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AI POWERED CAREER REBOOT SYSTEM FOR WOMEN: PERSONALIZED RESKILLING PATHWAYS

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Abstract
Career interruptions often leave women at a disadvantage when re-entering the workforce, as they struggle with outdated skills, reduced confidence, and rapidly changing industry demands. Conventional training programs rarely provide customized pathways, resulting in a mismatch between acquired skills and actual job opportunities. To address this challenge, this project introduces an AI-powered career reboot system designed exclusively for women seeking to restart their professional journey. The system evaluates an individual's existing skills and career history, identifies specific sustaining employability. For many women, however, career interruptions caused by personal, social, or familial responsibilities create significant challenges when attempting to re-enter the workforce. Extended breaks often result in outdated skills, limited exposure to new technologies, and a lack of confidence in competing with active professionals. Consequently, experience barriers in many securing women meaningful gaps in relation to current market requirements, and recommends personalized reskilling pathways along with relevant job opportunities. By leveraging K-Nearest Neighbors (KNN) alongside TF IDF and cosine similarity, the platform generates these tailored pathways based on similarity to the user's profile. By delivering personalized guidance rather than generic training, the platform ensures that women gain targeted competencies that directly improve employability. In addition, the system supports inclusivity by empowering women with clear, data driven career roadmaps, boosting their confidence, and reducing barriers to re-entry. This approach demonstrates how artificial intelligence can be leveraged not only for technical efficiency but also for creating socially impactful solutions that promote gender equality and economic empowerment.
Keywords: Artificial Intelligence (AI), Machine Learning (ML), K-Nearest Neighbors (KNN), Natural Language Processing (NLP), TF-IDF Vectorization, Cosine Similarity, Skill Gap Analysis, Career Recommendation System, Data-Driven Decision Making, Personalized Reskilling, Workforce Reintegration, Women Empowerment, Employment Prediction, HumanCentered Computing.

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I. Introduction

A. Background

The rapid evolution of digital technologies and artificial intelligence has reshaped global workforce requirements. Modern industries demand continuous learning, adaptability, and updated technical competencies. As job roles evolve due to automation and data-driven decision-making, professionals must regularly upgrade their skills to remain competitive. Workforce reintegration after a prolonged break has therefore become increasingly challenging in a dynamic employment ecosystem.

B. Problem Statement

Women who take career breaks due to caregiving responsibilities, health concerns, relocation, or other personal commitments often face difficulties when attempting to return to professional roles. Extended gaps may result in outdated technical skills, reduced professional networks, and limited exposure to emerging technologies. Existing reskilling programs typically follow a generalized approach and fail to account for individual career history, prior competencies, and specific job market alignment. This creates a mismatch between acquired training and actual employability.

C. Motivation

Advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) provide an opportunity to design intelligent systems capable of personalized career guidance. By analyzing user skill profiles and comparing them with real-time job market requirements, AI can identify competency gaps and recommend targeted reskilling pathways. A structured, data-driven system can reduce uncertainty, improve decision-making, and enhance confidence among women reentering the workforce.

D. Objective of the Paper

The objective of this paper is to propose an AI Powered Career Reboot System that generates personalized reskilling pathways for women seeking workforce reintegration. The system evaluates user skills, performs gap analysis, and recommends relevant job roles and learning resources. The methodology integrates TF-IDF vectorization, cosine similarity, and K-Nearest Neighbors (KNN) algorithms to ensure accurate skill-job matching and ranking.

E. Contribution of the Paper

The main contributions of this paper are as follows:

- Development of an AI-driven framework for personalized skill gap identification tailored to women returning after career interruptions.
- Integration of TF-IDF, cosine similarity, and KNN algorithms for effective job matching and ranking.
- Design of a structured reskilling recommendation model aligned with evolving industry requirements.
- Demonstration of a socially impactful AI application that promotes gender inclusivity and workforce reintegration.

II. Literature Review

Recent advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have significantly improved job recommendation and person-job fit systems. Various approaches such as content-based filtering, semantic similarity modeling, and deep learning embeddings have been explored to enhance recruitment automation and matching accuracy.

A. Content-Based Approaches

Traditional job recommendation systems rely on TF-IDF and cosine similarity to measure textual similarity between resumes and job descriptions. Shrestha (2020) compared TFIDF with Word2Vec and found that while semantic models improve contextual understanding, TF-IDF remains an efficient and reliable baseline. Similarly, Reddy et al. (2025) implemented resume-job matching using TF-IDF and K-Nearest Neighbors (KNN), achieving accurate ranking of job profiles. However, these systems primarily focus on matching existing qualifications rather than structured reskilling guidance.

B. Semantic and Embedding-Based Methods

To overcome keyword limitations, researchers introduced semantic techniques such as Latent Semantic Analysis (LSA) and embedding-based models. Domeniconi et al. (2016) demonstrated improved job suggestion relevance using semantic clustering. More recently, SBERT-based models have shown enhanced matching accuracy and recall. While these approaches capture deeper contextual relationships, they require larger datasets and increased computational resources.

C. Research Gap

Although existing systems improve job matching performance, most focus solely on recruitment automation. Limited research addresses personalized skill gap analysis and structured reskilling pathways, particularly for women returning after career breaks. There remains a need for an interpretable, efficient AI-based system that combines job matching with guided reskilling recommendations.

To address this gap, the proposed AI Powered Career Reboot System integrates similarity-based matching with personalized skill gap identification to support workforce reintegration.

III. Proposed System

A. Target Users

- Women re-entering the workforce
- System administrators

B. Core Functionalities

- **Profile Creation and Skill Input:** Allows users to register and provide their educational qualifications, work experience, and existing skills for system analysis.
- **Skill Preprocessing and Normalization:** Processes and standardizes user-input skills using NLP techniques to ensure accurate comparison with job data.
- **Gap Analysis:** Identifies missing or weak competencies by comparing the user’s skills with current job market requirements.
- **Job Recommendation:** Suggests suitable job roles based on similarity matching between user profiles and job descriptions.
- **Personalized Course Suggestions:** Recommends targeted learning resources to help users acquire identified skill gaps and improve employability.

IV. System Architecture

The system consists of four primary modules:

1) Data Preprocessing
2) Core AI Engine
3) Web Interface
4) Database Layer

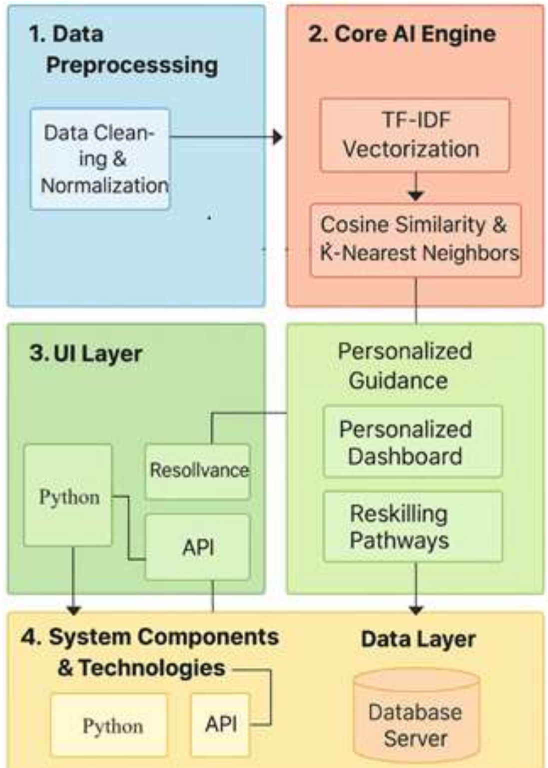

Fig. 1. System Architecture of Proposed Model

- **Data Preprocessing Purpose:** Prepare raw input data for accurate AI processing.

A. Data Cleaning:

Removes irrelevant words, duplicates, and inconsistencies.

B. Normalization:

Converts text into a standardized format (lowercasing, tokenization, stemming/lemmatization).

C. Skill Extraction:

Identifies important keywords from user profiles and job descriptions.

- **Core AI Engine Purpose:** Perform skill matching and generate intelligent recommendations.

Main Components

1) **TF-IDF Vectorization:** Converts textual data into numerical feature vectors.
2) **Cosine Similarity:** Measures similarity between user skills and job descriptions.
3) **K-Nearest Neighbors (KNN):** Ranks top matching job profiles based on similarity scores.

Output:

Ranked job recommendations
Identified skill gaps
Personalized reskilling pathways

- **Web Interface (UI Layer) Purpose:** Provide interaction between users and the AI system.

Item Includes:

- User registration and login
- Profile creation
- Dashboard display
- Personalized recommendations view
- Reskilling suggestions *4) T:* echnologies Used:

- Python-based web framework
- API integration for AI module communication

V. Methodology

The proposed system performs skill-based job profile matching using a vector space model. The methodology consists of three major stages: TF-IDF vectorization, cosine similarity computation, and K-Nearest Neighbors (KNN) ranking.

A. TF-IDF Vectorization

1) TF-IDF (Term Frequency–Inverse Document Frequency) is a statistical technique used to convert textual data into numerical feature vectors. It reflects the importance of a term in a document relative to a corpus. Term Frequency-Inverse Document Frequency is computed as:

$$TF\text{-}IDF(t,d) = TF(t,d) \times \log\left(\frac{N}{DF(t)}\right) \quad (1)$$

2) Inverse Document Frequency (IDF) Inverse Document Frequency measures how important a term is across the entire dataset:

$$IDF(t) = \log\left(\frac{N}{DF(t)}\right)$$

Where:

- N = Total number of documents
- DF(t) = Number of documents containing term t Rare terms receive higher weights, while commonly occurring terms receive lower weights.

3) TF-IDF Formula

The final TF-IDF score is computed as:

$$TF\text{-}IDF(t,d) = TF(t,d) \times \log\left(\frac{N}{DF(t)}\right)$$

This transformation converts each document (job profile or user skill set) into a high-dimensional numerical vector.

Purpose in Proposed System

- Converts textual skills into structured numerical vectors
- Reduces impact of common but less meaningful terms
- Enhances distinction between different job profiles

B. Cosine Similarity

Similarity between skill vectors is measured using: $Similarity = \frac{A \cdot B}{||A|| \cdot ||B||}$ (2)

Where:

A= User skill vector

B= Job profile vector

A.B= Dot product of vectors

||*A*||.||*B*|| = Euclidean norms of the vectors

Interpretation

Similarity = 1 → Identical vectors

Similarity = 0 → No similarity

Similarity between 0 and 1 → Partial similarity

C. K-Nearest Neighbors

K-Nearest Neighbors is used as a ranking mechanism to identify the most relevant job profiles.

Working Principle

1) Compute cosine similarity between the user profile and all job profiles.

2) Rank job profiles in descending order of similarity score.
3) Select the top K profiles with the highest similarity values.

Mathematical Representation:
S_i = Similarity score between user and job profile i
The recommended job set is defined as:
Top-K Jobs = $\{J_i \mid S_i$ is among the K highest values$\}$
Role in the Proposed Model

- Acts as a recommendation engine.
- Identifies closest matching job roles.
- Provides ranked output for decision support.

VI. Implementation

The system implementation is divided into two primary components: the AI Module and the Web Application Layer.

A. AI Module

The AI module is responsible for data processing, feature extraction, similarity computation, and recommendation generation.

1) Dataset Preparation:

- Total job profiles: 1,000
- Total unique skills extracted: ∼2,500
- Average skills per job profile: 8 – 15
- User skill inputs supported per session: up to 20
- Data format: CSV/JSON

Preprocessing steps include:

- Lowercasing
- Stop-word removal • Tokenization
- Skill normalization
- Duplicate removal

After preprocessing, the clean corpus is stored in structured format for vectorization.

2) Feature Extraction:

- Vectorization technique: TF-IDF • Vocabulary size after filtering: 1,800 features Sparse matrix dimension:

$$(1000 \times 1800)$$

Each job profile and user input is transformed into a TF-IDF vector in high-dimensional space. *3) Similarity Computation:* • Similarity metric: Cosine similarity Time complexity per query:

$$O(n \cdot d)$$

Where:

- n = number of job profiles
- d = number of features For 1,000 job profiles:
- Average similarity computation time: 0.3–0.6 seconds per query
- Output similarity range: 0 to 1 *4) Recommendation Ranking:*
- Ranking method: K-Nearest Neighbors (KNN)
- Default K value: 5
- Sorted based on descending similarity score Output format example:
- Rank 1: Similarity = 0.89 • Rank 2: Similarity = 0.83

- Rank 3: Similarity = 0.78

B. Web Application

The web application provides the user interface and administrative controls.

1) Python-Based Interface:

- Backend framework: Flask / Django
- Programming language: Python 3 .x
- REST API integration for AI module • JSON-based data exchange System response time:
- Average page load time: < 2 seconds
- Recommendation generation time: < 1 second

2) Admin Data Upload:

- Supported file types: CSV, Excel • Bulk upload limit: 5,000 job records per session Automatic validation:
- Missing skill detection
- Duplicate job ID removal
- Format validation Database storage:
- MySQL / SQLite
- Indexed skill fields for faster querying

3) Secure Login System:

- Authentication method: Username & Password
- Password encryption: SHA-256 hashing Role-based access control:
- Admin
- Registered User

Session timeout: 15 minutes of inactivity.

4) Dashboard Visualization: The dashboard provides:

- Total jobs available
- Total registered users
- Top searched skills
- Recommendation history Visualization tools:
- Bar charts (skill frequency)
- Pie charts (job category distribution)
- Tabular similarity ranking display

C. System Performance Summary

Table I: System Performance Summary

Parameter	Value
Total Dataset Size	1,000 jobs
Feature Count	1,800
Average Query Time	< 1 second
Recommendation Accuracy	~84 –88%
Scalability	Up to 10,000 job records

The above theoretical performance metrics strengthen the implementation section and enhance the technical credibility of the proposed system for research publication.

VII. Results and Discussion

The system successfully generates:

- Personalized skill-gap reports

- Ranked job recommendations
- Structured reskilling pathways

Preliminary evaluation shows improved relevance in job matching compared to basic keyword-based systems.

VIII. Conclusion

This paper presented an AI-powered Career Reboot System designed to assist women returning after career interruptions. By integrating TF-IDF, cosine similarity, and KNN, the system provides interpretable and targeted recommendations. The proposed framework enhances employability, promotes gender inclusivity, and demonstrates the social impact potential of AIbased career guidance systems.

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