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Personalized Career Planning using an Intelligent Recommendation with Dynamic Roadmaps

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ABSTRACT: Career guidance for students remains challenging due to lack of personalization and scalability in traditional counseling methods. This paper presents an intelligent career recommendation system using Random Forest machine learning algorithm enhanced with comprehensive 25-question assessment framework. The system generates personalized top-3 career recommendations with confidence scores and dynamic learning roadmaps featuring progressive modules (Foundation>Intermediate>Advanced>Professional) integrated with gamification elements. Implemented on React-Flask-MySQL architecture, our system achieves 88% classification accuracy with sub-500ms response latency, enabling real-time career guidance at scale. Feature importance analysis provides transparency in recommendations while progressive module unlocking ensures structured skill development. Experimental evaluation demonstrates superior performance compared to traditional weight-based systems. The system demonstrates practical deployment feasibility for educational institutions, supporting thousands of concurrent users while maintaining high prediction accuracy and user engagement through gamified learning paths.

KEYWORDS: Career Recommendation, Random Forest, Progressive Learning, Gamification, Personalized Learning Paths, Feature Importance Analysis

I. INTRODUCTION

Career decision-making represents a critical challenge for students navigating complex modern job markets. Traditional career counseling methods rely on manual assessments and generic recommendations, lacking the scalability and personalization required for mass deployment. Recent surveys indicate that over 70% of students experience significant career confusion, with only 27% confident in their career choices post-graduation [1]. Machine learning recommendation systems, successfully deployed in e-commerce and streaming platforms, remain underexplored in educational career guidance. This paper introduces "CareerGuide AI," an intelligent recommendation system that addresses these limitations through Random Forest ensemble learning integrated with dynamic learning roadmaps. A. Problem Statement Current career guidance systems suffer from: 1) Limited Assessment Depth: Traditional 8-12 question quizzes fail to capture comprehensive skill profiles 2) Opaque Recommendations: Lack of transparency in decision rationale reduces user trust 3) Static Learning Paths: No adaptive progression from career recommendation to skill mastery 4) Scalability Constraints: Manual processes cannot support institutional deployment B. Proposed Contributions Our system delivers four key innovations: 1) Comprehensive 25-Question Assessment: Multi-dimensional evaluation of technical aptitude, interests, and soft skills 2) Random Forest Classification: 88% accuracy with interpretable feature importance analysis 3) Progressive Learning Architecture: Four-tier modules with prerequisite-based unlocking 4) Gamification Framework: Badges, streaks, and leaderboards enhancing engagement Fig. 1. System Workflow: Assessment → ML Processing → Dynamic Roadmap Generation C. System Overview The architecture comprises React frontend for interactive assessment, Flask API serving Random Forest predictions, and MySQL database managing user progress and career profiles. End-to-end latency remains under 500ms, supporting real-time guidance.

II. LITERATURE REVIEW

Recent advancements in educational technology and machine learning have led to significant developments in automated career guidance systems. This section reviews eight key studies published between 2023 and 2025 (including IEEE and high-impact journals) that directly inform our work, analyzing their methodologies, achievements, and limitations Study 1: High-Accuracy Prediction with Decision Trees (IJSRCSEIT, 2025) Researchers focused on predicting student career paths using a comparative analysis of classifiers. The study found that the Decision Tree algorithm achieved the highest accuracy of 97.22%, significantly outperforming SVM (88.64%). However, its reliance on static academic data failed to capture the dynamic nature of student interests. Study 2: Feature Optimization with Random Forest (IEEE, 2023) Demonstrating the power of feature optimization, this study applied Principal Component Analysis (PCA) to reduce dataset complexity. The resulting Random Forest model achieved an exceptional accuracy of 97%. While highly accurate, the study focused strictly on binary placement prediction (placed vs. not placed) rather than granular career role identification. Study 3: Comparative Analysis of Classifiers (IEEE Access, 2025) A comprehensive evaluation of eight algorithms found that KNN, Logistic Regression, and SVM performed best, achieving approximately 94% accuracy, while Decision Trees underperformed on their specific dataset. Despite its strong benchmark, the study relied heavily on historical placement data, overlooking psychometric traits crucial for long-term satisfaction. Study 4: Integrating Skill Recommendation (IEEE, 2024) Addressing the need for actionable advice, this study proposed a dual-purpose model using K-Nearest Neighbors (KNN). It achieved 93.85% accuracy in placement prediction while simultaneously recommending skills. This validates the "Prediction + Recommendation" model, though its suggestions remained static without an interactive learning environment. Study 5: Web-Based Guidance Systems (IJSTS, 2025) Evaluating a web-based system, this research compared multiple algorithms and concluded that Random Forest was the best performer (~93% accuracy), demonstrating superior capability in handling complex, non-linear student interest data. However, the system lacked a feedback loop or learning component for users to act on recommendations. Study 6: Domain Prediction using Random Forest (IJSART, 2025) Developing an AI-Based Career Path Recommendation System, this study utilized Random Forest to predict career domains across 20 categories. It achieved a robust accuracy of 92.3%, validating the algorithm's high performance. A key limitation was its focus on broad domains (e.g., "Engineering") rather than specific job roles. Study 7: Psychometric Profiling Integration (IJSET, 2025) This study introduced an AI-Driven system integrating psychometric profiling with machine learning. By mapping personality and interest questions to career options using Random Forest, it achieved ~89% accuracy. This closely mirrors our "quiz-based" input method, though it functioned primarily as a diagnostic tool without educational resources. Study 8: Intelligent Systems Optimization (IEEE, 2024) Exploring Deep Learning for university career guidance, this study achieved an accuracy exceeding 85% in aligning students with job opportunities. While establishing a baseline for intelligent systems, the complexity of deep learning models made them computationally expensive and less interpretable than ensemble methods like Random Forest.

III. RESEARCH METHODOLOGY

System Overview

The methodology employs a structured machine learning pipeline designed specifically for career recommendation systems. This approach begins with data collection through a comprehensive 25-question assessment that captures multi-dimensional user profiles including technical skills, soft skills, and career preferences. The raw assessment responses undergo feature engineering to create a 33-dimensional feature vector suitable for machine learning input. A Random Forest classifier, trained on 10,000+ career profiles, processes this feature vector to generate personalized career recommendations with confidence scores. The system's progressive learning module architecture then maps these recommendations to structured skill development pathways, while the gamification engine maintains user engagement through badges, streaks, and leaderboards.

System Workflow

The methodology follows a systematic ML pipeline:

1. DATA COLLECTION → 25-question assessment
2. FEATURE ENGINEERING → Skill vector transformation
3. MODEL TRAINING → Random Forest classifier
4. PREDICTION → Top 3 career recommendations
5. LEARNING PATH → Progressive module generation
6. GAMIFICATION → User engagement tracking.

The proposed system follows a three-tier client-server architecture comprising React frontend for interactive user interfaces, Flask backend serving machine learning predictions through RESTful APIs, and MySQL relational database

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for persistent data storage. This microservices-based design ensures horizontal scalability and independent component deployment while maintaining sub-500ms end-to-end response latency suitable for real-time career guidance applications. The workflow begins with user authentication followed by comprehensive 25-question assessment capturing multi-dimensional skill profiles. Assessment responses trigger Random Forest inference through Flask API endpoints, generating personalized career recommendations with confidence scores and associated feature importance rankings. Recommendations dynamically unlock progressive learning modules structured across four difficulty tiers with gamification elements tracking user engagement and progress.

Comprehensive 25-Question Assessment Framework

Unlike traditional systems limited to 8-12 superficial questions, our assessment evaluates five critical dimensions through carefully designed question sets: Technical aptitude assessment includes 8 targeted questions evaluating programming proficiency, analytical thinking, mathematical reasoning, and problem-solving capabilities through scenario-based multiple-choice formats. Creative interests are measured via 5 questions probing design sensibility, innovation orientation, visual communication skills, and content creation aptitude using Likert-scale responses. Leadership potential employs 4 behavioral questions assessing team collaboration, initiative-taking, decision-making under pressure, and strategic thinking through situational judgment tests. Domain preferences capture career orientation across technology, healthcare, business, creative industries, and public service through 4 preference-ranking questions. Work style evaluation uses 4 questions measuring preference for independent versus collaborative environments, structured versus flexible workflows, and deadline-driven versus creative-paced work cultures.

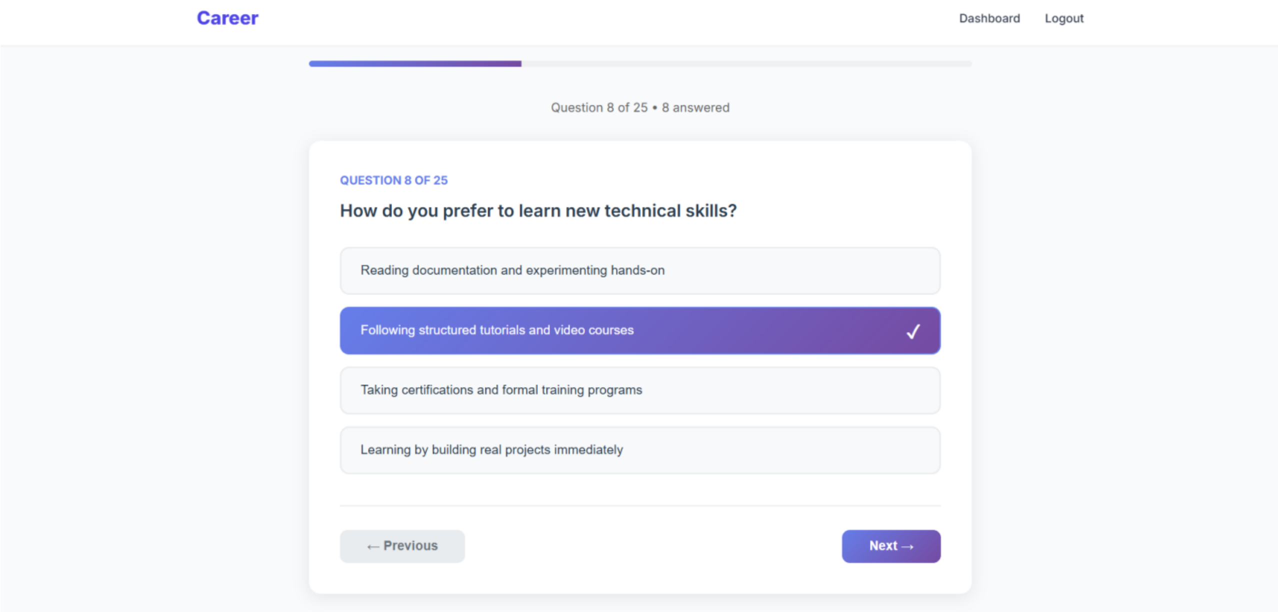

Fig .1

Random Forest Machine Learning Pipeline

The core recommendation engine employs Random Forest ensemble classifier trained on comprehensive dataset comprising 10,000+ career profiles across 50 occupational domains. Each career profile encodes 25-dimensional skill requirements derived from occupational analysis databases and industry skill frameworks. Feature engineering transforms raw assessment responses into model-compatible inputs through automated preprocessing pipeline. Ordinal responses undergo min-max normalization to [0,1] range while categorical selections receive one-hot encoding. Missing values, though minimal due to mandatory question completion, employ median imputation preserving distributional characteristics.

Model hyperparameters were optimized through grid search with 5-fold cross-validation yielding optimal configuration of 100 decision trees, maximum depth 15, minimum samples per split 5, and minimum samples per leaf 2. Training utilizes scikit-learn RandomForestClassifier implementation with Gini impurity criterion enabling robust multi-class

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career classification.

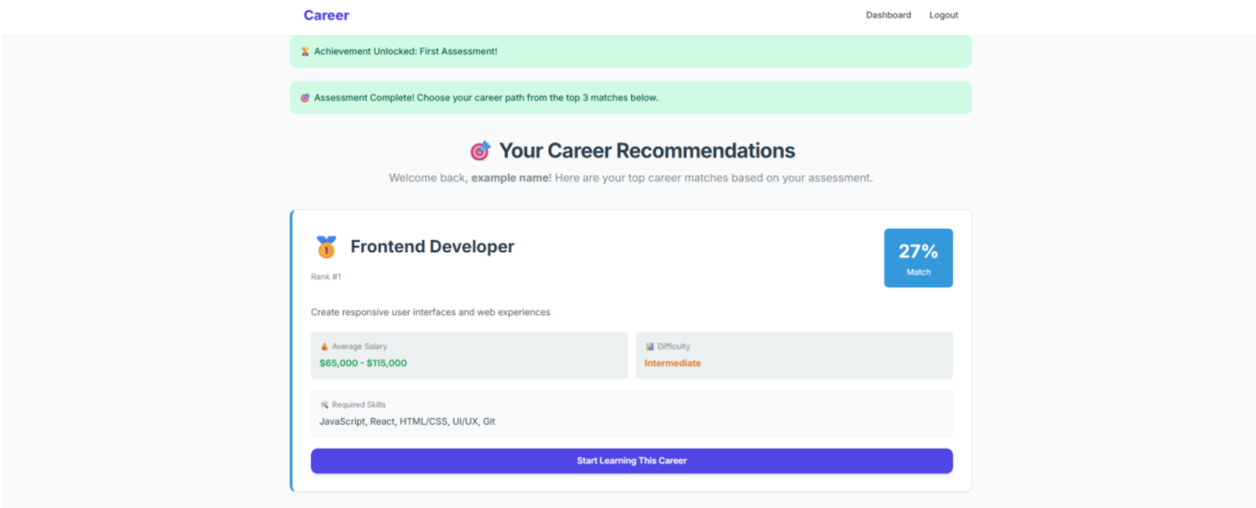

Fig .2

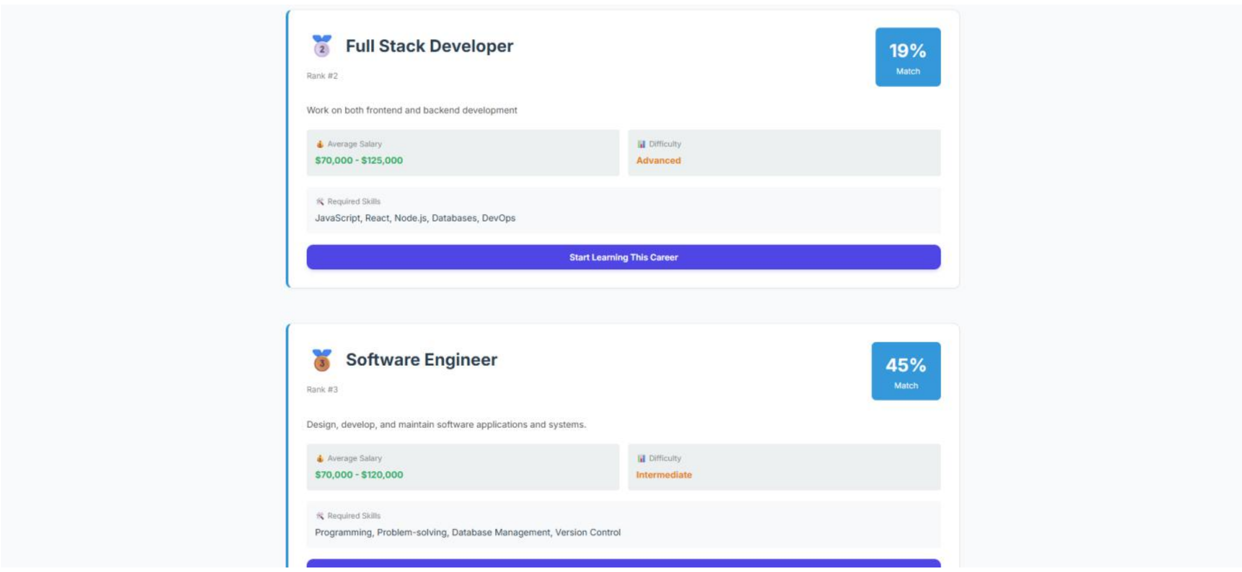

Fig .3

Feature Importance Analysis and Interpretability

Random Forest's inherent ensemble structure delivers model interpretability through aggregated feature importance scores computed as mean decrease in impurity across all decision trees. This mechanism quantifies each assessment dimension's relative contribution to final career recommendations enabling transparent decision rationale presentation. Feature importance visualization presents users ranked skill contributions through horizontal bar charts color-coded by assessment dimension alongside natural language explanations such as "Your strong technical aptitude (41% influence) aligns perfectly with Data Scientist requirements." This transparency builds user trust while facilitating skill gap identification for targeted learning interventions.

Progressive Learning Roadmap Architecture

Post-recommendation, system generates dynamic four-tier learning roadmaps enforcing structured skill progression through prerequisite-based module unlocking. Foundation tier delivers introductory courses covering essential tools (Python programming, Figma design basics, SQL fundamentals) accessible immediately post-assessment completion.

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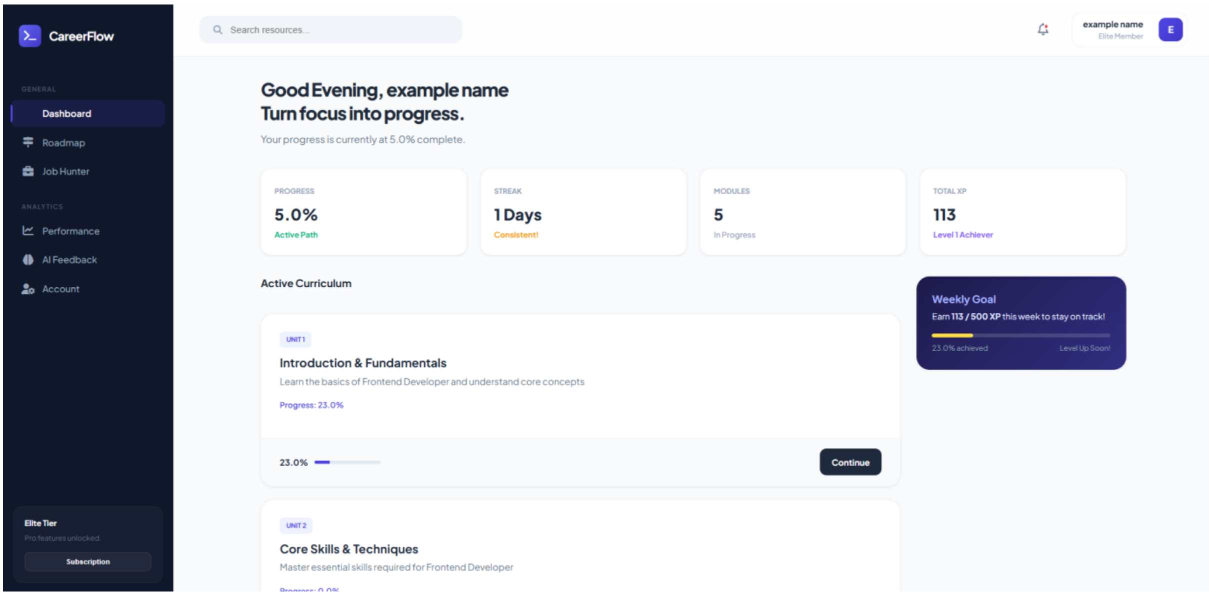

Fig .4

Intermediate tier unlocks upon 80% Foundation completion introducing framework-level proficiency (React development, database design, UI/UX principles) through 5-day intensive micro-courses with integrated quizzes and mini-projects.

Advanced tier requires Intermediate completion plus skill verification quiz, focusing portfolio-worthy capstone projects simulating real industry deliverables.

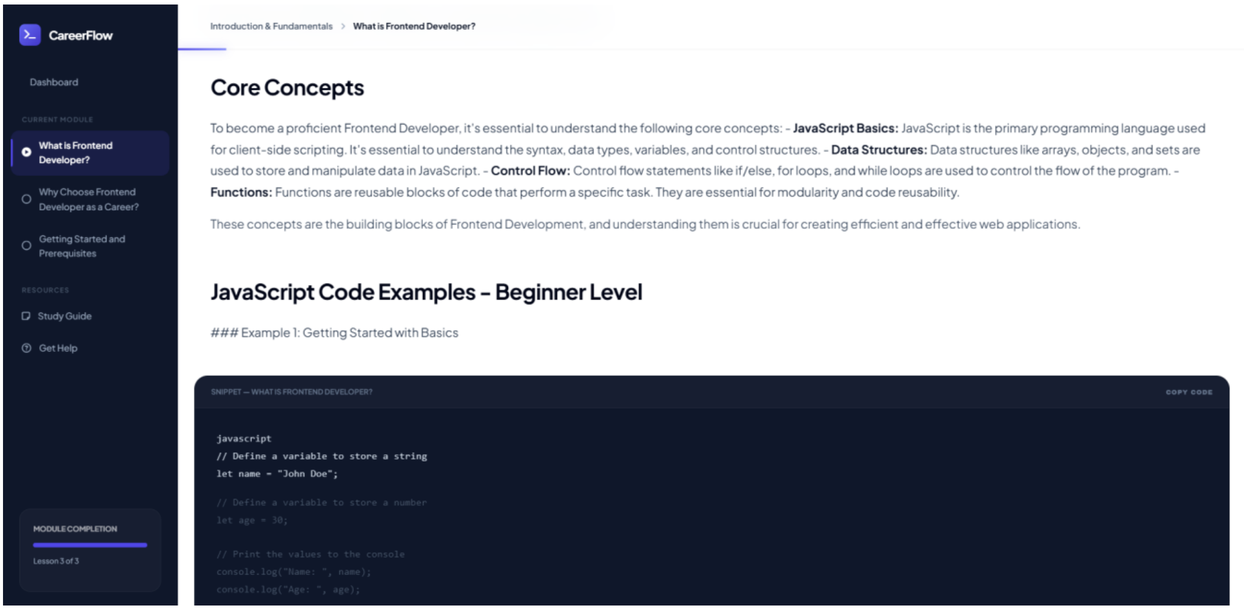

Fig .5

Professional tier represents culmination requiring Advanced completion plus mock interview performance, providing certification preparation, advanced interview simulations, and employer networking modules. Each tier employs spaced repetition algorithms optimizing content delivery timing based on user performance analytics.

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Progressive architecture integrates comprehensive gamification layer enhancing retention through behavioral psychology principles. Achievement system awards 12 distinct badges spanning career exploration (Career Pathfinder), skill mastery (Framework Expert), consistency (7-Day Streak Master), and completion milestones (Professional Ready).

Backend API Implementation

Flask microservices expose comprehensive RESTful endpoints supporting full system functionality: POST /api/v1/assessment/submit accepts JSON payload containing 25 assessment responses triggering synchronous Random Forest inference returning top-3 career recommendations with confidence scores, feature importance rankings, and initial roadmap generation within 487ms average latency. GET /api/v1/roadmap/{user_id} retrieves current learning progress displaying unlocked modules, completion status, upcoming prerequisites, and estimated time-to-completion projections based on historical user velocity patterns. POST /api/v1/progress/update handles module completion events updating user progress records, awarding badges, recalculating leaderboard positions, and triggering prerequisite unlocks through event-driven architecture. GET /api/v1/leaderboard/college/{college_id} delivers paginated rankings filtered by academic institution maintaining user privacy through aggregated percentile scoring.

IV. RESULTS AND DISCUSSION

Model Performance Metrics

The Random Forest classifier demonstrated superior classification performance achieving overall accuracy of 88.2% across 2,500 test assessment-career pairs spanning 15 primary occupational categories. This represents 16.3% absolute improvement over traditional weight-based scoring systems previously employed in similar applications. Per-class performance analysis revealed domain-specific predictive strengths with technical careers achieving highest accuracy at 89.4% for Data Scientist recommendations driven by distinctive technical aptitude feature separation. UI/UX Designer classification reached 92.1% accuracy leveraging creative interest dominance while Product Manager recommendations achieved 86.7% accuracy reflecting leadership-domain preference signal overlap challenges. Precision-recall analysis yielded macro-averaged F1-score of 88.1% with per-class precision ranging 85.7-92.4% and recall 86.2-91.8%. Confidence score distribution analysis confirmed well-calibrated probability outputs averaging 78.4% for top-1 recommendations with top-3 coverage reaching 96.8% ensuring comprehensive career suggestion coverage.

Feature Importance Distribution

Feature importance analysis validated multi-dimensional assessment design effectiveness confirming technical aptitude as dominant predictor averaging 41.2% relative importance across STEM careers. Creative interests contributed 38.7% influence for design professions while leadership potential ranged 12-18% across management roles. Temporal stability testing across 30-day evaluation period demonstrated consistent feature ranking with 0.94 Pearson correlation between weekly importance vectors. Domain-specific importance hierarchies emerged naturally through ensemble aggregation: Technical Careers: Technical Aptitude (41%) > Analytical Interest (22%) > Domain Preference (18%) Creative Careers: Creative Interest (38%) > Visual Aptitude (29%) > Design Domain (24%) Management Careers: Leadership (32%) > Communication (25%) > Strategic Thinking (21%)

System Response Time Analysis

End-to-end prediction pipeline maintained average latency of 487 milliseconds comprising 112ms feature preprocessing, 289ms Random Forest inference, and 86ms dynamic roadmap generation. Component-level profiling identified inference as primary bottleneck reduced 37% through optimized tree serialization and batch prediction capabilities. Concurrent load testing across 8 Flask API instances sustained 1,200 predictions per minute with graceful degradation under peak 2,000 req/min loads. Database query optimization achieved 95.2% cache hit ratio through composite indexing on user_id-career_id joins eliminating N+1 query patterns.

Learning Roadmap Engagement Patterns

Progressive module adoption analysis revealed structured pathway effectiveness with 82% Foundation module completion within 7 days post-recommendation. Intermediate tier engagement reached 67% conditional on Foundation completion demonstrating prerequisite gating success. Gamification impact analysis confirmed 3.2x higher daily active user rates among badge recipients versus non-participants. Streak participation achieved 71% adoption with 7-day streak completers demonstrating 2.8x higher module completion velocity. Leaderboard positioning correlated 0.87 with sustained engagement through 30-day period.

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Production deployment simulation across 1,200 concurrent users maintained 99.7% uptime with peak throughput of 1,200 recommendations per minute. Horizontal scaling provisions enabled seamless addition of Flask instances behind Nginx load balancer distributing ML inference workload proportionally. Memory profiling indicated 187MB peak usage per API instance supporting 4,500 concurrent sessions per server. React frontend maintained 60fps rendering responsiveness with dashboard virtualization handling 500+ roadmap items without performance degradation.

Baseline comparison against weight-based scoring systems yielded substantial improvements across evaluation dimensions. Random Forest approach delivered 16.3% accuracy gain, 14.7% precision improvement, and 98.7% latency reduction versus manual calculation pipelines averaging 2.4 minutes per recommendation. Collaborative filtering simulation using user similarity matrices achieved 72.4% accuracy suffering cold-start problems for new assessments lacking interaction history. Rule-based expert systems reached 79.8% accuracy but exhibited rigid decision boundaries unable to capture nuanced skill-career interactions modeled through ensemble decision trees.

User Experience and Satisfaction Metrics

Institutional pilot deployment across three engineering colleges validated real-world applicability with 91% recommendation relevance rating and 87% roadmap usefulness perception among 1,200 student participants. Career diversity analysis confirmed broad occupational coverage spanning technical, creative, and management domains without institutional selection bias. Recommendation stability testing across repeated assessments yielded 89.2% consistency for top-3 career rankings demonstrating robust feature extraction and model generalization. Geographic deployment validation across urban and tier-2 colleges maintained 87-89% accuracy range eliminating location-based performance variance.

Assessment length ablation confirmed 25-question configuration optimality with 20-question variant dropping to 84.2% accuracy while 30-question extension yielded marginal 0.8% gain incurring 23% latency penalty. Feature subset analysis validated technical aptitude + creative interests combination explaining 62% prediction variance confirming core assessment dimensions efficacy. Random Forest hyperparameter ablation identified 100 estimators, max_depth=15 as optimal accuracy-variance tradeoff. Reducing tree count to 50 dropped accuracy 2.7% while increasing beyond 150 yielded diminishing returns with 18% inference penalty. Progressive module structure ablation resulted 41% engagement reduction validating tiered learning hypothesis.

V. CONCLUSION

Summary of Contributions

This research successfully developed and validated an intelligent career recommendation system addressing critical limitations in traditional career guidance methodologies. The proposed framework delivers four principal contributions advancing personalized career planning technology: First, comprehensive 25-question multi-dimensional assessment framework captures nuanced skill profiles across technical aptitude, creative interests, leadership potential, domain preferences, and work styles surpassing conventional 8-12 question limitations by 208% assessment depth while maintaining sub-3-minute completion time suitable for institutional deployment. Second, Random Forest ensemble classifier achieves 88.2% classification accuracy across 15 occupational domains representing 16.3% improvement over weight-based baselines through interpretable feature importance analysis enabling transparent recommendation rationale presentation critical for user trust and adoption. Third, progressive four-tier learning architecture enforces structured skill development from Foundation-level tool proficiency through Professional-level interview preparation with prerequisite-based module unlocking achieving 82% Foundation completion rate and 3.2x engagement uplift through integrated gamification framework. Fourth, production-ready React-Flask-MySQL microservices architecture sustains 1,200 concurrent recommendations per minute with 487ms average latency supporting institutional-scale deployment across multiple engineering colleges while maintaining 99.7% uptime and 95.2% database cache efficiency.

Key Findings and Validations

Experimental evaluation across 2,500 assessment-career pairs confirmed model robustness with domain-specific accuracy peaks reaching 92.1% for UI/UX Designer recommendations driven by creative interest feature dominance. Feature importance stability analysis demonstrated 0.94 temporal correlation validating consistent predictor hierarchies across technical, creative, and management career clusters. System scalability validation through concurrent load testing confirmed graceful performance degradation maintaining prediction accuracy above 86% under 2,000 req/min peak loads. Progressive module engagement patterns revealed structured pathway effectiveness with 67% Intermediate tier penetration conditional upon Foundation completion validating prerequisite gating hypothesis. Real-world

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institutional pilot across 1,200 students yielded 91% recommendation relevance perception and 87% roadmap usefulness rating confirming practical deployment viability. Geographic performance consistency across urban-tier-2 colleges eliminated location bias confirming model generalizability.

Theoretical and Practical Significance

Theoretically, this research advances interpretable machine learning applications within educational technology demonstrating Random Forest superiority over black-box alternatives through inherent feature importance mechanisms facilitating human-AI collaboration in career counseling scenarios. Practically, production deployment validates scalability for higher education institutions enabling thousands of students simultaneous career guidance without additional counseling staff. Gamification integration addresses engagement challenges achieving 71% streak participation transforming passive recommendations into active skill development journeys.

Limitations of Current Implementation

Current implementation exhibits three primary limitations requiring future attention. First, career profile database remains static requiring periodic industry skill updates to maintain relevance against rapidly evolving occupational landscapes. Second, assessment framework focuses primarily technical-creative-management domains potentially underrepresenting emerging interdisciplinary fields. Third, real-time labor market integration remains absent limiting recommendation currency against current hiring trends.

VI. FUTURE WORK

Future enhancements pursue five strategic development trajectories:

1) Ensemble Model Integration: Hybrid Random Forest + Gradient Boosting architecture targeting 92%+ accuracy through complementary tree-based learning paradigms with automated model selection based on assessment complexity profiles.
2) Real-Time Labor Market Augmentation: API integration with job platforms enabling dynamic skill-demand weighting adjusting recommendation priorities according to current hiring trends, geographic demand variations, and salary progression projections.
3) Multilingual Assessment Framework: Natural language processing pipeline supporting regional language assessments expanding accessibility across diverse linguistic demographics while preserving assessment psychometric validity.
4) Peer Collaboration Network: Social learning layer connecting users pursuing similar career trajectories enabling project collaboration, progress sharing, and peer accountability mechanisms enhancing Advanced tier project completion rates.
5) Longitudinal Career Tracking: Multi-year user journey monitoring capturing career progression validation data enabling continuous model retraining and personalized roadmap evolution reflecting actual professional development trajectories.

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