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Design and Implementation of an Integrated Analytics and Recommendation Framework for the Punjab Government Rozgar and Karobar Mission (PGRKAM) Platform

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Abstract: The Punjab Government Rozgar and Karobar Mis-sion (PGRKAM) was created as a large-scale digital platform to connect job seekers and employers. While it has managed to attract a broad user base, its current format remains closer to a digital notice board than an intelligent job portal. This paper proposes a technical framework to improve PGRKAM by introducing advanced analytics and a hybrid recommendation system. The recommendation system makes use of Genetic Algorithms (GA) to match skills and qualifications with job requirements and Collaborative Filtering (CF) to learn from user behaviour patterns. To help administrators, the design also includes interactive dashboards that display trends in user activities, employer participation, and job market needs. The overall architecture is built to be scalable with data protection in mind, incorporating strong encryption to remain aligned with India's Personal Data Protection Bill (PDPB). With these improvements, PGRKAM can move from being a static listing of jobs to a responsive and intelligent job marketplace, improving job placements and greatly enhancing user satisfaction.
Index Terms: PGRKAM, Recommendation Systems, Ge-netic Algorithms, Collaborative Filtering, Data Analytics, E-Governance, PDPB Compliance.

I. INTRODUCTION

In today's job market, online platforms are becoming crucial points of connection between workers and employers. The Punjab Government's Rozgar and Karobar Mission (PGR) is an important government initiative in this direction, which aims at providing a common space for candidates and re-cruiters. However, the platform mainly works as a listing service, without advanced analytics or intelligence. This re-duces its effectiveness as administrators cannot easily identify problem areas, track engagement patterns, or measure how well jobs are being matched with candidates. Private platforms like LinkedIn or Indeed have raised the standard by using data and machine learning to deliver highly personal recommenda-tions. Users of those platforms get suggestions that match their profiles, enhancing the efficiency on both sides. If PGRKAM is equipped with similar analytical tools, it could serve as a government-mandated listing service and also as a state-level employment intelligence hub. This work presents a redesign of PGRKAM built around a recommendation engine that combines Collaborative Filtering with genetic optimization techniques. Additionally, analytics dashboards are proposed for government administrators and policy planners, enabling a more data-driven approach to bridging employment gaps.

II. RELATED WORK

Research in recommendation systems has shown that hybrid approaches—those that merge content-based and behaviour-based methods—generally perform better than single-technique models [6], [8], [10]. Content-based recom-mendations are strong in qualifications and skill matching, while collaborative filtering learns from past behaviour across users [7]. Together, they balance precision with adaptability. In India's e-governance space, examples such as the National Career Service (NCS) exist [11], [12]. However, they essen-tially stop at basic functionalities and are yet to offer real-time analytics or personalized intelligence [16]. This exposes a clear gap between public-sector and private-sector offerings, which motivated our work. Genetic Algorithms have been widely studied for matching problems, especially where both user profiles and job requirements involve multiple parameters [9]. The limitation, however, is that GAs alone can be heavy on computation.

Therefore, combining GA with collaborative filtering makes the system viable in real-world, large-scale scenarios like PGRKAM. Since employment and personal data are sensitive, it is of great importance to follow rules like the PDPB. A good system must incorporate robust, built-in encryption to hide personal details and clearly explain how data is used. The underlying security of such a system relies on modern cryptographic principles and lightweight security schemes to protect user data effectively, especially in large-scale deployments [1]–[5].

III. PROPOSED FRAMEWORK ARCHITECTURE

The proposed system is designed with a modular architecture that integrates a third-party analytics service with a custom-built recommendation engine to provide a comprehensive solution.

A. *System Overview*

The architecture is composed of two parallel data pipelines that converge at the visualization layer.

- Analytics Pipeline: User interactions on the PGRKAM web and mobile apps are captured by an integrated Analytics SDK, similar to established platforms like Google Analytics, Mixpanel, or Kissmetrics [13]–[15]. This SDK tracks events like page views, sessions, user demographics, and acquisition channels (via UTM param-eters) and sends this data directly to the analytics service for processing.
- Recommendation Pipeline: In parallel, user profile data, job listings, and application data are stored in the plat-form's primary database. This structured data is fed into a custom Recommendation Engine, which runs the GA and CF algorithms to generate job suggestions and analyze application outcomes.

Both pipelines feed into a unified Admin Analytics Dash-board. The dashboard pulls general user behavior metrics from the analytics service's API and specialized recommendation performance metrics from the custom engine. This creates a single, comprehensive view for administrators. This dual-pipeline architecture is illustrated in Fig. 1.

B. *Data Modeling*

The system relies on a well-structured data model within the PGRKAM primary database to power the recommendation engine. The core entities are:

- Users Table: Stores demographic details, education, and skill sets.
- Jobs Table: Contains detailed job requirements, location, and employer data.
- Events Table: Logs key interactions relevant to job matching, such as searches and clicks.
- Applications Table: Records application history and outcomes (success/failure).

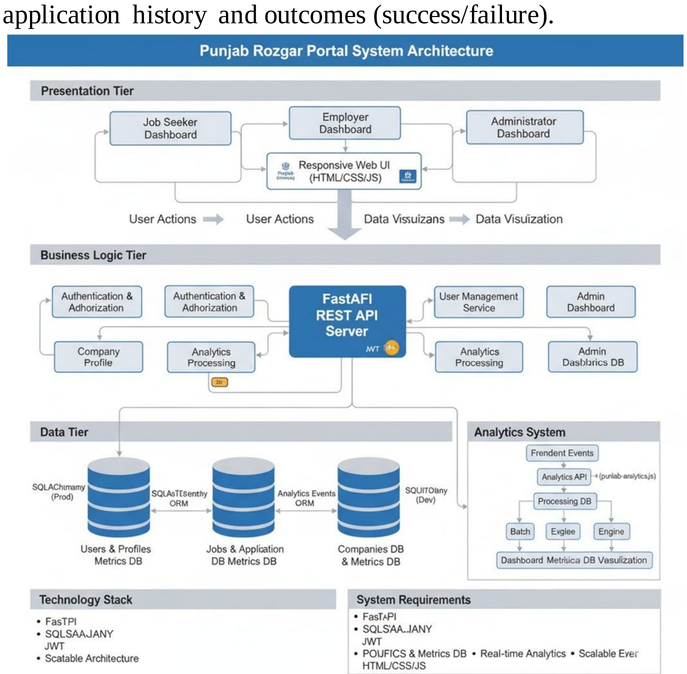

Fig. 1. System architecture illustrating data flow and core components.

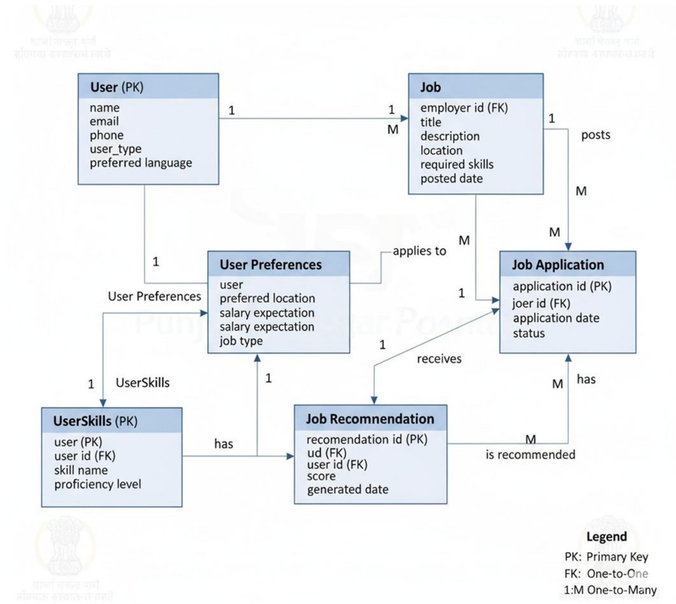

Fig. 2. Entity Relationship Diagram of the Job Recommendation System.

IV. HYBRID RECOMMENDATION ENGINE

A. *Collaborative Filtering for Behavior-Based Suggestions*

The Collaborative Filtering (CF) component generates rec-ommendations by identifying patterns in collective user behav-ior. It operates on the principle that users who have agreed in the past will agree in the future. We use the Pearson correlation coefficient to measure similarity between users:

$$\mathrm{sim}(u, v) = \frac{\sum_{i \in I_{uv}} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in I_{uv}} (r_{u,i} - \bar{r}_u)^2} \cdot \sqrt{\sum_{i \in I_{uv}} (r_{v,i} - \bar{r}_v)^2}} \quad (1)$$

where:

I_{uv} : the set of jobs that user u and user v have interacted (e.g., viewed or applied).

$r_{u,i}$: the rating or implicit interest score of user u for job i. $\bar{r}_u$: the average interest score of user u.

$\bar{r}_v$: the average interest score of user v.

B. *Genetic Algorithm for Optimal Profile Matching*

The Genetic Algorithm (GA) treats the job matching process as an optimization problem. It is used to find the best possible match between a candidate's profile and a job's requirements.

- Encoding: User profiles and job descriptions are encoded into chromosomal structures.
- Fitness Function: A fitness function evaluates how well a candidate matches a job based on weighted criteria like skills, experience, and location.

The fitness of a candidate C for a job J is:

$$F(U, J) = w_1 \cdot S(U_{\text{skills}}, J_{\text{req}}) + w_2 \cdot L(U_{\text{loc}}, J_{\text{loc}}) + w_3 \cdot E(U_{\text{exp}}, J_{\text{exp}}) \quad (2)$$

where:

$S(U_{\text{skills}}, J_{\text{req}})$: score of skills match (Jaccard similarity).

$L(U_{\text{loc}}, J_{\text{loc}})$: location match score.

$E(U_{\text{exp}}, J_{\text{exp}})$: experience match score.

w_1, w_2, w_3 : weights ($w_1 + w_2 + w_3 = 1$).

V. IMPLEMENTATION AND VISUALIZATION

A. Technology Stack

- Analytics Integration: The PGRKAM front-end (web and mobile) will integrate the Google Analytics SDK to send user behavior data to the Google Analytics platform.
- Backend Engine: The recommendation engine will be built in Python, using libraries like Scikit-learn and NumPy.
- Data Storage: A PostgreSQL database will store user, job, and application data, with Redis used for caching.
- Visualization: The admin dashboard will be a custom web application built with a framework like React or Angular, using visualization libraries such as D3.js or Chart.js. It will pull data from the Google Analytics Reporting API and a custom REST API connected to the recommendation engine.

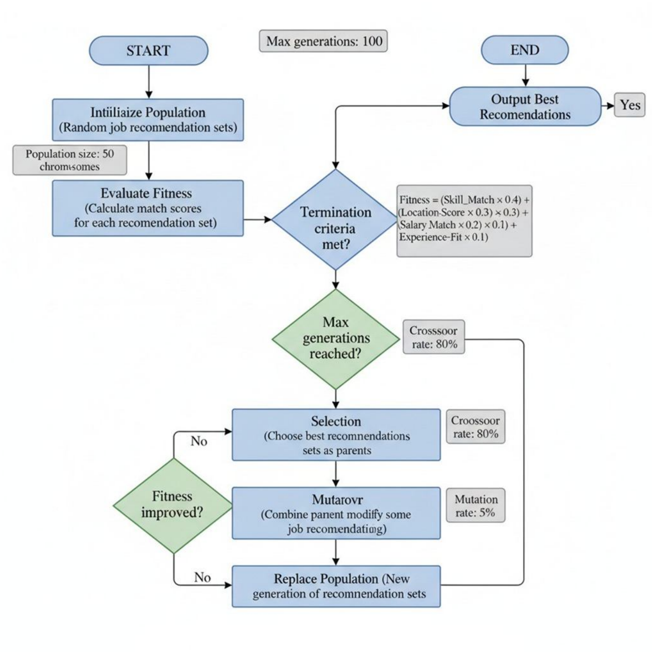

Fig. 3. Genetic Algorithm Flowchart for Job Recommendations.

Fig. 4. Analytics Dashboard Visualization of Job Market Trends and Engagement.

B. Administrator Analytics Dashboard

The dashboard will provide a unified view of all captured data, featuring:

- Acquisition & Demographics: Reports and charts on user traffic sources and demographics, powered by the Google Analytics API.
- User Engagement: Funnel visualizations showing the user journey from registration to application, helping to identify drop-off points.

- Recommendation Performance: Custom widgets display-ing the click-through rate of recommended jobs and the overall success rate of applications initiated through recommendations.
- Job Market Trends: Visualizations of the most in-demand skills and roles, derived from the recommendation en-gine's analysis.

VI. EVALUATION AND ANALYSIS

To build a complete picture of our proposed framework's performance, we designed an evaluation with two distinct parts. First, we conduct a technical assessment to measure the accuracy of our hybrid recommendation engine. Using the well-established metrics of Precision and Recall, we can determine how effectively the algorithm performs its core task of matching candidates with jobs. Second, we perform a comparative analysis, placing our integrated system alongside other common solutions to highlight its unique functional strengths. By combining these quantitative and qualitative views, we can confidently assess the framework's real-world impact on the PGRKAM platform.

A. Performance Evaluation Metrics

The success of any recommendation system hinges on its accuracy. We quantify this using Precision and Recall, standard measures for evaluating information retrieval systems. Precision answers the question: "Of the jobs we recommended, how many were a good fit?" In contrast, Recall addresses: "Of all the possible good jobs for a user, how many did we successfully find?" Together, these metrics provide a robust understanding of the engine's performance.

The formulas are defined as:

$$\text{Precision} = \frac{|\text{Relevant Jobs} \cap \text{Recommended Jobs}|}{|\text{Recommended Jobs}|} \quad (3)$$

$$\text{Recall} = \frac{|\text{Relevant Jobs} \cap \text{Recommended Jobs}|}{|\text{Relevant Jobs}|} \quad (4)$$

B. Comparative Analysis

High-performance scores are a great start, but they don't tell the whole story. The true strength of our framework lies in its integrated design, which weaves intelligent recommendations together with comprehensive analytics. To put this practical value into perspective, we compare our system against two common alternatives: a recommendation engine using only a single algorithm and a standard, off-the-shelf analytics plat-form. This comparison allows us to pinpoint exactly where our hybrid and integrated approach delivers superior functionality and deeper insights.

We present this analysis in two key tables. Table I focuses on the algorithmic performance, contrasting our hybrid (GA + CF) model against a GA-only approach to demonstrate the gains in recommendation quality. Following that, Table II takes a higher-level view, highlighting the essential government-focused features our system provides that are simply missing in a generic platform like Google Analytics.

TABLE I
COMPARATIVE ANALYSIS OF GA-BASED AND HYBRID APPROACHES

Metric	GA-based Approach	Hybrid (GA + CF) Approach
Precision	High	Very High
Recall	Moderate	High
Personalization Depth	Profile-based only	Profile + Behavior-based
Serendipity	Low	Moderate
Diversity	Limited	Enhanced

TABLE II
COMPARISON OF STANDARD ANALYTICS VS. PROPOSED SYSTEM

Feature	Standard Google Analytics	Proposed Integrated System
User Acquisition Tracking	Yes	Yes
Demographic Analysis	Yes	Yes (with localized Punjab data)
Job Recommendation Engine	No	Yes (GA + CF Hybrid)
Application Success Tracking	No	Yes
Government Policy Reporting	No	Yes

VII. CONCLUSION AND FUTURE WORKS

In this paper, we've laid out a plan to give the PGRKAM platform a major upgrade by adding smart analytics and a custom-built AI for recommending jobs. The idea is to watch how people use the site and use that information to make much better job matches, giving the people in charge the insights they need to improve everything. Our main goal is to turn the site from a simple job board into a dynamic hub that genuinely helps the people of Punjab find great opportunities. Looking ahead, we want to make this system even smarter. We plan to use Natural Language Processing (NLP) to really dig in and understand the fine details in resumes and job postings. We also aim to build models that can predict future job market trends, which will give the government solid data to make proactive and well-informed policy decisions.

VIII. ACKNOWLEDGMENT

We would like to express our heartfelt gratitude to the Punjab Ghar Ghar Rozgar and Karobar Mission (PGRKAM) for the opportunity to contribute to this meaningful initia-tive; their openness in allowing the integration and analysis of their platform laid the foundation for this research. Our deepest appreciation goes to Dr. Mohammed Mujeer Ulla, from the Department of Computer Science and Engineering at Presidency University, Bengaluru, whose constant guidance, encouragement, and thoughtful feedback were invaluable in shaping the direction of this work. We are also equally thankful to our colleagues and peers for fostering a supportive environ-ment and for their constructive discussions, which significantly enhanced the quality of this paper. Lastly, we acknowledge the role of Google Analytics as a conceptual foundation in designing our analytics pipeline. This work is a result of the collective efforts, insights, and support of all the individuals and institutions mentioned, to whom we are sincerely grateful.

REFERENCES

[1] M. Mujeerulla, Preethi, M. S. Khan, et al., "Demerits of elliptic curve cryptosystem with Bitcoin curves using Lenstra–Lenstra–Lovasz (LLL) lattice basis reduction," Arab J. Sci. Eng., vol. 49, pp. 4109–4124, 2024. doi: 10.1007/s13369-023-08116-w

[2] M. S. Khan, T. M. Chen, M. Sathiyanarayanan, M. Mujeerulla, and S. P. Raja, "Application of Lenstra–Lenstra–Lovasz on elliptic curve cryptosystem using IoT sensor nodes," Journal of ICT Standardization, vol. 12, no. 4, pp. 381–408, 2025. doi: 10.13052/jicts2245-800X.1242

[3] Preethi, M. M. Ulla, S. R., and R. M. Devadas, "Blockchain modeled swarm optimized Lyapunov smart contract deep reinforced secure tasks offloading in smart home," MethodsX, vol. 14, 2025, Art. no. 103305. doi: 10.1016/j.mex.2025.103305

[4] Preethi, M. M. Ulla, G. P. K. Yadav, K. S. Roy, R. A. Hazarika, and K. S. K., "Elliptic-Curve Cryptography Implementation on RISC-V Processors for Internet of Things Applications," Journal of Engineering, vol. 2024,Art. ID 5116219, 2024. doi: 10.1155/2024/5116219

[5] M. M. Ulla, Preethi, M. S. Khan, S. L., and S. B. J., "Lightweight Strobe Security Libdisco Scheme for IoT-Based Sensor Data," in Proc. 2024 8th Int. Conf. on CSITSS, 2024. doi: 10.1109/CSITSS64042.2024.10817029

[6] F. Ricci, L. Rokach, and B. Shapira, Recommender Systems Handbook. Springer, 2015.

[7] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, pp. 30–37, 2009.

[8] R. Burke, "Hybrid recommender systems: Survey and experiments," User Modeling and User-Adapted Interaction, vol. 12, no. 4, pp. 331–370, 2002.

[9] J. H. Holland, Adaptation in Natural and Artificial Systems. MIT Press, 1992.

[10] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich, Recommender Systems: An Introduction. Cambridge Univ. Press, 2010.

[11] S. Singh and S. Chatterjee, "E-governance initiatives in India: The case of National Career Service (NCS)," Gov. Info. Quarterly, vol. 36, no. 3, pp. 449–458, 2019.

[12] S. Bhatnagar, E-Government: From Vision to Implementation. SAGE, 2004.
[13] Google, "Google Analytics Documentation," 2023. [Online]. Available: https://developers.google.com/analytics
[14] Mixpanel, "Product Analytics Platform," 2023. [Online]. Available: https://mixpanel.com
[15] Kissmetrics, "Behavioral Analytics," 2023. [Online]. Available: https://www.kissmetrics.io
[16] K. B. C. Saxena, "Towards excellence in e-governance," Int. J. Public Sector Management, vol. 18, no. 6, pp. 498–513, 2005.