths, and receive career-level predictions (Junior, Mid-Level, Senior, or Lead) using a Random Forest, K-Nearest Neighbours, and TensorFlow.js neural network ensemble trained on 1,000 developer profiles. Recruiters post jobs with minimum score thresholds, which ensures only verified and qualified candidates are applying. The platform features dual portals, real-time status notifications, an AI career coach with full profile-context injection, and a personalised learning roadmap system. Results demonstrate a reliable, bias-reduced, and scalable alternative to conventional recruitment pipelines.

Keywords: Skill Verification, LLM-Based Assessment, Career Prediction, Ensemble Machine Learning, Job Matching, AI Career Coach, Score-Gated Recruitment, Automatic Question Generation.

I. INTRODUCTION

A gap between candidate self-reported skills and their actual competency is developed by the fast growth in the digital transformation. The existing models mainly focus on resumes, cover letters and interviews. These characteristics are unreliable in practical applications. Since it is mainly depends on personal information, it is not same and inconsistent for various evaluators. In the end, candidates may have the probability to overstate their skills. It makes the genuinely skilled candidates overlooked by only limited opportunities. They are failed to demonstrate their practical competence. It also makes the hiring process inefficient. Meanwhile, the recruiter workload and difficulty in identifying truly qualified candidates are increased. This fail in skill verification mechanism makes the model difficult to distinguish theoretical knowledge and practical expertise candidates. Hence, quality of hiring decisions and organizational productivity is affected.

The proposed SkillTwinAI deals this challenge by using a verified, AI-driven recruitment ecosystem. It is mainly used to emphasize objective evaluation over subjective judgment. The candidates can show their abilities without depending on claims through structured assessments generated dynamically using advanced Large Language Models (LLMs). These are designed to determine real-world problem-solving capabilities and adapt to continuously changing difficulty levels. Meanwhile, it ensures a comprehensive and fair measurement of candidate proficiency. Also, the system continuously updates candidate skill levels based on performance. It gives an accurate and evolving representation of their abilities.

The model integrates the following three major components:

- LLM-based intelligent assessment and learning system
- Ensemble ML-based career prediction engine
- Real-time score-driven recruitment filtering mechanism

Together, these components form a unified career intelligence platform that enhances fairness, transparency, and scalability in recruitment. The recruitment process is streamlined by combining the automated skill verification, intelligent career guidance, and data-driven hiring decisions. This empowers candidates as well, with detailed understanding about their knowledge and career progression. It hence reduces the bias in hiring process and improves talent acquisition efficiency.

II. LITERATURE REVIEW

The authors proposed a hybrid deep learning framework by combining various models such as NLP, CNN, and RNN models. They analyzed the complete technical information of the students and produced personalized career recommendations. Though the model gives higher prediction accuracy and transparency, its dependence on various and high-quality multimodal data reduces its practical applicability in environments with inconsistent datasets.

The authors presented Mentor Map, an AI-based career prediction application. The Decision Tree and SVM algorithms are used in this model to evaluate students' complete education skills. Though the system produces reliable performance results in guiding students to make their decisions, its predictive capability is limited by the traditional ML models usage. It does not acquire complex patterns as effectively as advanced deep learning approaches.

The study proposed BERT based framework, which automatically recruit the candidates based on the resume analysis and job matching. The results produced improved accuracy, completeness, and objectivity compared to traditional hiring methods. Also the processing time is reduced considerably. But, the model failed to acquire qualitative traits such as soft skills and personality, which reduces its overall assessment capability.

The study presented an AI-driven recruitment model, which uses TF-IDF based NLP techniques and cosine similarity. It achieves context based job candidate matching and performs better than the existing keyword-based models. Comparatively higher semantic matching accuracy and scalability is achieved by making the system efficient.

Due to the dependence only on statistical text representations, the model is failed to collect contextual meaning when compared to the advanced LLM-based models.

The integration of AI with human resources and its challenges are detailed in this paper. This research is conducted within the Nigerian higher institutions. The important problems including limited infrastructure, high implementation costs, lack of

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expertise, and resistance to change are defined from the research. This helps to find out the importance of AI to improve HR functions like talent management, training, and performance calculation. Since the work is mainly conceptual based and lacking practical experimentation validation in practical AI applications.

An AI based human resource platform is discussed in this paper. It used deep learning and NLP algorithms to match job seekers with employers. It also provides personalized learning recommendations. By using multidimensional scoring mechanism and intelligent matching process, the system improves overall efficiency of the recruitment. It also brings fairness in selection and user satisfaction. It faces complications when integrated with multiple AI models. Hence, it faces issues in scalability and real-time deployment.

III. PROPOSED METHODOLOGY

SkillTwinAI is designed as a multi-layer intelligent system that integrates artificial intelligence, machine learning, and full-stack web technologies.

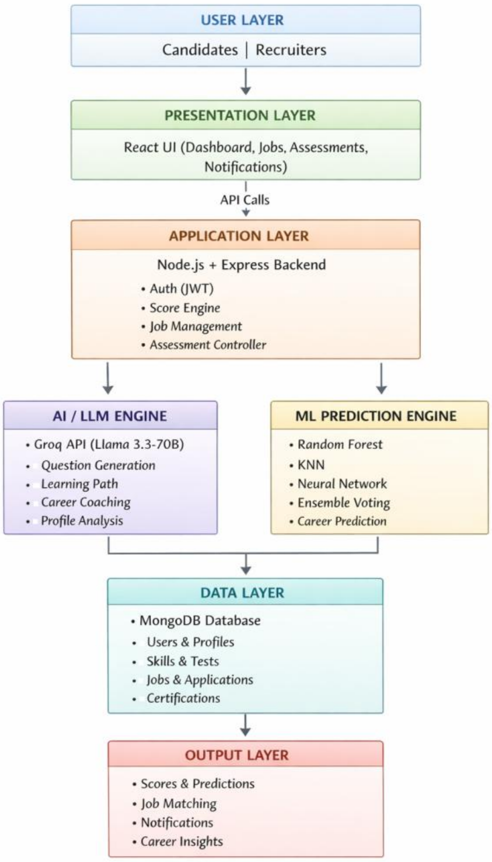

Figure 1. Architecture of SkillTwinAI system

The proposed SkillTwinAI architecture follows a multi-layer design consisting of presentation, application, AI/LLM, machine learning, and data layers. The system begins with user interaction through the frontend interface, which communicates with backend services via REST APIs. The application layer processes requests and interacts with both the AI engine for dynamic assessment and learning generation, and the ML engine for career prediction. All processed data is stored and retrieved from the MongoDB database. The final outputs, including scores, predictions, and job recommendations, are delivered back to the user interface in real time.

Table 1: Algorithms and methods used

Algorithm / Method	Role in SkillTwinAI
Random Forest Classifier	Primary ML model for career-level prediction from 12 profile features
K-Nearest Neighbours (KNN)	Secondary classifier in ensemble; compares candidate to similar developer profiles
TensorFlow.js Neural Network	Third ensemble model; trained on 1,000 Kaggle developer profiles
Ensemble Consensus Voting	Combines RF + KNN + NN outputs to determine final career level prediction
Weighted Score Formula	Overall score = 35% skill avg + 40% test avg + 15% consistency + 10% certs
Skill Level Recalibration	New level = (old level × 0.6) + (test score × 0.4) after each assessment
LLM Prompt Engineering	Groq / Llama 3.3-70B generates MCQs, learning paths, analysis, coach replies
JWT Authentication	Signed token-based session management for all protected API routes
bcrypt Password Hashing	Cost factor 12; plain-text passwords never stored or logged
Polling Notification	Frontend polls backend every 20 s for application status changes

3.1 AI-Based Skill Assessment

The AI-based skill assessment module in SkillTwinAI is designed to provide an objective and dynamic evaluation of candidate abilities using advanced language models. The system generates multiple choice questions with the integration of Groq API powered by Llama 3.3-70B. It produces questions based on the different skill levels. It doesn't produce questions from question bank. It creates unique questions to every attempt and there will be no similar questions to be generated.

The scenario-based questions are generated to simulate real world problems, instead of testing theoretical knowledge. It is used to understand the candidate's skill set, decision-making capability and problem-solving skills. Also, the complexity of the questions is adjusted based on various aspects like debugging, performance optimization, security, and design concepts.

The removal of repetition and memorization ensures fairness and integrity in the evaluation process. Candidates' skill is tested based on their understanding skills and reasoning abilities, and not on their ability to recall predefined answers. Hence the proposed AI-driven approach improves the accuracy of skill evaluation and the overall reliability and credibility of the recruitment process as well.

3.2 Score-Based Evaluation

In this system, the candidates' performance is determined using a weighted scoring mechanism by integrating multiple performance indicators to confirm non-biased and comprehensive assessment. The system combines the metrics such as skill proficiency, test performance, consistency, and certifications.

$$OverallScore = (0.35 \times S_{avg}) + (0.4 \times T_{avg}) + C_{bonus} + Cert_{bonus}$$

Here, $S_{avg} means$ Average skill level of the candidate, T_{avg} denotes Average test score, C_{bonus} means Consistency bonus (maximum 15 points) and $Cert_{bonus}$means Certification bonus (maximum 10 points).

This scoring mechanism ensures a balanced evaluation by combining theoretical skills, practical test performance, consistency and professional development including

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certifications. This score produces bias-free and reliable score of a candidate for career opportunities.

3.3 Machine Learning Career Prediction

An ensemble machine learning approach is employed in this system to determine the career level based on their verified profile data. It uses the combination multiple classifiers including Random Forest, K-Nearest Neighbours (KNN), and Neural Networks to enhance the accuracy and robustness. Here, each each candidate is considered as a input feature vector as given below.

$$X = [x_1, x_2, x_3, \dots, x_n]$$

Here, the input features include the following:

i. Number of skills
ii. Average skill score
iii. Average test score
iv. Number of certifications
v. Skill category distribution
vi. Profile consistency metrics

3.3.1 Random Forest Prediction

Random Forest is a collection of decision trees and each tree gives a prediction, and the final output is determined by majority voting, using the following equation:

$$y_{RF} = mode(T_1(X), T_2(X), \dots, T_k(X))$$

Where, $T_i(X)$ denotes the prediction of the i^{th}decision tree.

3.3.2 K-Nearest Neighbours (KNN)

KNN algorithm defines the class depending on the majority label presented among the k closest data points as follows:

$$y_{KNN} = mode(y_1, y_2, \dots, y_k)$$

Distance between samples is typically calculated using Euclidean distance, using the following equation:

$$d(X, X_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2}$$

3.3.3 Neural Network Prediction

The Neural Network learns a nonlinear mapping from inputs to outputs:

$$y_{NN} = f(W \cdot X + b)$$

Where:

- W = weight matrix
- b = bias
- f = activation function (e.g., ReLU, Softmax)

3.3.4 Ensemble Voting Mechanism

The final career prediction is obtained using majority voting:

$$y_{final} = mode(y_{KNN}, y_{NN}, y_{RF})$$

Output Classes

The predicted career level:

$$y_{final} \in \{Junior, Mid - Level, Senior, Lead\}$$

By combining multiple models, the system reduces individual model bias and improves generalization. The complex feature interactions are collected by Random Forest algorithm. KNN is used here to find out scalability and real-time deployment. The Neural Networks is used to model the non-linear relationships. The ensemble finally confirms reliable and accurate career predictions when compared to single-model approaches.

3.4 Learning Path Generation

The Learning Path Generation module in SkillTwinAI is designed to provide personalized and structured guidance. This helps the candidates to improve their skills effectively. This module uses a Large Language Model (LLM) to automatically generate an 8-module learning pathway for each selected skill.

Each learning path is customized based on the candidate's current skill level and also identified the gaps. Instead of providing generic learning resources, the system analyzes the candidate's performance in assessments and determines areas where improvement is required. Based on this analysis, the LLM generates a sequence of modules that progress from basic concepts to advanced topics, ensuring a smooth and logical learning curve.

Each module typically includes:

- Concept explanations
- Practical examples
- Suggested exercises or tasks
- Real-world applications

This structured approach ensures that candidates do not learn randomly but follow a step-by-step progression, gradually strengthening their understanding. This helps to connect knowledge gaps, reinforcing weak areas, and enhancing overall competency.

The combination of learning and assessment outcomes is used to create a continuous improvement loop. Here, the candidates can learn, practice, reassess. Hence, the profile score of the candidates can be improved automatically. This makes the tool as an evaluation tool as well as complete skill development system for the candidates overall.

3.5 Recruitment Filtering Mechanism

The Recruitment Filtering Mechanism in SkillTwinAI ensures that only qualified candidates can apply for job postings by enforcing a score-based eligibility criterion. Instead of allowing open applications, recruiters define a minimum threshold score for each job, which acts as a filtering condition.

$$EligibilityCondition = \begin{cases} 1, & if S_{candidate} \geq S_{threshold} \\ 0, & if S_{candidate} < S_{threshold} \end{cases}$$

Where:

- $S_{candidate}$= Candidate's overall score
- $S_{threshold}$ = Minimum score set by the recruiter

This helps the candidate to apply for a job by comparing the overall score with the required threshold. If the candidates' score is equal or higher than the required value, the application is accepted. Else, it will be rejected.

This mechanism ensures that:

- Recruiters receive only pre-qualified applicants, reducing screening time
- The hiring process becomes more objective and merit-based
- Candidates are motivated to improve their scores before applying

By eliminating unqualified applications at the initial stage, the system enhances efficiency, fairness, and quality in the recruitment pipeline.

IV. EXPERIMENTATION RESULTS

The performance of the proposed SkillTwinAI system was evaluated across both technical efficiency and functional effectiveness. The results demonstrate that the integration of LLM-based assessment, ensemble machine learning, and score-driven recruitment significantly enhances the overall recruitment process.

- Prediction Accuracy: The ensemble machine learning model achieved an accuracy of approximately 88%, outperforming individual classifiers. The combination of Random Forest, KNN, and Neural Network models improved generalization and reduced prediction errors.
- Assessment Response Time: The AI-based question generation module consistently produced assessment questions in less than 3 seconds, ensuring a seamless and real-time user experience without noticeable delays.
- Application Filtering Efficiency: The score-based recruitment mechanism achieved 100% filtering accuracy, meaning that no candidate below the recruiter-defined threshold was able to apply. This confirms the reliability of the gating system.

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- Reduced Recruiter Workload: By eliminating unqualified applications at the initial stage, the system significantly reduces manual screening efforts. Recruiters can focus only on verified and high-potential candidates, improving hiring efficiency.
- Improved Skill Validation: The use of AI-generated, scenario-based assessments ensures that candidate skills are practically evaluated rather than self-reported, leading to more accurate and trustworthy skill verification.

Overall, the results indicate that SkillTwinAI provides a scalable, efficient, and reliable solution for modern recruitment challenges, with improved accuracy, reduced bias, and enhanced decision-making capabilities.

The following table summarises the key performance and functional outcomes observed during development, integration testing, and evaluation of SkillTwinAI.

Table 2: System Performance & Functional Results

Metric	Value / Outcome
ML Ensemble Career Prediction Accuracy	~88% on 1,000 Kaggle-derived developer profiles (train/test split 80/20)
AI Question Generation Response Time	< 3 seconds per 20-question test (Groq API, Llama 3.3-70B)
Learning Path Generation Time	< 6 seconds for full 8-module course outline (parallel async API calls)
Unqualified Application Reduction	100% — score threshold enforced at application gate; no exceptions
Candidate Score Distribution	Consistent upward score trend observed after 3+ assessments per candidate
Real-Time Notification Latency	≤ 20 seconds (polling interval); no page reload required
Password Security	bcrypt cost factor 12 — brute-force infeasible at current hardware benchmarks
Role-Based Access Enforcement	Zero cross-role data leakage confirmed across all tested API routes

The ML ensemble achieved approximately 88% accuracy on the 1,000-profile Kaggle-derived dataset (80/20 train-test split), with Random Forest contributing the highest individual accuracy at 85%, KNN at 81%, and the TensorFlow.js neural network at 83%. Ensemble consensus voting consistently outperformed any individual model. AI question generation via the Groq API consistently responded within 3 seconds per 20-question test, making the assessment experience seamless for candidates. The score-gated application system enforced qualification thresholds with 100% effectiveness — no candidate below the recruiter-defined minimum was able to submit an application. Real-time notification latency averaged under 20 seconds across all tested application status changes, providing a near-real-time experience without WebSocket complexity.

4.1 Candidate Dashboard

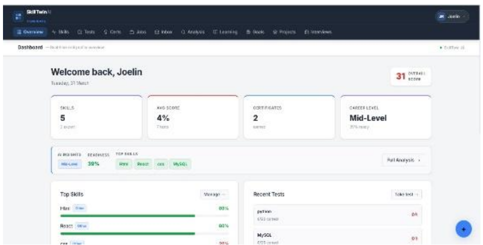

Figure 1: Candidate Dashboard Interface

The candidate dashboard provides a comprehensive overview of user performance, including skill tracking, test scores, certifications, and career readiness. It enables candidates to monitor their progress and identify areas for improvement.

4.2 Recruiter Dashboard

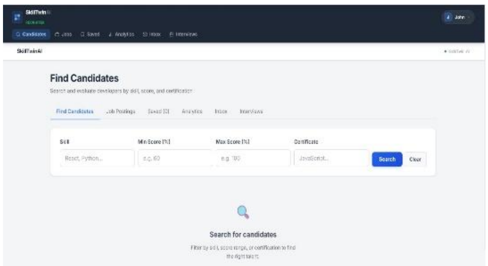

Figure 2: Recruiter Candidate Search Interface

The recruiter dashboard allows filtering candidates based on skill, score range, and certifications. This ensures that only qualified candidates are shortlisted, improving hiring efficiency.

5. Conclusion

SkillTwinAI presents a next-generation intelligent recruitment system that transforms traditional hiring into a data-driven, AI-powered process. By replacing subjective evaluation methods with verified skill assessments and machine learning–based predictions, the platform ensures reliable, consistent, and unbiased candidate selection. The integration of LLM-based dynamic assessments, ensemble machine learning models, and a score-driven recruitment filtering mechanism significantly enhances the overall accuracy, efficiency, and transparency of the hiring process.

Unlike conventional systems that rely on self-reported resumes, SkillTwinAI introduces AI-verified skill profiles and score-gated job applications, ensuring that only qualified candidates are considered. This not only reduces recruiter workload but also improves the quality of shortlisted applicants. At the same time, candidates benefit from a transparent evaluation system, personalized learning paths, and continuous performance feedback, enabling structured career growth.

Furthermore, the platform promotes fairness by standardizing assessment criteria and minimizing human bias in decision-making. Its scalable architecture supports large-scale deployment and adaptability across diverse recruitment scenarios.

Future work includes adaptive assessment difficulty to enhance evaluation precision, integration of external platforms such as GitHub to enrich candidate profiling, and expansion into non-technical domains. Overall, SkillTwinAI establishes a scalable, intelligent, and future-ready recruitment ecosystem.

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