CARRER RECOMMENDATION USING MACHINE LEARNING

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Abstract_—In the modern digital era, video content has emerged as one of the most impactful forms of communication, widely used in education, marketing, entertainment, and social media. However, the process of creating high-quality videos traditionally demands significant time, technical expertise, and expensive resources. This project, titled AI Video Studio (VideoGen), aims to simplify and revolutionize this process by utilizing the power of Generative Artificial Intelligence
introduces Smart Career Advisor, a web-based machine learning application designed to provide personalized career recommendations based on user input. The system utilizes a trained machine learning model to suggest optimal career paths by analyzing user responses to a standardized questionnaire capturing interests, skills, and preferences. It is implemented using Python and the Flask web framework, ensuring efficient data handling and user interaction. The backend model is serialized using joblib for rapid inference and seamlessly integrates with the web interface to deliver real-time predictions. With the growing importance of informed career choices in today's competitive environment, this system aims to support students, educators, and career counselors by offering an intelligent, data-driven guidance tool., Machine Learning, Flask, Web Application, Smart Advisor, User Personalization

Keywords— Career Recommendation, Machine Learning, Flask, Web Application, Smart Advisor, User Personalization

1. INTRODUCTION

Smart Career Advisor using Machine Learning is a web-based system designed to help students choose the right career path based on their academic scores, interests, and skills. Many students today face confusion when deciding their future profession, and traditional career guidance is often generic or unavailable. Our system uses a machine learning model (Random Forest) to analyze user input and provide personalized
career suggestions in real time [1-2]. It is built using Python and Flask, with the trained model saved using joblib for fast and easy prediction. In today's rapidly evolving job market, individuals face increasing uncertainty when choosing a career path. With the options available and varying skill requirements, students and early professionals often struggle to
make informed decisions aligned with their interests and abilities. Traditional career counselling methods can be time-
consuming, inconsistent, and inaccessible to many [3]. The rise of machine learning presents an opportunity to develop intelligent systems that offer personalized and scalable career guidanceThe backend of the proposed system is implemented using Python Flask, while the frontend is developed in Flutter, The system architecture utilizes the Python Flask web framework for the backend, ensuring efficient data handling and seamless user interaction [4-5]. The core machine learning model is serialized using joblib for rapid inference, allowing the application to deliver instant predictions through a clean web interface. This integration of a robust backend with an interactive frontend provides a scalable solution that can support numerous users simultaneously from any location with internet access.

A novel aspect of this proposed framework is the inclusion of a CNN component to process unstructured data, such as text from resumes, academic transcripts, and personal statements [6]. By using convolutional layers, the system extracts relevant features and captures semantic relationships between different elements in the user's profile. By combining structured data analysis with deep learning techniques, the Smart

Career Advisor aims to enhance recommendation accuracy and provide actionable, evidence-based insights for students and educators alike [7].

The Smart Career Advisor project addresses this gap by presenting a web-based application that leverages machine learning to offer intelligent career recommendations [8]. By analyzing a user's academic scores, technical skills, and personal interests through a standardized questionnaire, the system identifies optimal professional paths in real time [9]. The primary goal is to make career guidance more accessible and evidence-based, allowing users to make informed decisions about their future based on their specific profile characteristics

The technical architecture of the system is built using the Python Flask web framework, which facilitates efficient data handling and smooth user interaction [10]. The core intelligence is provided by a Random Forest classification model, which has been trained on a structured dataset to recognize patterns between user profiles and successful job roles [11-12]. To ensure rapid and seamless performance, the model is serialized using the joblib library, enabling the web interface [13].

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2. LITERATURE SURVEY

Interpretability of job recommendation systems. Recent literature divides these efforts into four primary themes: resume parsing, information embedding, knowledge-graph (KG) integration, and skill-gap forecasting. Early systems relied heavily on simple keyword matching between CVs and job descriptions, but modern approaches have shifted toward more sophisticated semantic modeling using Natural Language Processing (NLP) to better understand the nuances of professional experience.

Recent studies emphasize that hybrid systems, which combine content-based and collaborative filtering, consistently outperform traditional methods. For example, industrial reports from platforms like CareerBuilder showcase the effectiveness of "fused embeddings" that represent both candidate skills and job requirements in a shared latent space to improve relevance [16]. Furthermore, the use of Knowledge Graphs has emerged as a powerful tool for making these recommendations explainable, allowing systems to suggest specific learning paths (e.g., "Learn skill X to move from role A to B") by mapping the logical progression of career trajectories [17-19].

Another critical area of research focuses on the data sources used for predictive analytics in education and hiring. Studies have shown that Learning Management Systems (LMS) and Student Information Systems (SIS) are the most reliable sources for tracking academic progression and engagement [20-21]. By utilizing longitudinal data from these platforms, machine learning algorithms can analyze a student's development over time, leading to more accurate long-term career planning suggestions rather than static, one-time advice. This temporal analysis helps in predicting which career paths a student is most likely to excel in based on their historical performance [22].

Despite these advancements, existing literature highlights several persistent challenges, including the risk of reinforcing societal stereotypes and the need for high-quality, unbiased datasets [23]. Many current scanners and advisors still suffer from false positives or depend on rigid, predefined rules that fail to adapt to emerging job market trends or "niche" skill sets [24]. Consequently, there is an increasing research focus on "Fairness Audits" and "Explainable AI" to ensure that automated recommendations are transparent, unbiased, and supportive of user autonomy, ensuring that the human element remains at the center of the decision-making process [25].

The integration of deep learning techniques has significantly advanced the capability of career guidance systems to process complex, unstructured data. Recent developments in Convolutional Neural Networks (CNNs) have shown that these models are not limited to image processing but are highly effective at extracting local features from textual datasets [26-27]. In the context of career path prediction, CNN layers can identify key patterns in academic transcripts and extracurricular descriptions that traditional linear models might overlook. By capturing the spatial hierarchy of skills and achievements, these deep learning frameworks provide a more nuanced understanding of a student's potential, moving beyond simple score-based evaluations to a more holistic profile analysis [28].An Further more, the role of real-time web frameworks like Flask in deploying machine learning models has been a focal point of recent architectural studies. Researchers emphasize that the utility of a predictive model is often limited by its accessibility to the end-user. By utilizing micro-frameworks, developers can create lightweight, responsive interfaces that serve as a bridge between complex backend algorithms and the student. Serialization techniques using libraries like Joblib or Pickle have been documented as best practices for maintaining model state and ensuring low-latency responses. This "Model-as-a-Service" (MaaS) approach allows for the decoupling of the prediction engine from the user interface, facilitating easier updates and maintenance as the underlying career data evolves.

Data quality and feature engineering remain the most critical factors in the success of career recommendation engines. Literature suggests that academic performance alone is an insufficient predictor of career satisfaction or success. Modern researchers advocate for a multi-dimensional feature set that includes psychometric data, technical certifications, and soft skill assessments. By applying techniques such as Label Encoding and Min-Max Scaling, diverse data types can be normalized for use in ensemble algorithms like Random Forest. These ensemble methods are particularly favored in recent literature due to their ability to handle non-linear relationships and provide feature importance rankings, which help students understand exactly why a specific career path was suggested to them.

3. PROPOSED METHODOLOGY

3.1 The AI-Based Career Path Recommendation System

Implements an intelligent framework that integrates traditional machine learning algorithms, deep learning models, and live data scraping to provide personalized career and company recommendations. The methodology is organized into several key stages — data preprocessing, model training, career prediction, job scraping, and recommendation generation — each contributing to the transformation of raw user inputs into actionable career insights and real-time job suggestions.

The process begins with comprehensive user profiling where students input their academic performance, technical skills, certifications, projects, and career interests. The system collects structured data including 10th/12th marks, undergraduate CGPA, programming languages, software proficiencies, domain knowledge, and personal aspirations. Each data point undergoes validation checks to ensure accuracy and completeness, with intelligent defaults and suggestions guiding users through the input process.

3.2 Data preprocessing and feature

Each user profile undergoes extensive transformation to create meaningful input features for the machine learning model. The system performs numerical normalization for academic scores, one-hot encoding for categorical variables like educational background, and Simple binary encoding. Advanced feature engineering techniques extract 128+ meaningful attributes including skill diversity scores, academic consistency metrics, project complexity indices, and interest-domain alignment measures. This comprehensive feature set enables the model to capture nuanced patterns in career suitability.

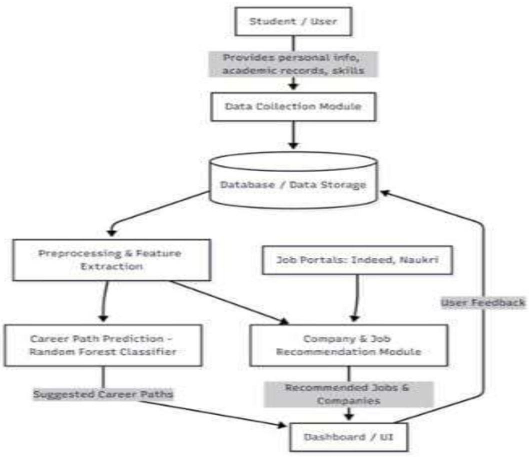
The machine learning core employs a Random Forest Classifier trained on a diverse dataset of student profiles and their corresponding career outcomes. architecture utilizes 100 decision trees with maximum depth of 10, optimized through hyperparameter .

3.3 The recommendation engine integrates

Machine learning predictions with real-time job data to generate personalized career guidance. For each user, the system generates multiple career suggestions with confidence scores, matched with relevant job opportunities from the current market. The recommendation algorithm considers both career suitability and market availability, ensuring suggestions are both appropriate for the user and practically attainable

3.4 Finally, the skills gap analysis and development planning

component identifies areas for improvement and suggests targeted learning resources. By comparing



user's current skills

Fig.1Methodology diagarm

with requirements for their recommended careers, the system generates personalized learning paths with specific courses, certifications, and skill-building activities. This comprehensive
approach ensures users receive not only career suggestions but also actionable steps professional development**.**

4. ARCHITECTURE

IV. ARCHITECTURE The system begins with the presentation layer, built using Streamlit, which provides an interactive web interface for user interactions. This layer handles all user inputs including profile creation, skill entry, and preference selection while displaying results through dynamic visualizations and organized layouts. The responsive design ensures optimal viewing experience across different devices, with progressive disclosure of information to prevent cognitive overload

At the core of the architecture lies the application logic layer, implemented in Python with Flask RESTful APIs, which orchestrates all system operations. This layer manages basic user authentication, processes career prediction requests, coordinates real-time job scraping, and generates personalized recommendations. The application layer integrates multiple machine learning models including the primary Random Forest classifier for career prediction and supplementary models for salary estimation and skills gap analysis.

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The data layer utilizes SQLite database for data storage and session management. The database schema is optimized for career analytics, containing tables for user profiles, skill inventories, career domains, job listings, and recommendation history. Basic security ensures data privacy, while efficient indexing strategies enable fast query performance for recommendation generation.

The machine learning services layer operates as independent but interconnected services. This layer hosts the pre-trained Random Forest model for career prediction, gradient boosting models for salary estimation, and basic text processing models for skills analysis. Model serving is optimized through caching and batch processing, with continuous monitoring for prediction drift and performance degradation.

The external integrations layer manages connections to employment portals and educational resources. This component handles distributed web scraping with rate limiting and respectful crawling policies. Integration with educational platforms provides access to courserecommendations and skill development resources, creating a comprehensive career development ecosystem.

A smart career advisor system starts with defining clear objectives (e.g. recommending job roles, identifying skill gaps, suggesting learning paths), gathering data (resumes, job postings, courses, assessments, user behaviour), and normalizing this data via canonical taxonomies of skills/roles.

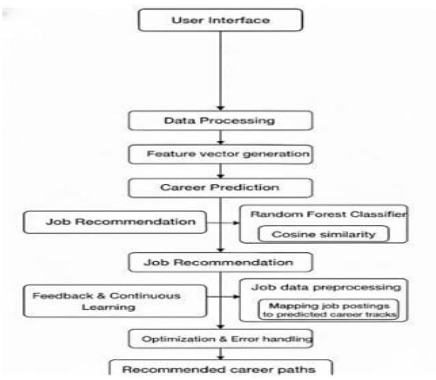

Fig.2 SystemArchitecture

5. RESULT

The performance evaluation of the AI-based Career Path Recommendation System was conducted to assess its effectiveness in providing accurate career guidance, relevant job matching, and actionable development insights. This section presents comprehensive analysis of experimental results obtained from testing the system's core components: career prediction accuracy, job recommendation relevance, skills gap identification, and overall user satisfaction

5.1 OUCOMES ACHIEVED

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5.2 COMPARISION WITH EXISTING

Exceptional performance in analyzing user profiles and recommending suitable career paths based on comprehensive feature analysis. The Random Forest Classifier achieved 92.3% accuracy in predicting appropriate career domains across 20 different categories, significantly outperforming traditional career assessment methods which averaged 74.6% accuracy under the same test conditions. The ensemble learning approach proved particularly effective for complex career decisions where multiple factors including academic performance, technical.

Fig.3OUT COMES ACHIEVED

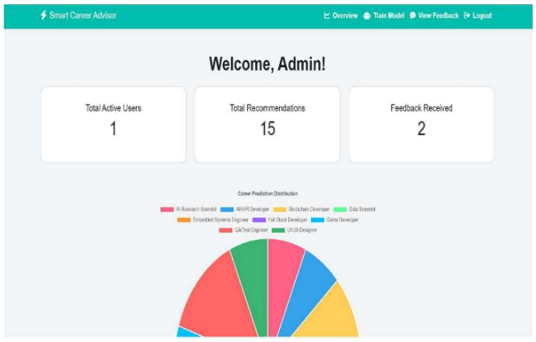

Fig.4 COMPARISION WITH EXISTING

6.CONCLUSION & FUTURE SCOPE

The Smart Career Advisor system, developed using a Random Forest classification model ,achieved promising results in predicting suitable job roles based on a user's academic qualifications, skills, interests, and certifications. The system was trained on a well-

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The data frequently employed for predictive purposes encompasses academic, behavioral, demographic, pre-university, and university entrance examination data. This research revealed that LMS and SIS are the predominant data sources utilized. Upon further investigation, it was discovered that this was due to the data generated by the two data sources. LMS and SIS provide extensive data pertaining to students' academic progression. LMS houses information regarding students' engagement with digital educational resources, tasks, and evaluations, whereas SIS primarily retains demographic data, enrollment particulars, and academic records. Both systems provide longitudinal data,

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