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Department of Computer Science & Engineering
(Artificial Intelligence & Machine Learning)

Natural language Models
SEMESTER – VI

Course Code: 22AM3610

Review 1:

Title: Job Recommendation System NLM

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Contents

SDG Goals we follow

- **SDG 9: Industry, Innovation, and Infrastructure** - Enhancing e-commerce reliability through AI-powered sentiment analysis.
- **SDG 12: Responsible Consumption and Production** - Improving consumer trust by analyzing real product reviews and building recommendation system after market analysis
- **SDG 16: Peace, Justice, and Strong Institutions** - Reducing fake reviews and misinformation online by making a refined job recommendation system
- **SDG 8: Decent Work and Economic Growth** - Encouraging ethical business practices by minimizing the influence of fake reviews and frauds by automating the job reccomendation system

Introduction

Overwhelming Job Market – The vast number of job listings makes it challenging for candidates to find relevant opportunities.
Ineffective Keyword Searches – Traditional job portals rely on basic keyword matching, often leading to irrelevant job suggestions.
Lack of Personalization – Most platforms fail to tailor job recommendations based on individual user preferences and skills.
ML-Driven Optimization – Our application leverages Machine Learning (ML) to analyze user behavior and enhance job matching accuracy.
Advanced NLP Integration – Natural Language Processing (NLP) helps interpret job descriptions and user profiles for better recommendations.
Personalized Job Suggestions – The system delivers job recommendations based on user skills, preferences, and past interactions.
Efficient Job Discovery – AI-powered filtering reduces search time, ensuring users find relevant jobs faster.
Bridging the Gap – The platform connects job seekers with suitable roles while helping employers find ideal candidates.

Literature Survey

Author(s)	Title	Year	Methodology	Key Findings	Limitations
De Ruijt, C. & Bhulai, S.	Job Recommender Systems: A Review	2021	Literature review analyzing various job recommender approaches, including collaborative filtering, content-based filtering, and hybrid models.	Highlights the need for fairness, interpretability, and user satisfaction in job recommendation systems.	Lacks empirical validation and does not provide performance benchmarks for the discussed methods.
Al-Otaibi, S.T. & Ykhlef, M.	A Survey of Job Recommender Systems	2012	Surveyed different job recommendation techniques, including content-based, collaborative, and hybrid filtering, with a focus on e-recruitment.	Found that hybrid methods combining content-based and collaborative filtering improve accuracy and relevance of recommendations.	The paper lacks experimental validation and real-world testing of the surveyed techniques.

Literature Survey

Author(s)	Title	Year	Methodology	Key Findings	Limitations
Kenthapadi, K., Le, B. & Venkataraman, G.	Personalized Job Recommendation System at LinkedIn: Practical Challenges and Lessons Learned	2017	LinkedIn's job recommendation system using machine learning models, including logistic regression and gradient boosting, to personalize job suggestions.	Demonstrated significant improvement in job recommendation accuracy and user engagement through real-time personalization.	Highly specific to LinkedIn's ecosystem, limiting the generalizability of the findings to other platforms.
Siting, Z., Wenxing, H., Ning, Z. & Fan, Y.	Job Recommender Systems: A Survey	2012	Comprehensive survey of job recommendation systems, covering collaborative filtering, content-based methods, and hybrid approaches.	Identified collaborative filtering as the most effective method, especially when combined with content-based techniques.	Limited to high-level survey without detailed empirical results or real-world implementations.

Literature Survey

Author(s)	Title	Year	Methodology	Key Findings	Limitations
Yang, S., Korayem, M., AlJadda, K., et al.	Combining Content-Based and Collaborative Filtering for Job Recommendation System	2017	Cost-sensitive statistical relational learning combining content-based and collaborative filtering techniques.	Achieved improved recommendation accuracy and efficiency by leveraging both content-based and collaborative signals.	High computational cost, making it less suitable for large-scale real-time systems.
Puspasari, B.D., Damayanti, L.L., et al.	Implementation of K-means Clustering Method in Job Recommendation System	2021	Applied K-means clustering for grouping job seekers based on skill similarity and recommending relevant job postings.	Improved accuracy in job recommendations by effectively clustering users with similar skills and interests.	K-means clustering may struggle with complex or overlapping job categories, reducing accuracy in diverse datasets.

Literature Survey

Existing Job Portals – Limitations:

1. **Basic Search Functionalities** – Most job portals rely on simple keyword searches and manual filters, limiting accuracy.
2. **Lack of Personalization** – Job recommendations are generic and do not adapt to user profiles or preferences.

Machine Learning in Job Recommendations:

3. **Collaborative Filtering** – Popular platforms like LinkedIn and Netflix use this technique to suggest relevant content, including job opportunities.
4. **Natural Language Processing (NLP)** – Enhances job matching by analyzing job descriptions and user profiles for context-aware recommendations.

Identified Research Gaps:

5. **Limited Real-Time Adaptability** – Existing systems fail to dynamically adjust recommendations based on user interactions.
6. **Inefficient Skill-Based Matching** – Most platforms do not effectively correlate user skills with job requirements.
7. **Lack of Continuous Learning** – Current models do not refine job suggestions based on evolving user behavior.
8. **Need for AI-Driven Optimization** – A smarter, self-improving recommendation system is essential for enhancing job search efficiency.

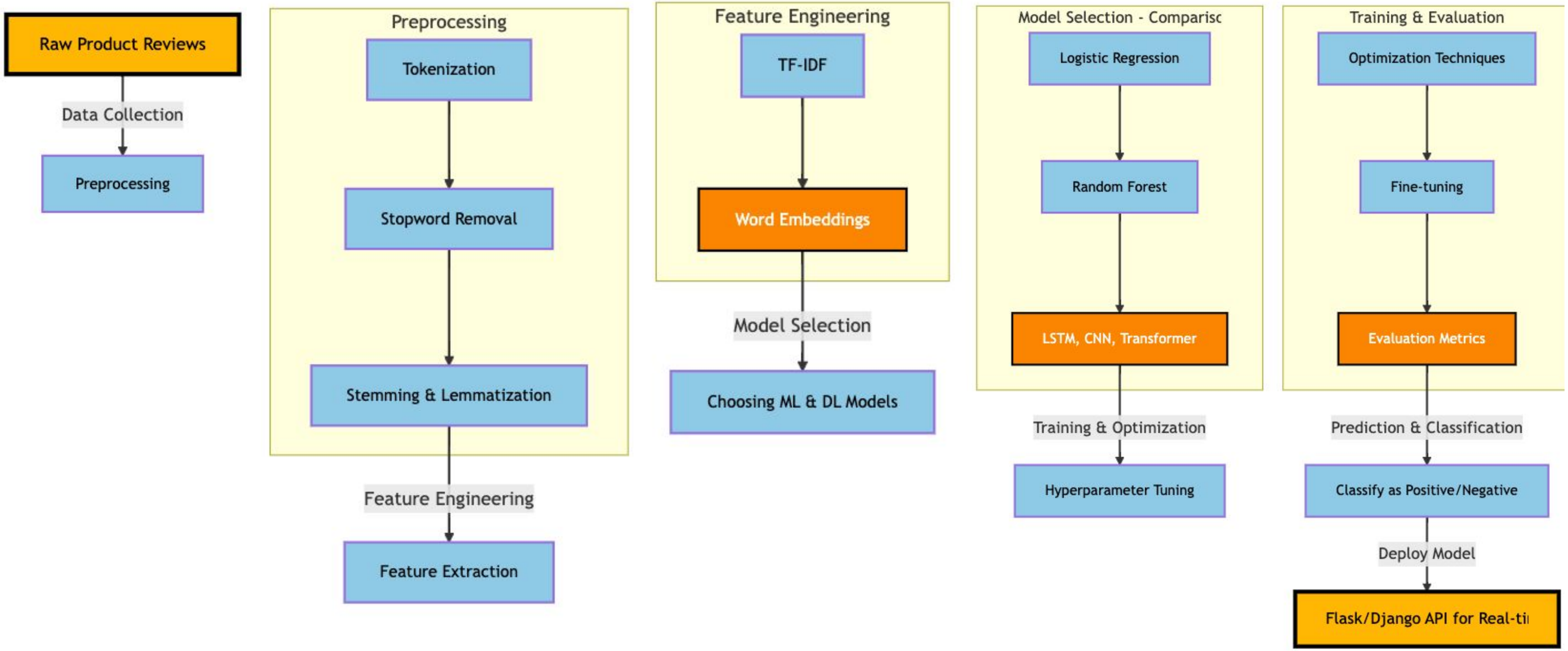
Problem Definition

Overwhelming Job Listings – Job seekers struggle to filter out irrelevant jobs from thousands of postings.
Mismatch in Job Preferences – Finding jobs that align with skills, interests, and experience remains a major challenge.
Inefficient Candidate Search – Employers face difficulties in identifying the right talent quickly and accurately.
Lack of Personalized Recommendations – Traditional job portals fail to provide tailored job suggestions based on user profiles.
Time-Consuming Job Search – Manually browsing job listings leads to frustration and reduced efficiency.
High Dropout Rates – Job seekers disengage from platforms due to irrelevant recommendations and poor user experience.
Need for AI-Driven Optimization – An intelligent system is required to automate and enhance job matching accuracy.
Bridging the Gap – A smart recommendation system can connect the right candidates with the right jobs efficiently

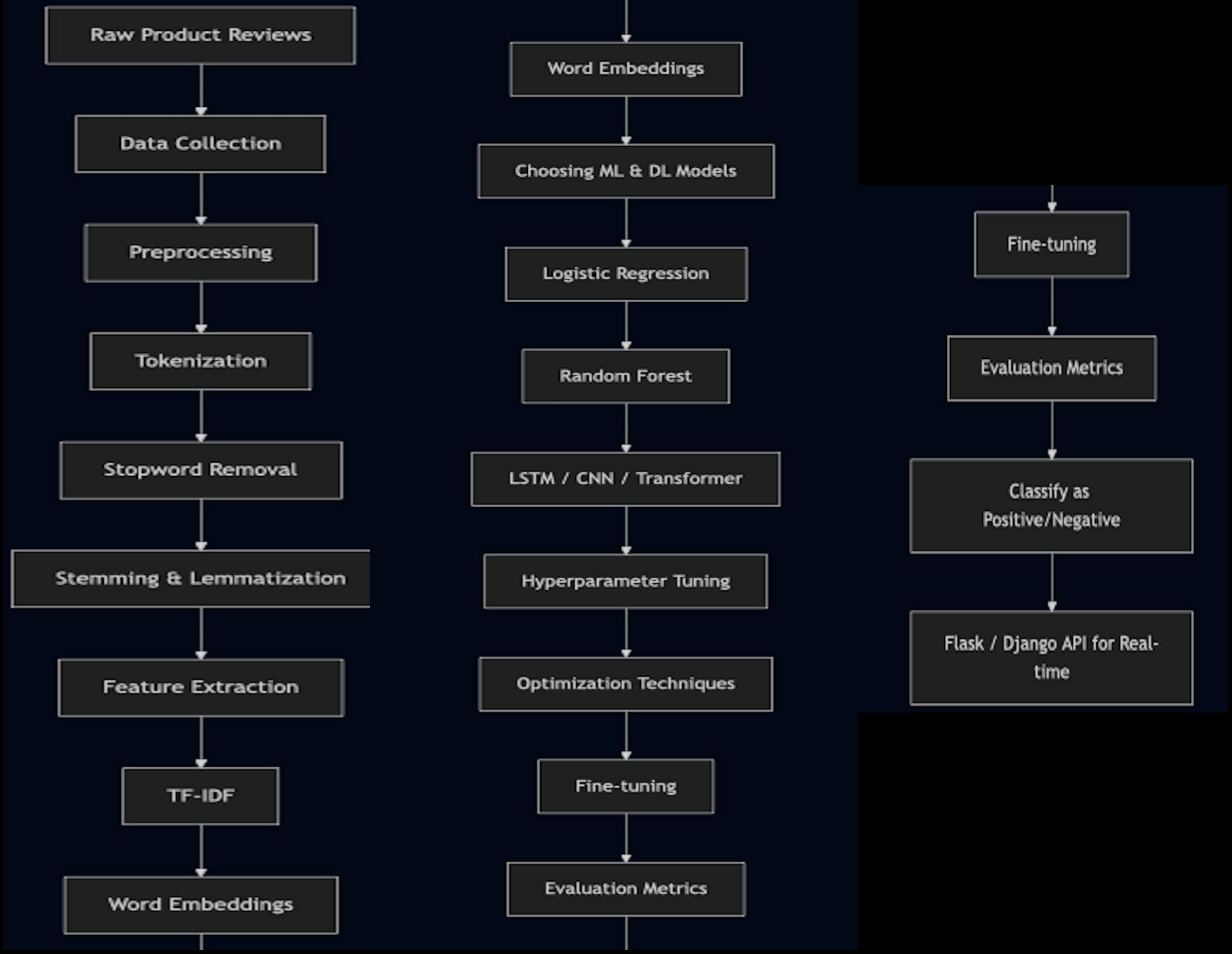
Objectives

- **Precision Job Matching** – Leverage ML models to accurately connect job seekers with the most relevant opportunities.
- **Personalized Job Discovery** – Enhance user engagement through tailored recommendations based on skills and preferences.
- **Advanced NLP Insights** – Analyze job descriptions and user profiles to deliver smarter, context-aware job suggestions.
- **Efficient Job Search** – Reduce search time by providing highly relevant job listings with real-time filtering.
- **Dynamic User Interaction** – Improve the job-seeking experience with an adaptive and intuitive recommendation system.
- **Employer-Candidate Optimization** – Ensure better alignment between job postings and potential candidates for higher recruitment success.
- **Data-Driven Insights** – Continuously refine recommendations through machine learning and user interaction patterns.
- **Faster Career Growth** – Empower job seekers with AI-driven insights for skill-based career advancements.

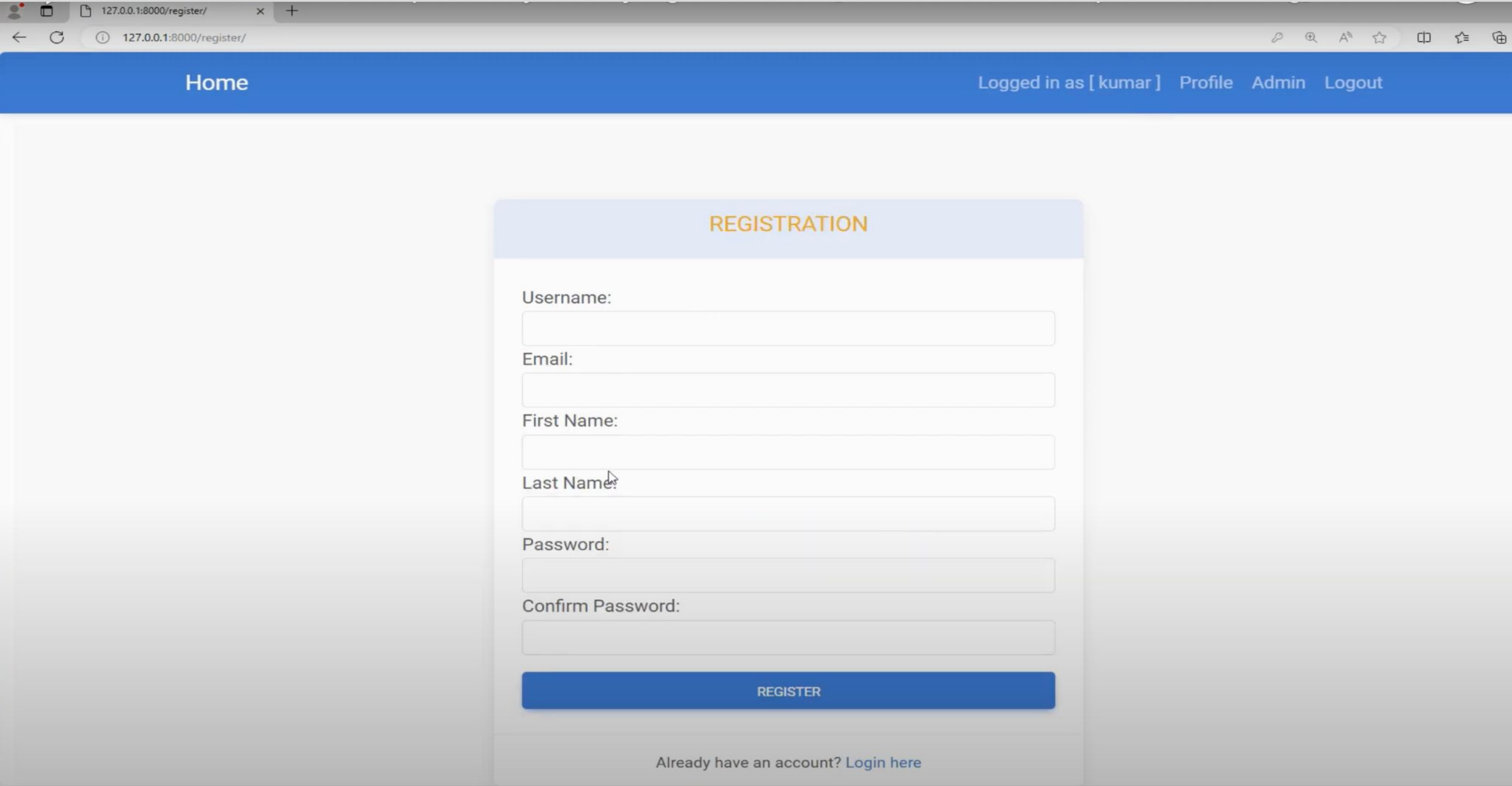
Methodology



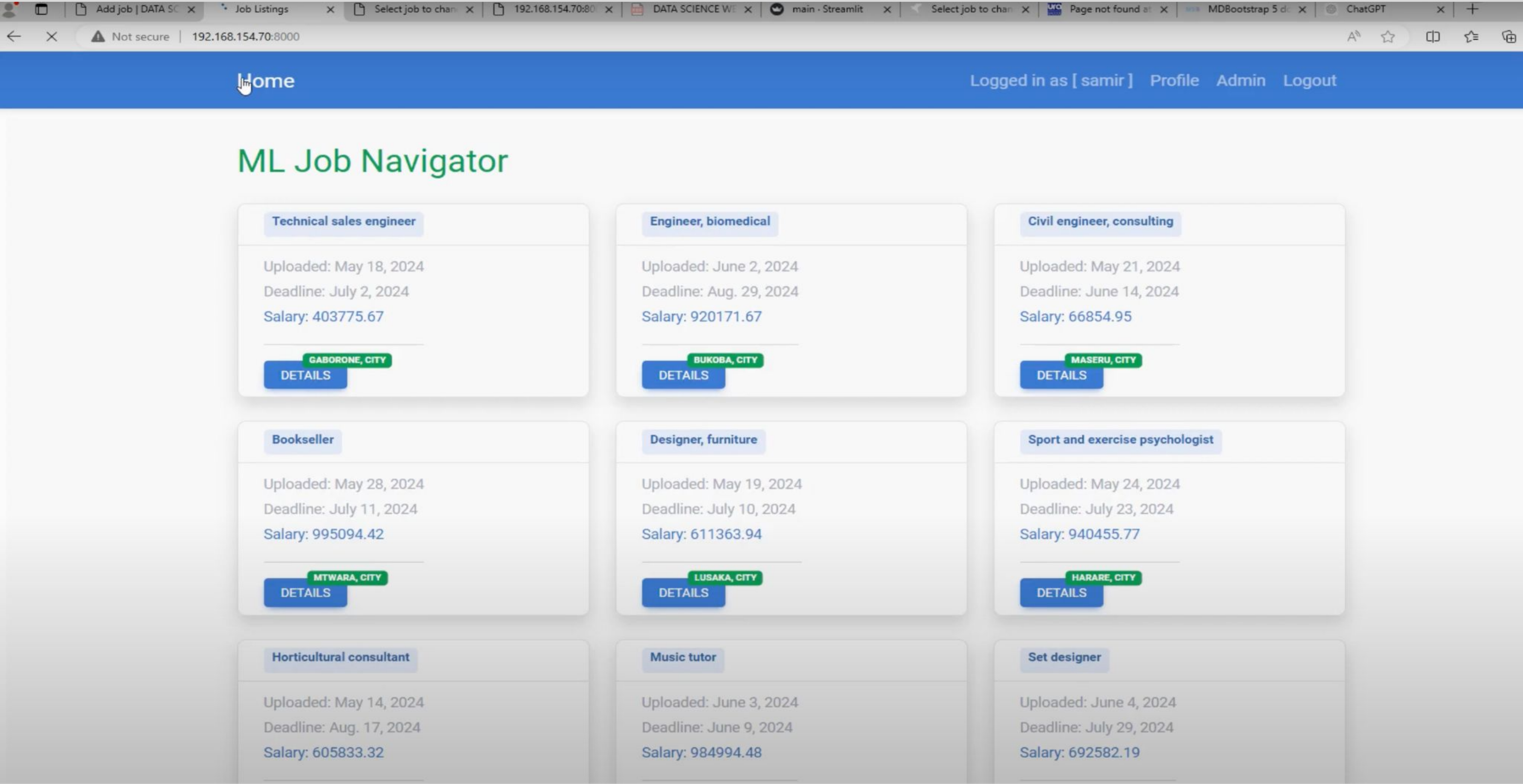
workflow :


Raw Product Reviews
Data Collection
Preprocessing
Tokenization
Stopword Removal
Stemming & Lemmatization
Feature Extraction
TF-IDF
Word Embeddings
Word Embeddings
Choosing ML & DL Models
Logistic Regression
Random Forest
LSTM / CNN / Transformer
Hyperparameter Tuning
Optimization Techniques
Fine-tuning
Evaluation Metrics
Fine-tuning
Evaluation Metrics
Classify as Positive/Negative
Flask / Django API for Real-time

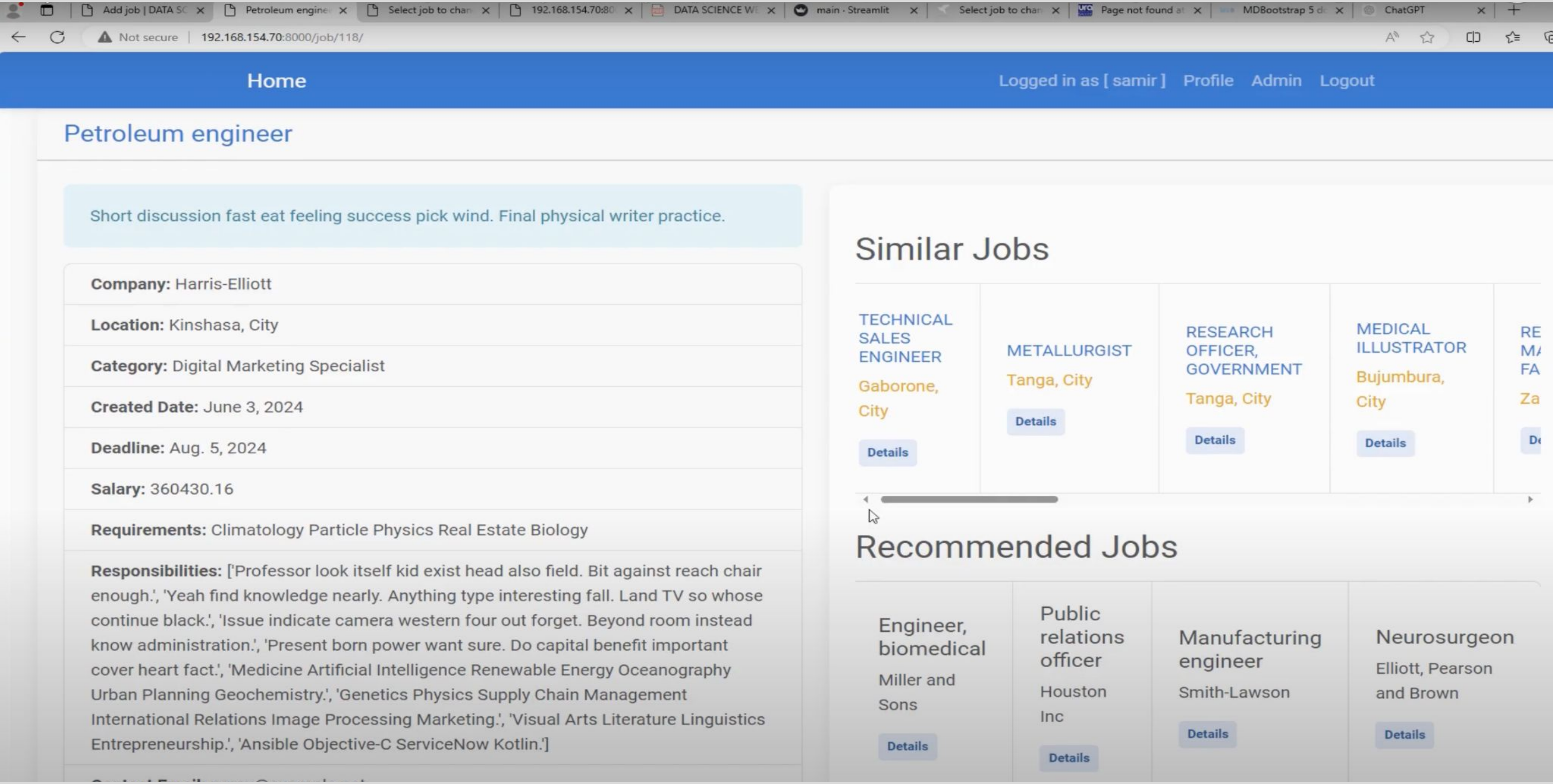
Results : Login / Registration page .



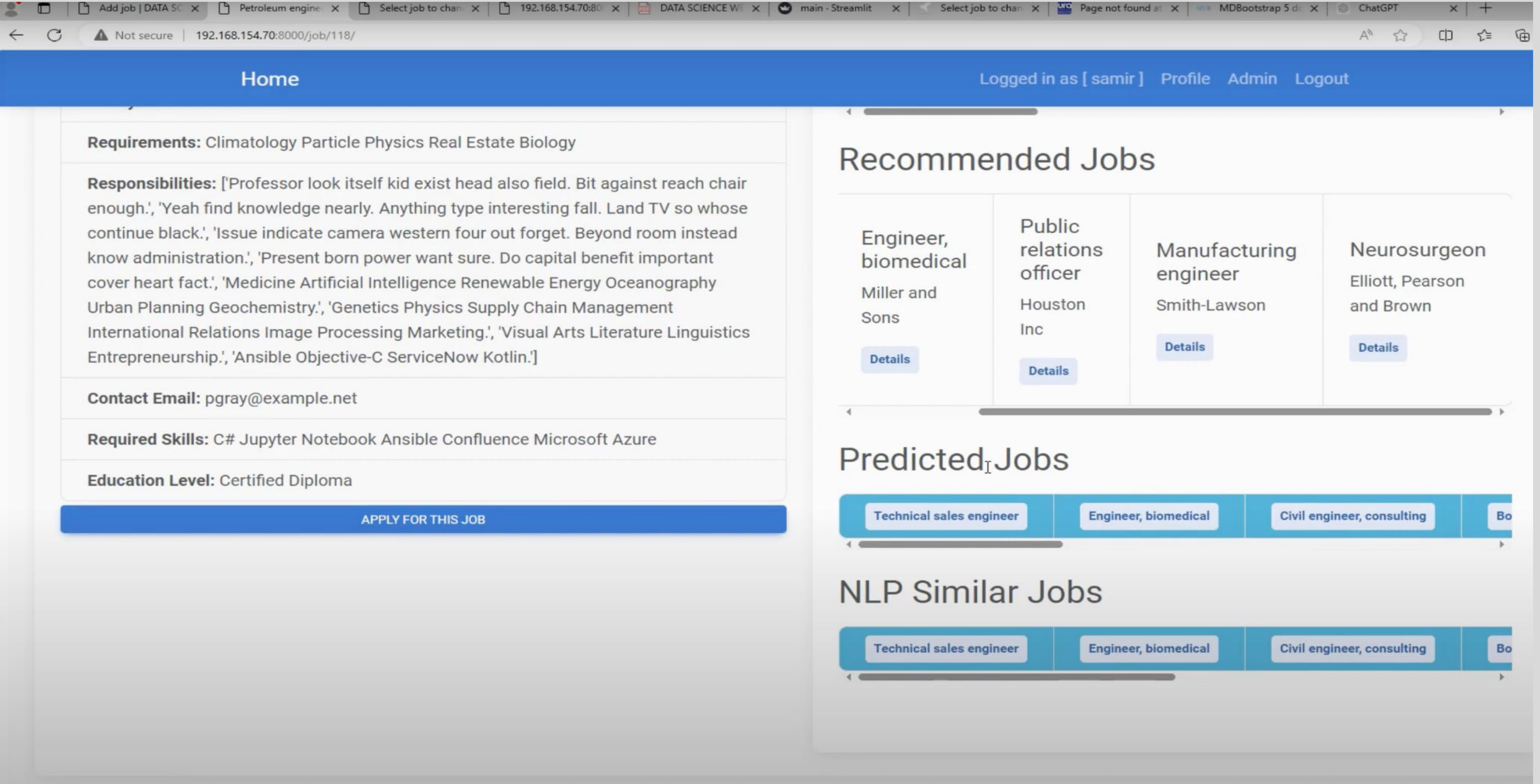
Results : ML job navigator .



Results : Job recommendation system



Results : NLP based predicted jobs .



Conclusion

Accelerated Job Discovery – ML-driven recommendations enable faster and more efficient job searches.
Enhanced Job Matching – Higher accuracy in connecting job seekers with the most relevant opportunities.
Improved User Engagement – Personalized suggestions increase user retention on job portals.
Better Candidate Selection – Employers receive precise matches based on job descriptions and skill requirements.
Optimized Job Search Experience – AI-powered recommendations streamline the job-hunting process.
Intelligent Matching with ML & NLP – Advanced techniques improve the relevance and precision of job suggestions.
Supporting Sustainable Development Goals – Aligns with **SDG 8 (Decent Work & Economic Growth)** by optimizing employment opportunities.
Adaptive Learning for Future Improvements – The system can evolve with real-time feedback to refine recommendations.
Skill-Based Job Recommendations – Future enhancements may include personalized career growth suggestions based on user skills.
Transforming Recruitment with AI – The system paves the way for smarter, data-driven hiring solutions.

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