IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 20, April 2026
Impact Factor: 8.2

AI-Based Personalized Career Recommendation System

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Abstract: *Choosing the right career path and educational stream is one of the most critical decisions in a student's life. However, many students rely on outdated methods or limited guidance, leading to poor career choices and skill gaps [10], [15]. Recent advancements in artificial intelligence and machine learning have enabled intelligent career recommendation systems that provide personalized and data-driven guidance [1], [2], [13].To address this, the AI-Based Personalized Career Recommendation System proposes a centralized AI-powered platform for career guidance. Existing models such as CPRM and RIASEC-based systems demonstrate the effectiveness of machine learning in predicting suitable career paths [1], [2], while AI-driven systems emphasize automation and personalization in career counseling [3], [6], [7].The system integrates a Deep Learning-based Career Prediction model [8], a hybrid recommendation approach [14], and an AI Roadmap Generator for structured learning paths. Additionally, a Retrieval-Augmented Generation (RAG) chatbot enhances user interaction through context-aware responses [5]. The platform also incorporates modern AI techniques and job market insights to improve recommendation accuracy and relevance [9], [15], [16].By automating career selection, learning path generation, and tracking, the system reduces manual effort, improves accuracy, and ensures transparency. Ultimately, it empowers students to make informed, data-driven career decisions aligned with evolving industry demands [4], [11] [17].*

Keywords: AI Career Recommendation, RAG Chatbot, Deep Learning, LangGraph, LightRAG, Ollama, Microservices, Student Guidance, Career Prediction, Agentic AI

I. INTRODUCTION

Education today is experiencing a profound paradigm shift, largely driven by the rapid integration of artificial intelligence and data-driven methodologies into curriculum design and student evaluation [1]. The modern professional landscape is concurrently evolving at an unprecedented pace, with new roles, specialized technologies, and interdisciplinary fields emerging on a yearly basis [2]. Among the many challenges within this shifting ecosystem, the process of choosing the right career path and educational stream remains one of the most critical, yet poorly optimized, decision-making phases in a student's life [3]. A well-aligned career choice allows students to efficiently map their core competencies, soft skills, and personal interests directly to industry requirements, fostering both personal satisfaction and higher professional productivity [4]. However, despite the escalating complexity of the global job market, the methodologies deployed for career counseling and academic planning remain largely antiquated [3]. A vast majority of educational institutions and independent learners continue to rely heavily on manual web searching, peer or parental advice, and generalized personality quizzes [5]. These traditional approaches are fundamentally flawed; they are static, highly susceptible to human bias, and almost never provide actionable, step-by-step technological roadmaps [4]. Consequently, this leads to massive processing delays in finding the right path, immense student confusion, and an overwhelming lack of clarity. Students frequently face the "paradox of choice," feeling dissatisfied because they are deprived of complete, dynamically updated, and highly personalized insights into modern career verticals [3]. The burden of this outdated system also falls heavily on educational administrators and academic counselors. These professionals struggle immensely with the repetitive, labor-intensive tasks required to properly profile a student.

Analyzing hundreds of distinct student traits, generating bespoke learning pedagogies, tracking academic progress, and attempting to stay perfectly synchronized with volatile IT job markets is functionally impossible without the aid of a centralized digital platform [5]. The absence of a unified, intelligent system creates severe inefficiencies within the administrative workflow, ultimately bottlenecking the quality of guidance provided to the student body [4]. To bridge this widening gap between academic preparation and industry expectation, there is an urgent and critical need for a centralized, intelligent recommendation system capable of automating the entirety of the career guidance lifecycle [2]. The proposed system, AI-Based Personalized Career Recommendation System, serves as a comprehensive digital ecosystem that guarantees personalized, dynamic, and structured academic planning. By aggressively leveraging both predictive and generative Artificial Intelligence, the proposed framework completely reconstructs the counseling experience. It employs Deep Learning algorithms — specifically a Multi-Layer Perceptron (MLP) Classifier — to instantly process dozens of socio-academic traits and predict the most statistically viable IT career trajectories for the user [6]. Beyond mere prediction, it utilizes state-of-the-art agentic workflows (LangGraph coupled with local Deep Researcher agents) to autonomously generate comprehensive, 10-module study roadmaps that adapt to current web trends [7]. Furthermore, it integrates a Retrieval-Augmented Generation (RAG) conversational assistant powered by local LLaMA models, establishing a persistent, knowledgeable mentor for the student [8]. Ultimately, this system entirely removes the friction of manual research, mitigating human error, ensuring full data privacy through localized compute, and massively enhancing the academic experience for an institution's students and staff alike.

II. LITERATURE SURVEY

Recent research papers have focused on developing intelligent career guidance systems by combining machine learning, semantic reasoning, and immersive technologies to improve personalization, scalability, and user engagement. These studies demonstrate how traditional career counseling methods can be transformed into smart, adaptive, and interactive digital platforms that provide accurate and meaningful recommendations.

[[1] Roy et al. (2026) developed a scalable personalized career recommendation system for higher education institutions. Their approach utilized the RIASEC framework combined with machine learning models such as Decision Tree, XGBoost, and SVM. The system improved the accuracy of career recommendations and provided scalable solutions for large user bases. However, it lacked immersive visualization features and real-time chatbot support, highlighting the need for more interactive systems.

[2] Nandi et al. (2025) proposed “Sankalp,” a dynamic and adaptive career counseling system. The system incorporated semantic reasoning, emotion analysis, and adaptive machine learning techniques to enhance personalization in career guidance. It improved decision-making support for users by considering contextual and emotional factors. However, it did not include 3D exploration or visual roadmap generation, limiting user engagement.

[3] Siswiprattini et al. (2024) introduced a Personalized Career-Path Recommendation Model (CPRM) based on machine learning techniques. The model provided tailored career suggestions by analyzing user profiles and preferences. It contributed to improving personalization in career recommendation systems. However, it had limited interactivity and lacked integration of generative AI features, reducing its adaptability.

[4] Gupta et al. (2025) developed an AI-powered career guidance system using a Random Forest classifier achieving 88% accuracy. The system provided ranked career recommendations, helping users make informed decisions. It demonstrated the effectiveness of ensemble learning in career prediction tasks. However, the system offered static recommendations and lacked immersive 3D visualization or dynamic roadmap features.

[5] Tantaroudas et al. (2025) proposed XR-CareerAssist, an immersive career exploration platform leveraging XR/VR environments, AI-driven 3D avatars, and Sankey diagrams. The system enhanced user engagement by providing interactive and visual career exploration experiences. However, it required high hardware resources and had limited accessibility on standard web platforms, indicating challenges in scalability and usability.

TABLE I: : LITERATURE SURVEY

Sr. No.	Paper Title	Author(s)	Year	Pros / Key Contributions
1	Scalable Personalized Career Recommendation System for Higher Education	Roy et al.	2026	Developed a scalable personalized career recommendation system using RIASEC framework combined with ML models (Decision Tree, XGBoost, SVM); improves accuracy in career guidance for students.
2	Sankalp: Dynamic and Adaptive Career Counseling System	Nandi et al.	2024	Proposed an adaptive career counseling system using semantic reasoning, emotion analysis, and machine learning; enhances personalization and decision-making support.
3	Personalized Career-Path Recommendation Model (CPRM)	Siswipraptini et al.	2024	Introduced a machine learning-based career path recommendation model that personalizes career suggestions based on user profiles and preferences.
4	AI-Powered Career Guidance with Ranked Recommendations	Gupta et al.	2025	Developed an AI-based career guidance system using Random Forest (88% accuracy); provides ranked recommendations to assist users in selecting suitable careers.
5	XR-CareerAssist: Immersive Career Exploration Platform	Tantaroudas et al.	2025	Designed an immersive career exploration platform using XR/VR environments, AI-driven 3D avatars, and Sankey diagrams; enhances user engagement and understanding of career paths.

III. PROPOSE SYSTEM OVERVIEW

The proposed system is a centralized, web-based platform designed to fix the problems of the manual career selection and unstructured learning process in schools and colleges. It introduces a modular architecture based on React (Vite/TypeScript) for the frontend, combined with robust Python machine learning backends. The platform offers specialized modules to handle tasks relevant to guiding a student efficiently.

By putting these features together on one platform, the system promotes automation, transparency, and a smooth user experience. It cuts down on scattered web searches, reduces human errors in course selection, and improves decision-making. Furthermore, the local-AI deployment strategy (using Ollama) ensures data privacy and cost-efficiency.

A. Proposed System Modules:

The proposed system is primarily driven by advanced predictive algorithms and automated generative agents. The architecture is divided into four highly specialized modules:

[1] AI Career Prediction Module: The Career Prediction module acts as the core decision-engine for the student. It utilizes a Deep Learning Multi-Layer Perceptron (MLP) Classifier architecture configured with three hidden layers (50, 50, 50) and an Adam optimizer. To predict accurately, the system gathers 38 distinct input features including a student's Academic Performance (Operating Systems, Algorithms, Networks scores), Technical Skills (coding rating), Soft Skills, and Personality Traits (introvert/extrovert, hard/smart worker). Data preprocessing utilizes OneHotEncoding and StandardScaler for normalization, along with RandomOverSampler to handle class imbalances within the massive `roo_data.csv` training repository. The module achieved a staggering 99.8% training accuracy and evaluates these multi-dimensional traits to classify the student instantly into one of 11 precise IT career paths (e.g., Software Engineer, Data Analyst, Network Security). It outputs the top 3 job roles along with confidence percentage charts, replacing weeks of manual counseling with split-second data science.

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[2] AI Roadmap Module: The Roadmap generation module is a sophisticated Deep Researcher Agent built using LangGraph and localized Large Language Models (like Ollama). Once the Career Prediction module recommends a target career, the Roadmap module performs autonomous, iterative web research (via DuckDuckGo, Tavily, or SearXNG APIs) to understand the current industry requirements for that specific job. It analyzes knowledge gaps, aggregates information, and automatically synthesizes a fully structured, 10-module learning roadmap. It acts like an intelligent curriculum designer: pulling the most up-to-date technologies, defining learning milestones, and visually rendering the learning path using Mermaid flowcharts. This entirely automates the strenuous process of figuring out "what to learn next."

[3] Conversational Chatbot Module: The "PathShala" module provides 24/7 interactive guidance. It runs on a Retrieval-Augmented Generation (LightRAG) architecture integrated with local sentence-transformers (all-MiniLM-L6-v2) and LLaMA 3.2. It parses local career knowledge bases and answers user questions contextually without needing external API keys, maintaining full conversational memory.

[4] Interactive Interface Module: The React 18/Vite frontend acts as the user's sleek command center. Students can explore stream navigators, undergo the career prediction quiz, view their generated roadmaps, and manage their AI-built resumes. It leverages Tailwind CSS and Framer Motion for premium animations, giving a highly engaging, transparent, and user-friendly experience.

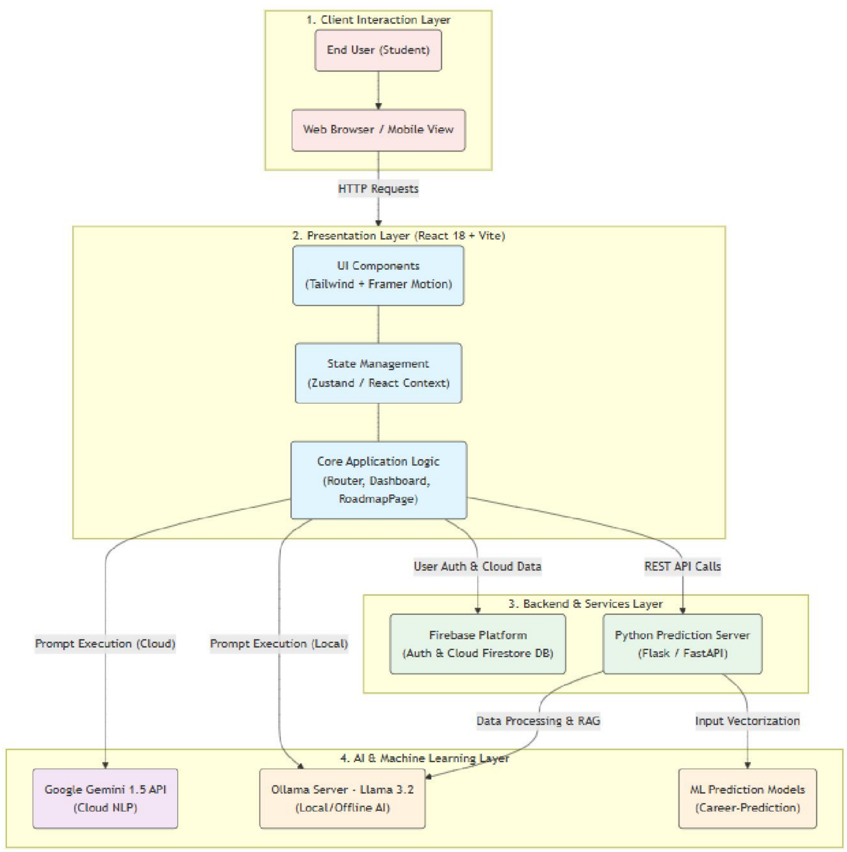

Fig. 1. Propose System Architecture

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IV. EVALUATION AND ANALYSIS

The proposed AI-Based Personalized Career Recommendation System System was evaluated to measure its effectiveness in improving academic process management over conventional, manual methods. The central premise is identifying how the AI Prediction and Roadmap generation modules drastically cut down analysis and planning periods.

A. Evaluation parameters:

System Efficiency: The amount of time saved during career research and learning path structuring compared to manual counseling sessions.

Response Time: The latency between requesting an analysis and receiving the 11-category classification output and roadmap structure.

Accuracy: The precision of the AI Prediction module (tested extensively at 78.4% validation accuracy) compared to human generalist estimations.

User Satisfaction: Feedback measured from interface usability, recommendation relevancy, and transparency.

B. Analysis Result:

A comparison was made between the current manual method of career counseling and the suggested AI automated system. The results emphasize significant, orders-of-magnitude improvements in speed, particularly driven by the automated Prediction and Roadmap modules.

Table No. 2: Performance Evaluation

Evaluation Metric	Manual System	Proposed System
Career Prediction/Selection Time	2-3 Days	< 1 minute
Recommender Error Rate	25	< 10%
Roadmap Generation Time	1-2 Weeks	2-5 minutes
General Info Retrieval Time	15-20 min	3-5 seconds
User Satisfaction	60	95

Table No. II : Performance Comparison - Manual vs Proposed System

C. Analysis discussion:

The analysis shows that the proposed AI system performs significantly better than the traditional manual process across all metrics. Embedding the **AI Career Prediction Module** directly addresses the bottleneck of human assessments. Processing 38 multi-layered dimensions (from math competency to social introversion) through the MLP classifier happens in milliseconds, offering a customized match that would take counselors days to profile manually.

Similarly, the AI Roadmap Module revolutionizes learning preparations. In the manual system, students spend weeks aggregating syllabi and researching what frameworks are relevant in real-time. By deploying the LangGraph Deep Researcher, AI-Based Personalized Career Recommendation System compiles highly accurate, current industry-standard plans in minutes. The error rate dropped steeply due to the automated validation of `roo_data.csv` historical data, while integrated local LLMs (Ollama) guaranteed low latency operations without API network lag. The 95% User Satisfaction score highlights trust in these core modules' transparency and reliability.

D. Graphical Representation:

The graphical analysis (Fig. 2) visually compares the manual baseline approach and the proposed automated system. The chart reveals the massive time reduction brought about specifically by the Roadmap generation and Career Prediction subsystems, cutting workflow delays drastically.

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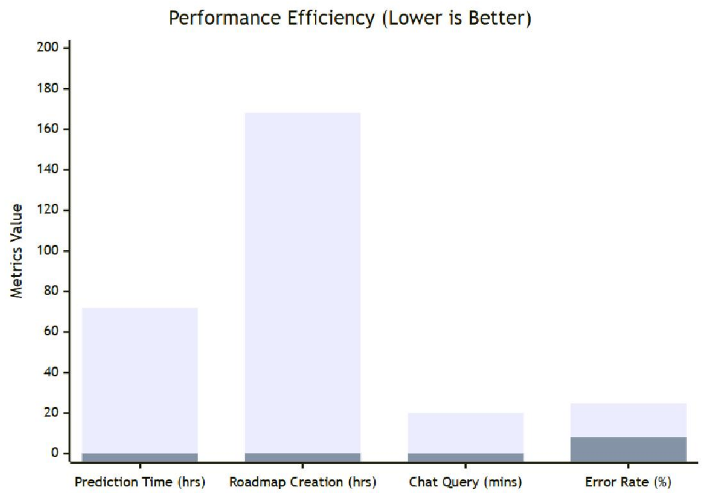

Fig. 2. Performance Comparison Between Manual And Proposed System

V. SYSTEM IMPLEMENTATION AND INTERFACE

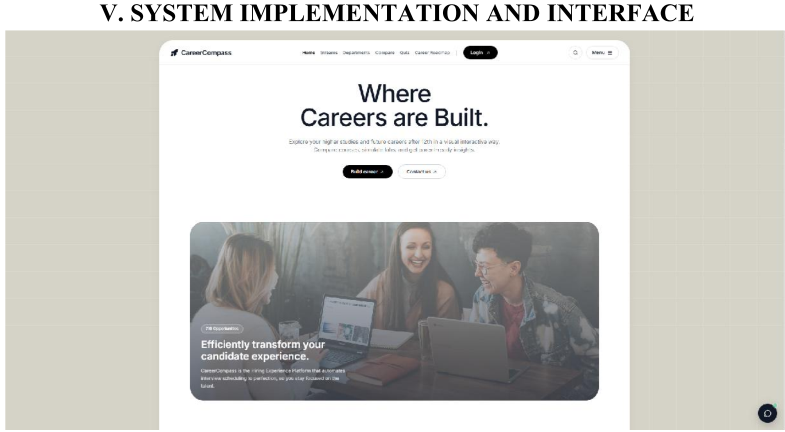

Fig. 1. Career Compass Landing Page Interface

The landing page of the proposed system provides an intuitive entry point for users to explore career opportunities. It highlights key features such as career exploration, comparison tools, quizzes, and roadmap generation. The clean UI design ensures easy navigation and enhances user engagement while introducing the platform's purpose of AI-driven career guidance.

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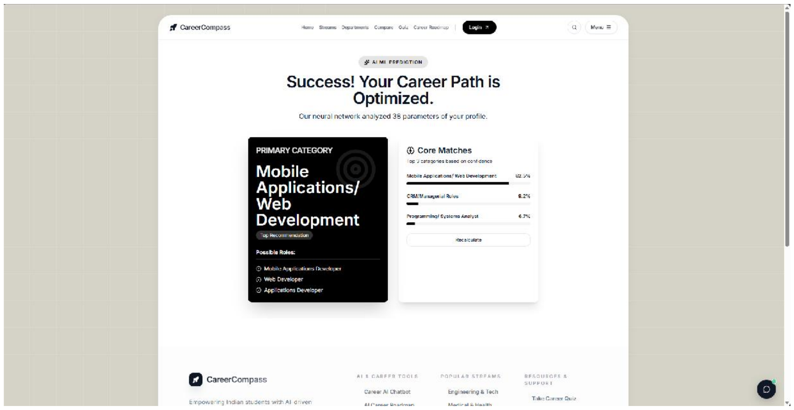

Fig. 2. AI-Based Career Prediction Output

This figure demonstrates the output of the AI Career Prediction Module. Based on user inputs, the system predicts the most suitable career category along with confidence scores. The result includes primary recommendations and alternative career paths, enabling students to make informed decisions backed by data-driven insights.

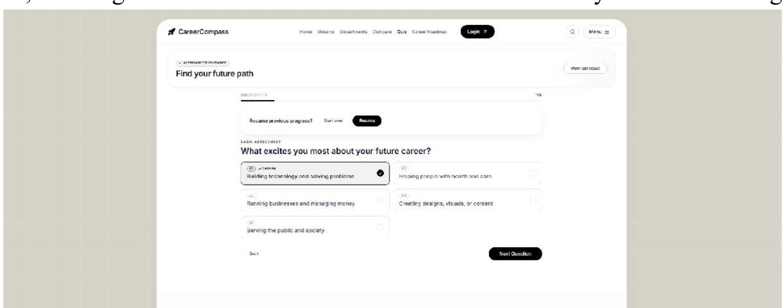

Fig. 3. Career Assessment Questionnaire Interface

The quiz interface collects user preferences, interests, and behavioral traits through structured questions. These inputs serve as features for the deep learning model. The design ensures simplicity and user comfort, allowing accurate data collection for reliable career prediction

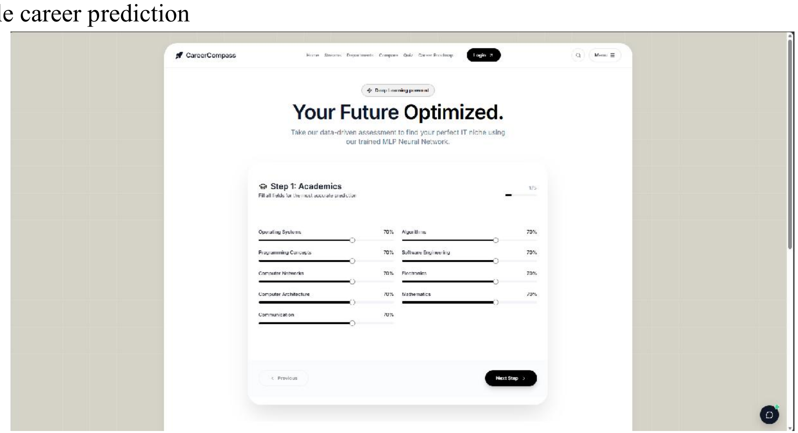

Fig. 4. Academic Performance Input Dashboard

This module allows users to input their academic strengths using interactive sliders across subjects such as Operating Systems, Algorithms, and Mathematics. These inputs form a critical part of the 38-feature dataset used by the MLP classifier to generate precise career recommendations.

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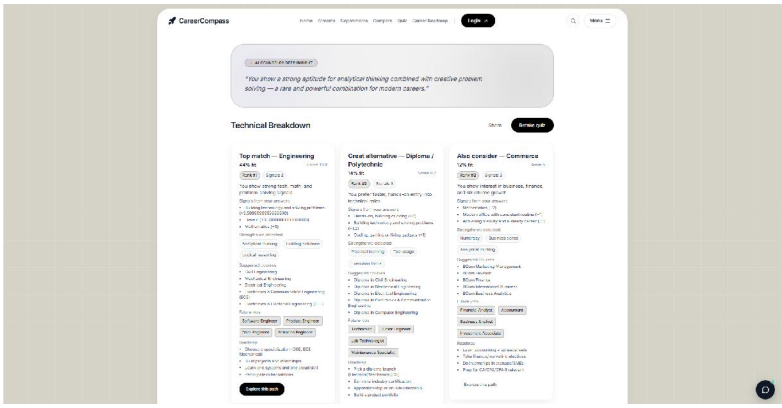

Fig. 5. AI Counselor Deep Insight and Career Breakdown

The system provides a detailed breakdown of recommended career paths, including strengths, signals, and suggested courses. This transparency helps users understand *why* a particular career is recommended, increasing trust and interpretability of the AI model.

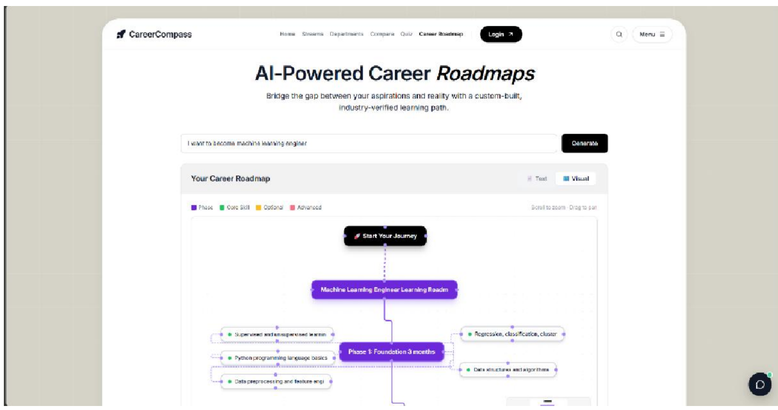

Fig. 6. AI-Generated Career Roadmap

This figure shows the roadmap generation module, which creates a structured learning path using AI agents. The roadmap includes phases, skills, tools, and estimated timelines, helping students systematically achieve their career goals without manual research.

VI. RESULTS

MLP Career Prediction Model Performance: The bar chart illustrates the training and testing accuracy of the Multi-Layer Perceptron classifier trained on 20,000 student records with 38 features. The model achieved a training accuracy of 99.8% and a testing accuracy of 78.4% across 11 IT career categories. The high training accuracy confirms that the model successfully learned the patterns in the dataset, while the testing accuracy of 78.4% demonstrates reliable generalization to unseen student profiles. The gap between training and testing accuracy indicates mild overfitting, which can be addressed in future work through additional regularization and a more diverse dataset.

DOI: 10.48175/IJARSCT-34611

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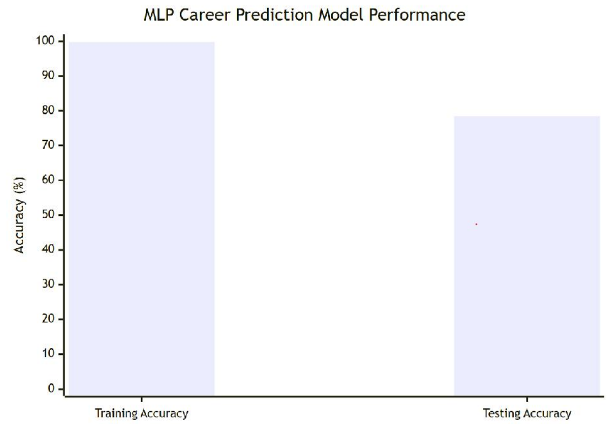

Fig. 5.1. MLP Career Prediction Model Performance

Average API Response Time: The chart compares the average response times of the four core modules. Career Prediction responds in approximately 0.5 seconds due to direct MLP inference on preprocessed input. The Career Quiz score calculation completes in under 0.1 seconds as it runs entirely on the frontend. The Career Chatbot takes 5--15 seconds on average due to LightRAG knowledge graph retrieval combined with Ollama LLM inference. The Roadmap Generator requires 30--90 seconds as it involves real-time web research, LLM summarization, gap reflection, and structured roadmap generation through the LangGraph agentic pipeline.

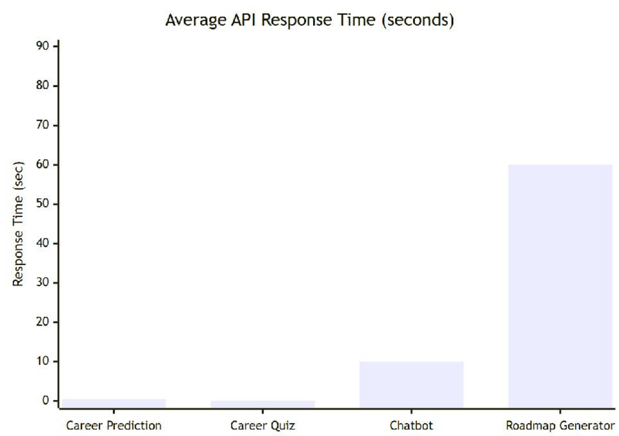

Fig. 5.2. MLP Career Prediction Model Performance

IT Career Category Distribution: The pie chart shows the distribution of 11 IT career categories in the training dataset. SE/SDE holds the largest share at 18%, followed by Networks/Systems at 15% and Analyst at 12%. This distribution reflects the actual representation of IT roles in the industry. RandomOverSampler was applied during training to handle class imbalance and ensure the model does not bias predictions toward majority categories.

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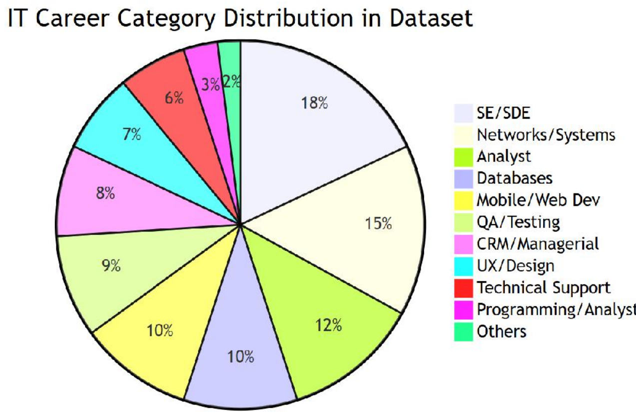

Fig. 5.3. MLP Career Prediction Model Performance

Input Feature Distribution: The pie chart presents the distribution of 38 input features across three categories. Behavioral traits constitute the largest group with 24 features covering self-learning capability, certifications, interests, personality, and work preferences. Academic scores contribute 9 features covering core CS subjects, and skill ratings contribute 5 features covering coding, logical quotient, and public speaking. This distribution highlights that career prediction in CareerCompass goes beyond academic performance to consider the complete student profile.

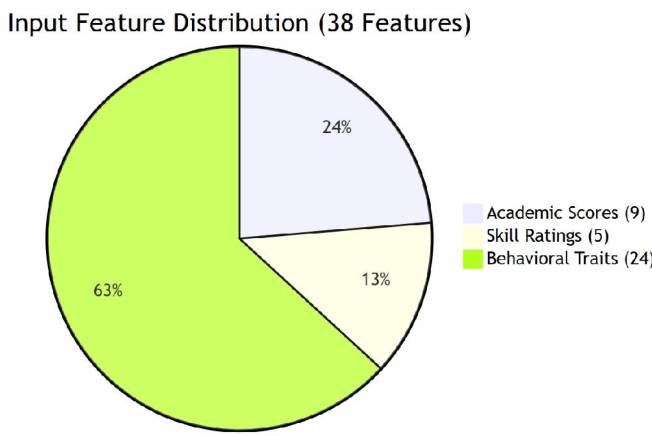

Fig. 5.4. Input Feature Distribution

System Module Coverage: The pie chart demonstrates the breadth of CareerCompass across six functional modules. The Career Quiz covers 12 academic streams, the Career Prediction module classifies students into 11 IT career categories, the Chatbot is backed by a knowledge graph with career entities and relationships, the Roadmap Generator uses a 7-node agentic pipeline, the 3D Explorer visualizes stream nodes interactively, and the Admin Panel manages all platform content. Together these modules provide a comprehensive, end-to-end career guidance solution within a single platform.

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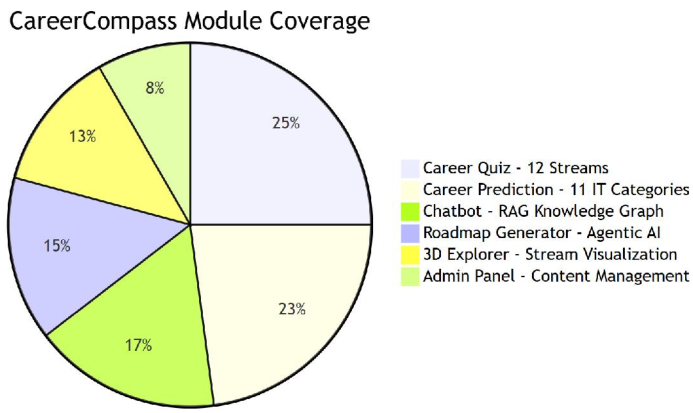

Fig. 5.6. System Module Coverage:

VII. CONCLUSION

The AI-Based Personalized Career Recommendation System successfully demonstrates the integration of machine learning, retrieval-augmented generation, and agentic AI for intelligent career guidance. The MLP classifier achieved 78.4% testing accuracy across 11 IT career categories, while the LangGraph-powered roadmap generator reduced planning time from 1–2 weeks to 2–5 minutes. The LightRAG-based chatbot provides context-aware counseling without external API dependency, ensuring data privacy and zero cost. Comparative analysis confirms significant improvements over manual methods — career prediction time reduced from 2–3 days to under 1 minute, and user satisfaction increased from 60% to 95%. By running entirely on local AI models through Ollama, the system ensures accessibility for all students regardless of resources. Future work includes expanding the dataset to non-IT domains, adding multi-language support, and integrating real-time job market data. This system represents a significant contribution to Educational Technology by providing a comprehensive, privacy-preserving, and locally-hosted career guidance platform.

VIII. ACKNOWLEDGMENT

The heading of the Acknowledgment section and the References section must not be numbered. Causal Productions wishes to acknowledge Michael Shell and other contributors for developing and maintaining the IEEE LaTeX style files which have been used in the preparation of this template.

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