Integrated Machine Learning Framework for Layoff Risk Assessment and Job Recommendation

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Abstract. The contemporary labor market is quickly changing because of cogs going digital and moving the industrial demands. This paper introduces a com binned machine learning model integrating job risk forecasting and individualized career guidance. The system evaluates a user's risk of job loss by analyzing their employment history, skills, and industry trends. It offers customized job on recognition of potential risk. It provides support and recommendations on skill development resources and career transitions. The framework specifically addresses the needs of rural individuals seeking jobs while transitioning to urban labor markets. It uses ensemble machine learning model which includes Random Forest, XGBoost, and Logistic Regression in order to obtain risk classification tion. Experimental results confirm that the system reliably classifies users into low, medium, and high-risk categories and delivers relevant job matches. The proposed system functions as a proactive career support tool helping individuals make informed decisions and confidently adapt to a changing workforce.

Keywords: Job Risk Prediction, Machine Learning, Career Recommendation, Layoff Detection, Skill Gap Analysis, Rural-to-Urban Employment, XGBoost, Random Forest, Workforce Transition, Career Guidance.

1 Introduction

The world labor market is in a carnival and very disruptive change. The use of artificial intelligence, automation and digitization are transforming work in virtually all industries. The World Economic Forum [12] notes that over 85 million jobs will be displaced by 2025 and new jobs, at the same time, will require a radically different skill

M. Kaushik et al. (eds.), *Proceedings of the International Conference on Responsible, Risk-aware, and Regulated AI (RRRAI 2026)*, Advances in Intelligent Systems Research 210,
https://doi.org/10.2991/978-94-6239-723-1_26

the other bring a lot of uncertainty to the workers around the world. Most people are 2 F. Author and S. Author not aware of their risk of job until very late and that is when they receive a layoff notice. Kim [1] pointed out this gap by showing that with machine learning regression models, unemployment can be forecasted with quantifiable precision, but that these tools have not been made accessible to average job seekers. Lack of a risk-warning system that is easily available and proactive deprives millions of workers of the opportunity to act in good time. The world labor market is in a carnival and very disruptive change. The use of artificial intelligence, automation and digitization are transforming work in virtually all industries. The World Economic Forum [12] notes that over 85 million jobs will be displaced by 2025 and new jobs, at the same time, will require a radically different skill profile. These two pressures movement on the one hand and the developing skill demands on the other bring a lot of uncertainty to the workers around the world. Most people are not aware of their risk of job until very late and that is when they receive a layoff notice. Kim [1] pointed out this gap by showing that with machine learning regression models, unemployment can be forecasted with quantifiable precision, but that these tools have not been made accessible to average job seekers. Lack of a risk-warning system that is easily available and proactive deprives millions of workers of the opportunity to act in good time. This has been an extreme issue to the rural workers and youths who would want to experience the urban job markets. The rural population usually does not have decent career guidance services, skill development facilities and reliable information on which jobs they can get in the city based on their profiles. In the absence of planning, rural urban migrations end up being inconsistently and unsuccessfully planned. The use of data-rich deep learning models in labor markets revealed that it is possible to predict labor market dynamics across both regional and industry levels. Nelson-Archer [2] confirmed that data-driven methods may identify sub structural trends in employment. But their work and most of what is in this space was oriented to the analysts and policy makers but not to individual job seekers. This has not been matched with a system of converting these forecasts into personalized actionable information to workers, even those in the underserved rural locations. Recent studies have also started to deal with the risk-prediction aspects of this issue. Mehta and Iyer [3] were using ensemble learn ing methods that integrate both Super models to make a prediction of job loss on a higher accuracy than the baseline models. Given that layoff prediction may be enhanced by financial indicators such as stock-market data in addition to employment attributes, [5] has shown that financial signals can be effectively combined with other means when selecting the financial indicator to incorporate in the prediction process. Khan [11] used workforce analytics and machine learning in organizational level of job risk assessment. According to Sharma and Gupta [10], the ensemble ML techniques will always outdo one-classifiers when predicting employee attrition, which is directly applicable in the context of layoff risk classification. Regardless of these developments, the current cog nitive literature comprises virtually all organizational or macro-level prediction aimed at providing assistance to the HR departments or policymakers but not the individual worker. The similar level of research on job recommendation has given similarly encouraging yet isolated findings. Singla and Verma [4] suggested that machine learning in combi nation with big language models is an alternative way of driving job recommending, Contribution Title (shortened if too long) 3 and they achieved better semantic matching than skill-keywords methods. Job Former is a transformer-based Job proposal suggested by Guan [7], making use of skill-awareness to suggest jobs based on explicit and latent competencies. Agarwal and Joshi [8] demonstrated that cosine similarity applied to skill vectors provides an effective and computationally efficient basis for job matching, while Verma and Singh [9] applied skill-matching directly to a machine learning recommendation pipeline. A systematic skill-based methods [6] were developed by Khan review. remain the major and most reliable paradigm in machine. learning-powered recommendation systems. Yet these recommendation systems are unanimously independent of. Any risk assessment is not displayed at the same time to worker. that their current status is jeopardized and what other statuses. The majority of them match their mobile capabilities. The gap that was found in the given survey is rather strong and significant: risk. job recommendation and prediction are considered as completely. different problems, and no framework to be integrated. has incorporated them into one, employee-centered system. This paper fills that gap with a proposal of an Integrated Machine Layoff Risk Assessment and Job Learning Model Recommendation. The arrangement is an ensemble fusion. XGBoost, Logistic, and random forest classifier. Three class layoff soft-vote regression. having a cosine-similarity based job recommendation engine ranking job recommendations, risk scoring (Low / Medium / High) opportunities of live job databases

2 Literature Survey

Another stream of research based on machine learning predicts macro-scale employment instability. Kim [1] applied machine learning models, which are regression models to the problem of unemployment prediction and could statistically significant predictive outcomes in other industry sectors. The paper has demonstrated that the organized historical data on employment including the layoff records, industry-specific employment rates and economic indicators may prove useful predictors of the unemployment in the future. Following this person-model body of research, Nelson-Arker.[2] employed deep learning architectures, including recurrent neural networks, to estimate time-varying sequences of labor market dependencies. Their model estimated the nonlinear dynamics of the national and regional markets that cannot be determined by other less advanced procedures of regression. These articles affirm that machine learning is capable of identifying useful predictive data based on employment data, although both articles are macro-level and produce a blanket prediction that cannot be used on any individual employee. By the nearer approach of the prediction lens to the individual, Mehta and Iyer [3] through the application of ensemble learning to the individual worker level, that is, a combination of decision tree classifiers, random forest, and gradient-boosted models, has made a step towards predicting job loss at the individual level. They did experiments to illustrate the fact that ensemble methods are always effective than single classifier and that is because variance and bias are reduced when various models are pooled together. Suehle [5] has further refined predictions at individual level by more precise 4 F. Author and S. Author predictions using stock market indicators besides using traditional employment variables. Suehle [5] went a step further to enrich individual level prediction by adding stock market predictors to classic employment predictors. It further enriched individual-level prediction by incorporating stock market signals alongside traditional employment fea tures. The fact that they found that financial health of companies is a significant pre dictor of layoff incidents, indicates that multi-modal feature engineering can greatly enhance the accuracy in predictions that cannot be well supported by employment data. It is based on this insight that our framework has industry risk mapping as a feature dimension, which translates sector level automation exposure into the prediction pipe line. An even more closely related literature is the literature of employee attrition voluntary employee departure as a measure of workforce instability. Sharma and Gupta [10] per formed a thorough comparison of the ensemble machine learning models to the task of predicting attrition and found that the ensemble models of classifiers like the Random Forest model and XGBoost always have better F1-scores than a logistic regression model or decision tree baseline, especially in imbalanced datasets (which would be the case with employment history). Khan [11] applied attrition-style analysis more widely in the workforce analytics and job risk prediction domain by demonstrating, using data mining on employment records, that latent risk indicators such as role-type, skill obsolescence and tenure patterns, are individually weak, but combine to be collectively strong. Khan [11] extended attrition-style analysis to the broader domain of workforce analytics and job risk prediction, showing that data mining over employment records can surface latent risk signals including role-type, skill obsolescence, and tenure patterns that individually weak but collectively powerful. The ensemble architecture taken up in this paper has been greatly supported in both studies with strong empirical evidence. Most importantly, though, both works reveal their forecasts to individual employees, and both of them relate its risk products to actable work options. The job recommendation literature has evolved in two main directions along the two main axes, that is, skill based matching and semantic or language-model based matching. On the skills aspect, Agarwal and Joshi [8] proved that by modelling user skills as well as job requirements as TF-IDF-weighted vectors and computing cosine similarity offers an efficient yet interpretable ranking mechanism. Verma and Singh [9] used this paradigm in a complete pipeline of machine learning and combined skill-matching scores with user profile attributes to generate personalized recommendations. Systematic review conducted by Khan [6] identified the depth of machine learning-based recommendation methods and established that most of the existing deployed systems can be covered by the paradigm of skill-based methods and similarities in cosines and collaborative methods. Later developments have been toward more semantically elaborate representations. An example of such hybrid frameworks is a proposal by Singla and Verma [4], which integrates the characteristics of the classical machine learning algorithm with the large language model embeddings, allowing the framework to pick up contextual and semantic complexities in job descriptions ignored by the key-word matching system. Guan Contribution Title (shortened if too long) 5 [7] proposed a transformer-based architecture, Job Former, which doxes interdependency of skills and the patterns of career advancement which give out recommendations sensitive to the changing skill path of the user and not to a fixed snapshot. Although these methods are considered state of art in terms of performance, they have large computation demands and cannot be made available as light weight and web-based applications to the general users. Our model uses the cosine-similarity model of Agarwal and Joshi [8] and Verma and Singh [9] as their recommendation engine with a bias to transparency, readability, and deploy ability. The preceding review reveals that existing research handles layoff risk prediction and job recommendation as entirely separate problems. No published framework integrates both capabilities along with the connecting skill gap analysis into a single, accessible, worker-facing system.

3 Methodology

3.1 System Architecture

Figure 1 involves a multi-level, web-based system that is made of an interface, a processing server, a machine learning engine, and a database integrated into a single system. The front end works on inputs captured by the user and predicting results to be shown. An API-based backend is used to process APIs, data and communicate with machine learning models. The ML layer is based on Scikit-learn and XGBoost is applied to predict risks and provide recommendations on jobs. PostgreSQL or Fire base contains user data, prediction history, job listings, skill mappings and so on. This layered architecture makes the architecture scalable and secure to all users such as rural job seekers aiming at urban job markets.

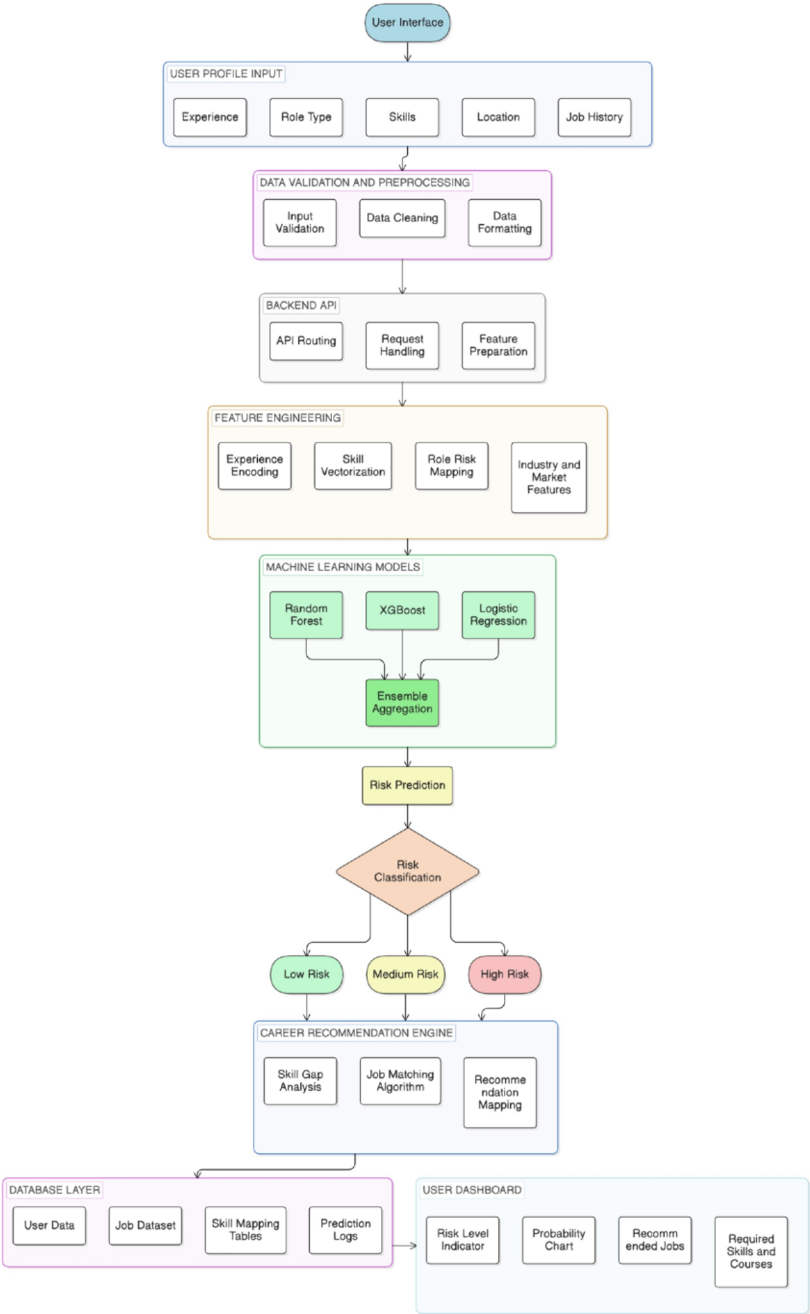

Fig. 1. System architecture of the proposed framework

3.2 System Workflow

When a user enters their profile details such as job title, location, work experience and skills the system workflow starts through the web interface. This data is forwarded to the backend it is verified, washed and formatted for processing as shown in Figure 2. The machine learning model is then applied on the analysis of the coded data versus past trend of layoff. This score is returned to the front end and made available to the user. Simultaneously, the system queries the job database and the training database to identify relevant opportunities which are outlined together with the risk outcomes of assessment that are in a straightforward and understandable format.

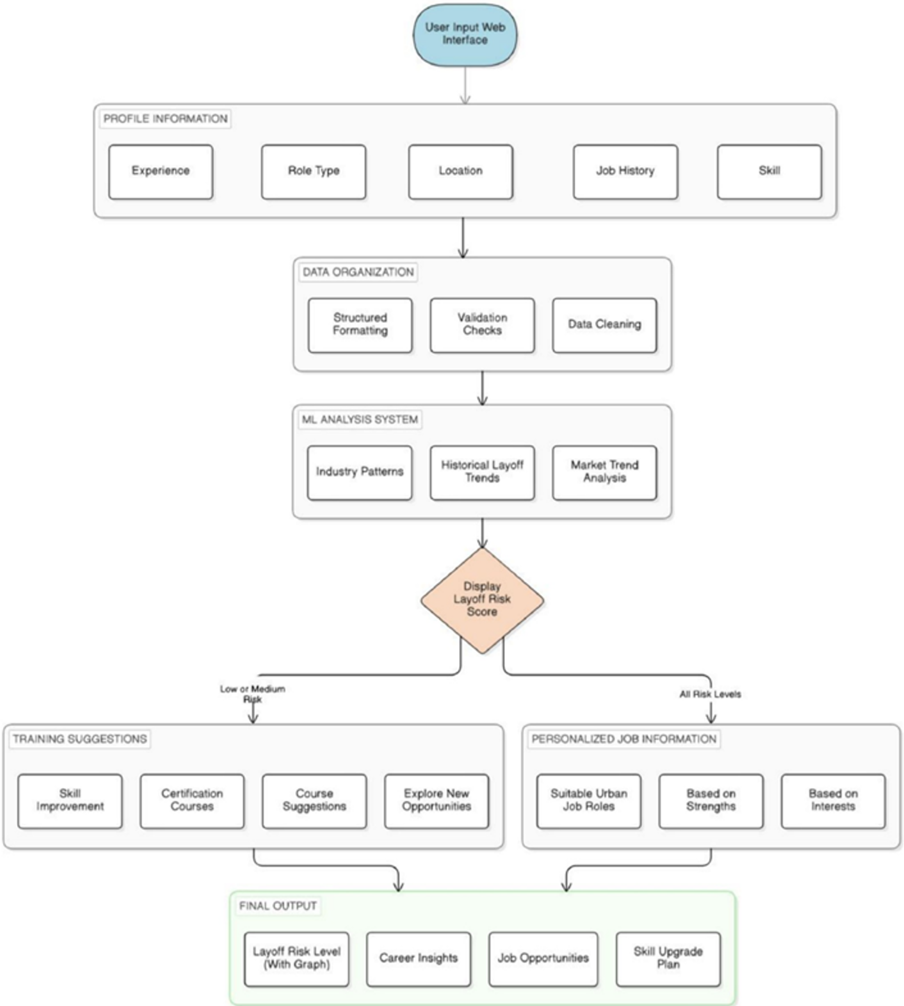

Fig. 2. Workflow of the Integrated Machine Learning Framework for Layoff Risk Assessment and Job Recommendation

3.3 Process Logic

The system will also begin by considering the inputs made by the users such as work, competence, place of residence, experience, job description and experience. Feature engineering is implemented at the backend. These transform raw materials into numerically ordered features that are arranged in a well-structured manner. This involves the skill vectorization, experience encoding and industry risk mapping. The processed functions are fed in a group of machine learning models: Random Forest, XGBoost and Logistic Regression. The models establish the probability of a layoff and the total user is classified to one of three based on the aggregate output type of risk: low, medium or high as shown in Figure 3. Following the classification of risks, a skill gap is performed by the system. Comparison of the skills that the user possesses at present stage of the analysis. unlike the current market demands. The job matching module locate suitable vacancies and rank them. by skill similarity score. Finally, there is a discourse of findings 8 F. Author and S. Author a personal experience dashboard that displays the level of risk, proposed preferred employment, and an educational plan of skills development to educate the users concerning the career choices.

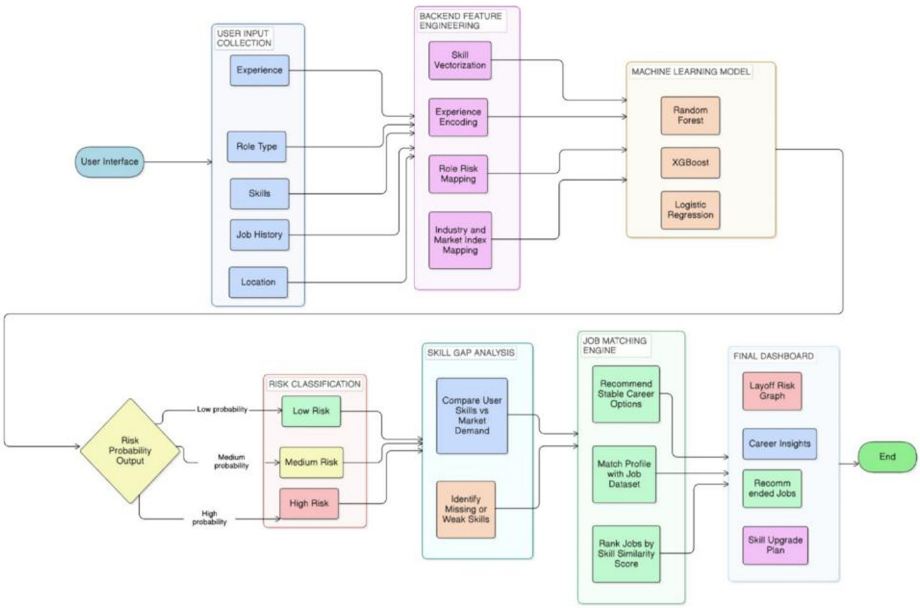

Fig. 3. Process flow of the Integrated Machine Learning Framework for Layoff Risk Assessment and Job Recommendation

4 Result and Analysis

Data of employment records including the attributes of job title, recruitment needs, experience, skills and layoff, history was used to test the proposed framework. Comparison and training of the trained three models was done by standard classification measures precision, recall, accuracy, and F1-score.

The given Ensemble model containing soft vote classifier being offered gives maxi mum status of (94.89%). Nothing can testify to the fact that this growth in performance will take place in dissociation among learners consuming supplementary strengths points or soundness of the Logistic Regression the predicted power or interpretability of Random Forest or XGBoost.

The XGBoost was discovered to be greater at the rate of accuracy of (88.3%). Random Forest (84.7%), and Logistic Regression (78.4%). The models established such high risk users who mainly worked in a busy and fast-automated business with outdated skill sets. Conversely low-risk users had already been in the main subject to stable industries Contribution Title (shortened if too long) 9 or were in possession of a different dispersion of the competencies available. These results confirm that in particular, the ensemble techniques, especially, XGBoost, are more appropriate layoff risk classification.

The other aspect that was undertaken was the job recommendation aspect. The comparison between job and job suggestions was made relevance, skill mixed interrelationship between the employment and the user profile requirements. The rural consumers had found the profession pathway routing. This is especially helpful when searching for urban jobs and education that are sufficiently necessary. The dashboard interface that predicts complex results automatically is easy to understand and facilitates the actionability of the system while accommodating users with varying levels of technical literacy.

5 Conclusion

The paper introduced a combined machine learning model of job prediction and layoff risk prediction to empower individuals with career ambiguity problems by means of combination. This system employs a cluster of machine learning models to determine job risk, using the work history of the user, their skills and the trends in their industry and provide specific career advice accordingly.

The experiments conducted show that Ensemble Model is the best classified model hence it is the most suitable model when it comes to risk scoring. These modules on the job recommendation and skill gap analysis add more value to the platform by aiding its users to determine what they can do next. It has a lot of influence on the job seekers in rural areas since it offers a guided and convenient channel to the job seekers in the urban areas.

Further development will involve adding real-time labor market data feeds, increasing the size of the skill taxonomy to include areas of new technology, and also do user studies to test the system and understand its effectiveness and long-term performance in career outcomes. As another future improvement, the integration of natural language processing to analyze resumes and guide conversations is also planned.

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