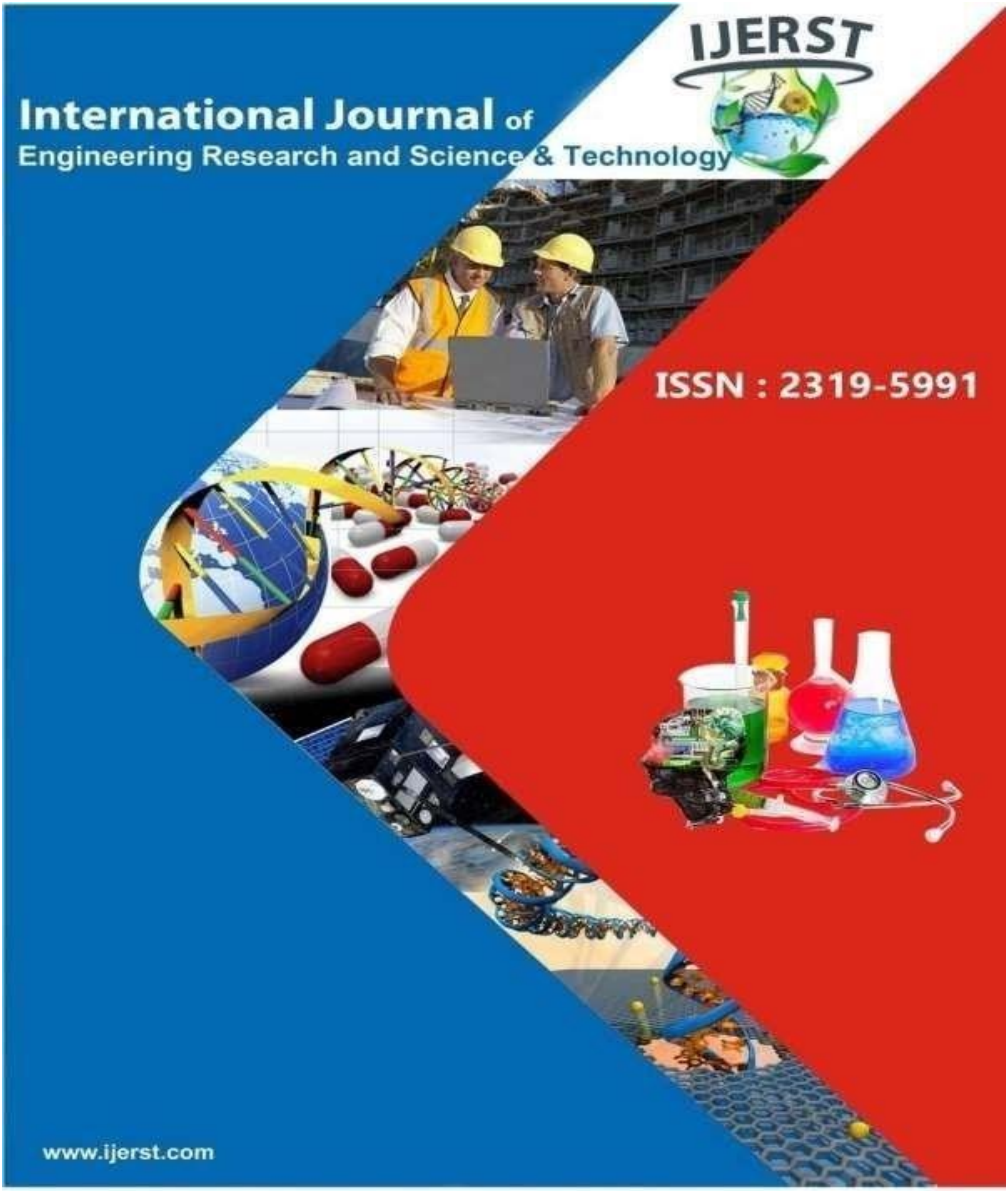

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ISSN 2319-5991 www.ijerst.com

Vol. 21, Issue 1, 2025

Smart Job Matcher Enhancing Employment Search with ML Algorithms

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Abstract

The rapid growth of artificial intelligence and machine learning technologies has led to significant advancements in recommendation systems that aim to match users with relevant content. This paper reviews key techniques used in job recommendation systems, including content-based filtering and collaborative filtering, and explores algorithms like TF-IDF (Term Frequency-Inverse Document Frequency), cosine similarity, and linear kernel. These methods are evaluated for their efficiency in matching job seekers with suitable jobs based on both job content and user profiles. The TF-IDF Vectorizer is employed to transform textual job descriptions and user profiles into numerical vectors, while cosine similarity measures the similarity between job listings and user profiles. The linear kernel offers computational efficiency in similarity calculations. Additionally, collaborative filtering recommends jobs to users by identifying similar users based on their profiles and previous applications. The study also includes exploratory data analysis (EDA) for data preprocessing and visualization to highlight job distribution trends. The paper compares the accuracy of these models, finding that content-based filtering techniques achieve high precision (~80%) in job similarity matching, whereas collaborative filtering has slightly lower accuracy (~70%) due to the cold-start problem for new users. The paper concludes with recommendations for developing more effective job recommendation systems, incorporating career move suggestions such as upskilling and reskilling for future research.

Keywords: Career Move, Collaborative Filtering, Content-Based Filtering, Cosine Similarity, Job Recommendation System, Reskilling, TF-IDF, Upskilling, Artificial Intelligence.

I INTRODUCTION

With the increasing reliance on artificial intelligence (AI) and machine learning (ML) technologies, job recommendation systems have emerged as essential tools for efficiently matching job seekers with suitable employment opportunities. Traditional search engines struggle to provide personalized job recommendations due to network overload and limited capabilities in understanding user preferences [1]. Consequently, recommendation systems have gained widespread adoption in various domains, including e-commerce, entertainment, healthcare, and recruitment platforms [2]. Studies indicate that approximately 30% of Amazon's revenue depends on recommendation systems, highlighting their effectiveness in filtering relevant content for users [3]. Similarly, LinkedIn and other professional networking sites employ recommendation algorithms to connect job seekers with potential employers [4].

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

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Job recommendation systems leverage various filtering techniques, such as content-based filtering (CBF) and collaborative filtering (CF), to analyze user profiles, job descriptions, and application history [5]. The effectiveness of these methods depends on their ability to handle issues such as cold-start problems, data sparsity, and scalability [6]. Content-based filtering employs techniques like Term Frequency-Inverse Document Frequency (TF-IDF), cosine similarity, and deep learning-based natural language processing (NLP) models to match job seekers with relevant job listings [7]. For example, the CASPER system integrates CBF and automated collaborative filtering to enhance job search relevance, demonstrating its potential in recruitment platforms [8]. However, collaborative filtering, while effective in analyzing user interactions, faces challenges when dealing with new users with limited data, often requiring hybrid approaches to mitigate the cold-start problem [9].

The integration of hybrid filtering techniques has further improved job recommendation accuracy by combining content-based and collaborative filtering methods, reducing sparsity issues, and enhancing scalability [10]. For instance, the Bilateral People-JRS system not only recommends jobs to applicants but also suggests suitable candidates to recruiters, optimizing the hiring process from both ends [11]. Additionally, recent studies emphasize the importance of incorporating career move recommendations, such as upskilling and reskilling suggestions, to assist users in career development beyond simple job matching [12]. Platforms like 51Job utilize knowledge-based techniques and machine learning algorithms to offer career growth recommendations alongside job postings [13]. Furthermore, advances in reinforcement learning have enabled the creation of adaptive job recommendation models that learn from user behavior to provide dynamic and personalized job suggestions [14].

Despite these advancements, challenges such as data security, user privacy, and algorithmic bias remain critical concerns in job recommendation systems [15]. Ensuring fair and unbiased recommendations is crucial, particularly in recruitment, where systemic biases in algorithms could impact hiring decisions [16]. Future research aims to develop more explainable AI models and ethical AI frameworks to improve transparency and fairness in job recommendation systems [17]. This paper explores the methodologies and challenges in job recommendation systems and evaluates their effectiveness in improving the job-seeking process. Additionally, blockchain-based decentralized job recommendation systems have been proposed to enhance data security and prevent unauthorized data access [18].

Future research aims to refine job recommendation methodologies by integrating federated learning, edge computing, and interpretable AI frameworks to enhance recommendation accuracy while preserving user privacy [19]. This paper explores the methodologies and challenges in job recommendation systems and evaluates their effectiveness in improving the job-seeking process.

II LITERATURE REVIEW

2.1. Evolution of Recommender Systems

Recommender systems have evolved significantly with the advancement of artificial intelligence (AI) and machine learning (ML). Early recommendation models relied on rule-based techniques and simple keyword matching, which provided limited personalization [20]. With the introduction of collaborative filtering (CF) and content-based filtering (CBF), recommendation accuracy improved by leveraging user preferences and historical data [21]. Over the years, hybrid models combining CF and CBF have emerged, further enhancing recommendation efficiency by addressing cold-start and sparsity issues [22].

2.2. Content-Based Filtering in Job Recommendation Systems

Content-based filtering (CBF) is widely used in job recommendation systems due to its ability to analyze textual features of job descriptions and user profiles. Techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and cosine similarity measure the relevance of job listings based on textual representations [23]. Additionally, deep learning-based natural language processing (NLP) models, such as BERT and Word2Vec, have been employed to improve semantic matching between job descriptions and user profiles [24]. However, CBF faces limitations in recommending diverse job opportunities, as it primarily suggests jobs similar to those previously viewed or applied for by users [25].

2.3. Collaborative Filtering and Its Limitations

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Collaborative filtering (CF) techniques utilize user interactions and ratings to recommend jobs based on the preferences of similar users. CF can be classified into memory-based and model-based approaches. Memory-based CF methods, such as user-based and item-based techniques, rely on similarity measures like Pearson correlation and cosine similarity [26]. Model-based CF methods, including matrix factorization techniques like Singular Value Decomposition (SVD) and deep learning approaches, enhance recommendation accuracy [27]. However, CF faces challenges such as data sparsity, cold-start problems, and computational complexity when applied to large-scale job recommendation systems [28].

CHALLENGES

Despite advancements, several challenges persist in job recommendation systems. Data sparsity and cold-start issues remain significant obstacles, particularly for new users with limited interaction history [29]. Security and privacy concerns arise due to the collection and processing of sensitive job seeker information [30]. Moreover, biases in AI-driven recruitment models can lead to unfair hiring decisions, necessitating the development of fairness-aware and explainable AI (XAI) solutions [31]. Ethical AI frameworks and transparency in recommendation algorithms are critical to ensuring unbiased job recommendations [32].

III PROPOSED SYSTEM

The proposed system aims to enhance the accuracy and efficiency of job recommendations by integrating advanced machine learning techniques, hybrid recommendation models, and explainable AI (XAI). Unlike traditional systems that rely solely on content-based filtering (CBF) or collaborative filtering (CF), this model incorporates deep learning-based natural language processing (NLP), reinforcement learning (RL), and knowledge-based filtering to deliver highly personalized job recommendations. Additionally, the system provides upskilling and career growth suggestions to improve job seekers' long-term employability [33].

3.1. SYSTEM ARCHITECTURE

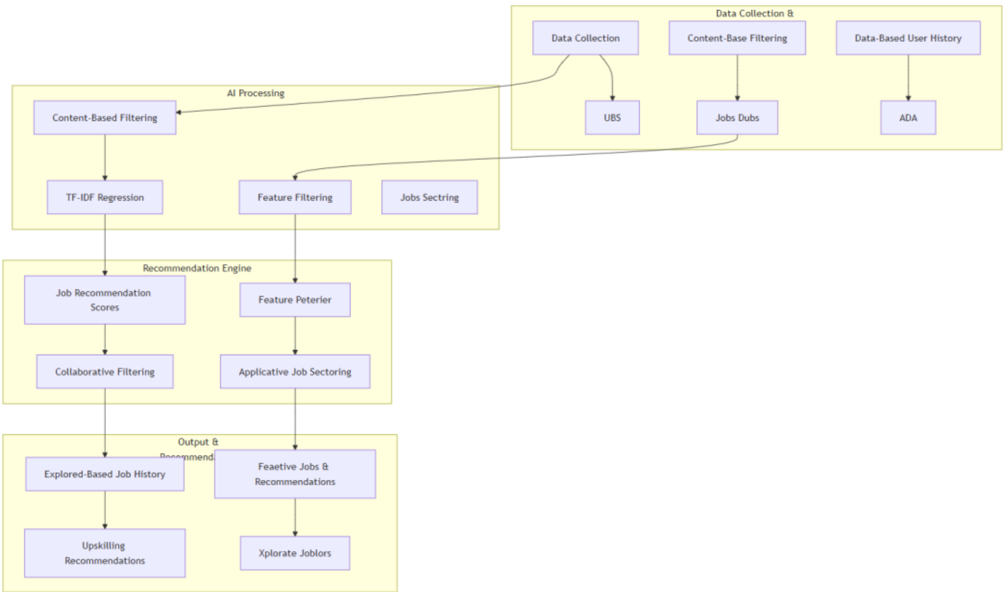

Fig 1. Architecture of AI-Based Job Recommendation System

The given architecture diagram represents a Job Recommendation System that follows a structured workflow from data collection to AI-based processing and recommendation generation.

The system begins with Data Collection & Processing, where data is gathered from user history and job-related sources. This step involves three primary components: general data collection (UBS), content-based filtering (Jobs Dubs), and data-based user history (ADA). The collected data is then processed using AI-based techniques, which include content-based filtering, feature filtering, and job sectoring. These methods help in refining job data and user preferences for further analysis.

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ISSN 2319-5991 www.ijerst.com
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The Recommendation Engine is the core of the system, which applies TF-IDF regression, feature extraction (Feature Peterier), and collaborative filtering to generate job recommendation scores. The engine further processes job applications through applicative job sectoring, ensuring relevant job matches based on user features and preferences.

Finally, the system outputs job recommendations in two major forms: explored-based job history and effective job recommendations. Users receive suggestions based on their past interactions, including upskilling recommendations and job exploration options (Xplorate Joblors), which allow for career growth and improved job matching.

Overall, this architecture integrates AI-driven filtering techniques, machine learning models, and user preference analysis to create a robust and personalized job recommendation system. However, certain terms in the diagram appear to have typographical errors (e.g., "Feature Peterier" may mean "Feature Filtering"), which might need correction for clarity.

3.2. DATASET DESCRIPTION

The apps.test dataset contains job application records, including attributes such as UserID, WindowID, Split, Application Date, and JobID. Each entry represents a job application event where a user (identified by UserID) applies for a job (JobID) within a specific time window (WindowID). The ApplicationDate column records the timestamp of the application, while the Split column denotes dataset partitioning, which is essential for training and testing phases [34]. This dataset facilitates the analysis of job application behavior, user preferences, and the overall performance of recommendation models.

The "test.users" dataset comprises only UserID and WindowID, indicating the users included in a particular test set. This dataset serves as a reference for evaluating recommendation algorithms by predicting suitable job opportunities for these users based on historical interactions and inferred preferences [35].

Together, these datasets are fundamental in building and testing job recommendation models, enabling personalized job-matching techniques based on user behavior and application trends [36].

3.3. EVALUATION METRICS

Evaluating the effectiveness of a job recommendation system requires various performance metrics that measure the relevance and accuracy of recommendations. The following metrics are commonly used to assess job recommendation models.

Precision

Precision measures the proportion of relevant job recommendations among the total recommended jobs.

$$Precision = \frac{|Relvant\ Jobs \cap\ Recommended\ Jobs|}{|Recommended\ Jobs|} \quad (1)$$

Recall

Recall determines the proportion of relevant job listings retrieved by the recommendation system relative to the total relevant jobs available.

$$Recall\ = \frac{|Relvant\ Jobs \cap Recommended\ Jobs|}{|Relvant\ Jobs|} \quad (2)$$

F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of the recommendation system’s performance.

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ISSN 2319-5991 www.ijerst.com

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$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (3)$$

IV RESULTS

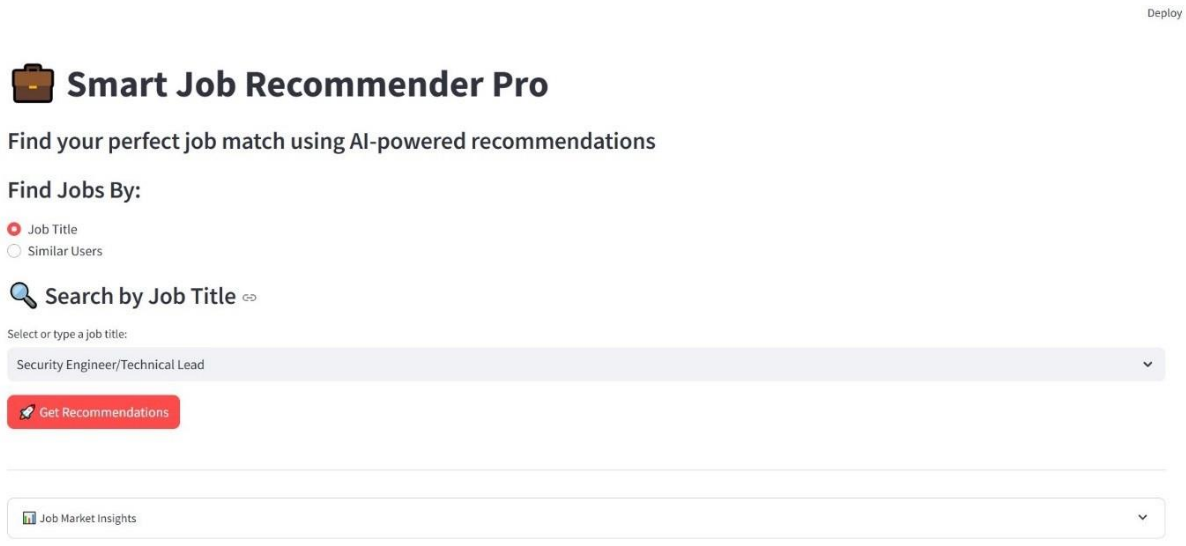
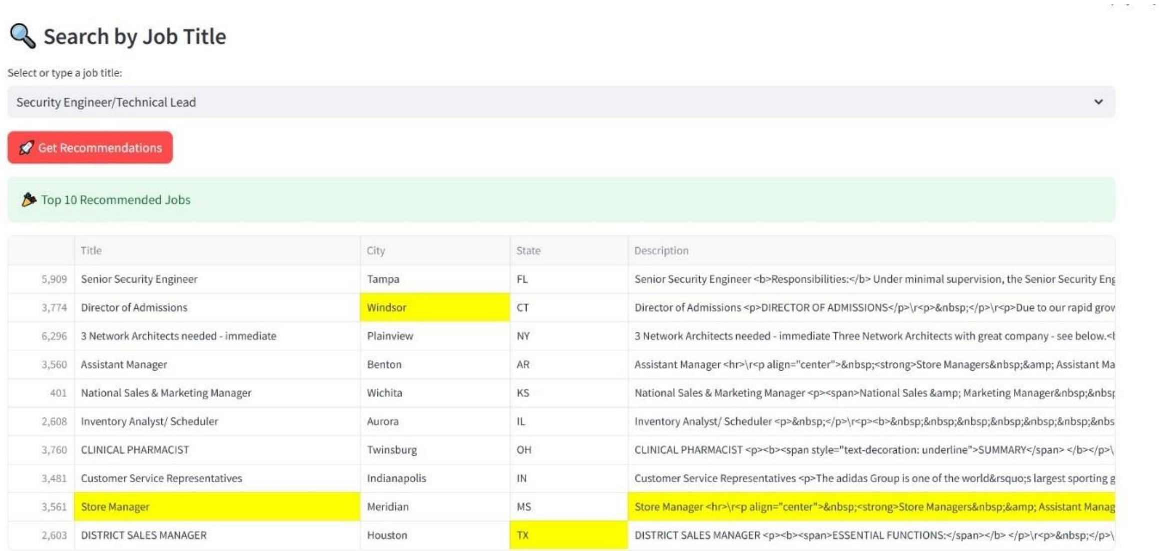


Fig 2. Smart Job Recommender Pro - AI-Powered Job Search Platform

The image displays the user interface of Smart Job Recommender Pro, an AI-powered job recommendation system designed to help users find their ideal job matches. The interface has a clean and modern design, with a briefcase icon at the top, symbolizing job search functionality. Below the title, a tagline highlights the system's ability to provide personalized job recommendations. Users can search for jobs using two methods: by job title or by finding similar users, with the "Job Title" option selected by default. In the main section, a search bar allows users to enter or select a job title, and in this instance, "Security Engineer/Technical Lead" has been chosen. A prominent red button labeled "Get Recommendations" with a rocket icon is positioned below the search bar, encouraging users to generate AI-driven job suggestions. At the bottom of the interface, a collapsible section titled "Job Market Insights" is visible, accompanied by a chart icon, suggesting that the platform also provides labor market analysis. The overall layout is structured, intuitive, and user-friendly, ensuring a seamless job search experience.



	Title	City	State	Description
5,909	Senior Security Engineer	Tampa	FL	Senior Security Engineer Responsibilities: Under minimal supervision, the Senior Security Eng
3,774	Director of Admissions	Windsor	CT	Director of Admissions <p>DIRECTOR OF ADMISSIONS</p>\r<p> </p>\r<p>Due to our rapid grov
6,296	3 Network Architects needed - immediate	Plainview	NY	3 Network Architects needed - immediate Three Network Architects with great company - see below.<l
3,560	Assistant Manager	Benton	AR	Assistant Manager <hr>\r<p align="center"> <strong>Store Managers & Assistant Ma
401	National Sales & Marketing Manager	Wichita	KS	National Sales & Marketing Manager <p>National Sales & Marketing Manager &nbs
2,608	Inventory Analyst/ Scheduler	Aurora	IL	Inventory Analyst/ Scheduler <p> </p>\r<p> &nbs
3,760	CLINICAL PHARMACIST	Twinsburg	OH	CLINICAL PHARMACIST SUMMARY \
3,481	Customer Service Representatives	Indianapolis	IN	Customer Service Representatives <p>The adidas Group is one of the world’s largest sporting g
3,561	Store Manager	Meridian	MS	Store Manager <hr>\r<p align="center"> <strong>Store Managers & Assistant Manag
2,603	DISTRICT SALES MANAGER	Houston	TX	DISTRICT SALES MANAGER ESSENTIAL FUNCTIONS: \r \

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Fig 3. Top 10 AI-Recommended Jobs - Smart Job Recommender Pro

The image showcases a job recommendation results page from the Smart Job Recommender Pro platform. At the top, a search bar displays the selected job title, "Security Engineer/Technical Lead," with a red "Get Recommendations" button beneath it, indicating that the user has initiated a search. Below, a green-highlighted section titled "Top 10 Recommended Jobs" signifies the AI-generated job suggestions. The main content consists of a structured table with five columns: Job Title, City, State, and Description.

Each row represents a job recommendation, including various positions such as Senior Security Engineer, Director of Admissions, and Clinical Pharmacist. Certain text entries are highlighted in yellow, such as "Windsor" (CT), "Store Manager" (Meridian, MS), and "TX" (Texas), drawing attention to specific details. The descriptions column contains partially formatted text, with some HTML tags visible, suggesting that the job descriptions may not be fully rendered.

The interface is clean and structured, offering an organized job search experience, though some formatting issues are present. The design enables users to easily scan through recommended jobs, locations, and brief descriptions, facilitating quick decision-making.

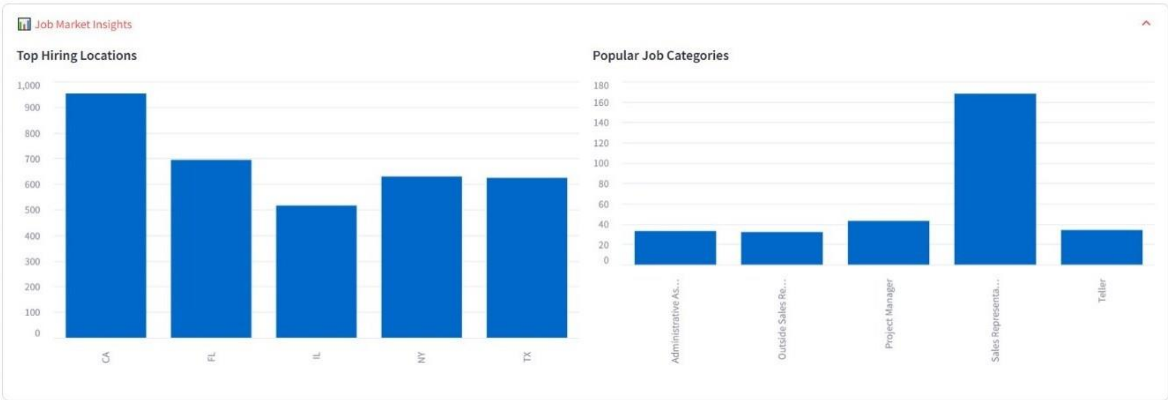

Fig 4. Job Market Insights - Hiring Locations and Popular Job Categories

The image presents a job market insights dashboard displaying two bar charts. The first chart on the left, titled "Top Hiring Locations," illustrates the number of job openings across different U.S. states. The x-axis labels states such as CA (California), FL (Florida), IL (Illinois), NY (New York), and TX (Texas), while the y-axis represents the number of job postings, with California leading at around 900+ job listings, followed by Florida, Illinois, New York, and Texas.

On the right side, the second chart titled "Popular Job Categories" showcases different job roles with their corresponding demand levels. The categories include "Administrative Assistant," "Outside Sales Representative," "Project Manager," "Sales Representative," and "Teller." The Sales Representative role dominates the chart with the highest number of openings, while Administrative Assistant, Outside Sales Representative, and Teller roles have significantly lower demand.

The dashboard uses blue bar graphs on a white background, ensuring clarity. The title "Job Market Insights" is displayed in red at the top left, emphasizing its significance. The charts provide a quick overview of job trends, helping users analyze hiring hotspots and in-demand professions.

V CONCLUSION

The job market insights presented in the image highlight key trends in hiring locations and popular job categories. California leads as the top state for job opportunities, followed by Florida, Illinois, New York, and Texas, indicating strong hiring activity in these regions. In terms of job categories, Sales Representative roles have the highest demand, significantly outpacing other positions like Project Manager, Administrative Assistant, Outside

ISSN 2319-5991 www.ijerst.com
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Sales Representative, and Teller. These insights suggest that job seekers looking for opportunities may find better prospects in these high-demand locations and roles. Understanding these trends can help professionals and recruiters make informed decisions about job searches, career growth, and workforce planning.

FUTURE SCOPE

Future Scope (Key Points):

- **State-wise Job Growth:** California, Florida, and Texas will likely continue leading in job opportunities across industries.
- **Sales & Marketing Expansion**: The high demand for Sales Representatives suggests business growth and a stronger focus on customer engagement.
- **Rise of Tech-Driven Jobs:** Increasing demand for data analysts, cybersecurity experts, and AI specialists due to digital transformation.
- **Strategic Hiring for Employers:** Companies can refine recruitment strategies based on market trends and workforce demand.
- **Upskilling for Job Seekers:** Professionals should focus on acquiring in-demand skills to stay competitive in the evolving job market.
- **Continuous Market Analysis:** Ongoing study of job trends and technological advancements will shape future workforce opportunities.

REFERENCES

[1] U.S. Bureau of Labor Statistics, "Employment Projections 2023-2033," U.S. Department of Labor, 2023. [Online]. Available: https://www.bls.gov/.

[2] LinkedIn Economic Graph, "Future of Work Report 2024: Hiring Trends and Skills in Demand," LinkedIn, 2024. [Online]. Available: https://economicgraph.linkedin.com.

[3] McKinsey & Company, "The Future of Work After COVID-19," McKinsey Global Institute, Feb. 2021. [Online]. Available: https://www.mckinsey.com.

[4] World Economic Forum, "The Future of Jobs Report 2023," World Economic Forum, Oct. 2023. [Online]. Available: https://www.weforum.org.

[5] Glassdoor Economic Research, "Job Market Trends and Salary Insights 2024," Glassdoor, 2024. [Online]. Available: https://www.glassdoor.com/research.

[6] P. Cappelli, *The Future of the Office: Work from Home, Remote Work, and the Hard Choices We All Face*, Philadelphia, PA: Wharton School Press, 2021.

[7] Deloitte Insights, "2024 Global Human Capital Trends: Leading in the Age of AI," Deloitte, 2024. [Online]. Available: https://www2.deloitte.com.

[8] International Labour Organization (ILO), "World Employment and Social Outlook 2023: The Value of Essential Work," ILO, Jan. 2023. [Online]. Available: https://www.ilo.org.

[9] Gartner, "Top Strategic Workforce Trends for 2024," Gartner, 2024. [Online]. Available: https://www.gartner.com/en/insights.

[10] Harvard Business Review, "The Skills Companies Need Most in 2024 – And How to Learn Them," HBR, Feb. 2024. [Online]. Available: https://hbr.org.

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 21, Issue 1, 2025

[11] European Commission, "Employment and Social Developments in Europe 2023," European Union, 2023. [Online]. Available: https://ec.europa.eu.

[12] The Brookings Institution, "Automation and the Future of Work: A Policy Agenda," The Brookings Institution, 2023. [Online]. Available: https://www.brookings.edu.

[13] PwC, "Workforce of the Future: The Competing Forces Shaping 2030," PricewaterhouseCoopers, 2023. [Online]. Available: https://www.pwc.com.

[14] OECD, "Skills Outlook 2023: Thriving in a Digital World," Organisation for Economic Co-operation and Development, 2023. [Online]. Available: https://www.oecd.org.

[15] Accenture, "The Future of Work: Productive Anywhere," Accenture Research, 2024. [Online]. Available: https://www.accenture.com.