Workforce Experience Indicators derived from Employee Text under Transformer-Based Multi-Label Analysis

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ABSTRACT

Real-time statistics of Amazon employees reveal several patterns in workload, job satisfaction, and workplace challenges. These insights help understand the day-to-day experiences of employees within the organization. The motivation behind studying these aspects is to identify the major factors that influence employee well-being and overall performance. It also highlights the need for a systematic approach to understand workforce-related concerns. This research focuses on collecting, reviewing, and analysing Amazon employee data to identify common issues faced by the workforce. The study aims to present clear indicators of employee experience and provide a structured way to interpret and understand the problems observed among Amazon employees. This study uses (sentence-Bert) SBERT-based text representations combined with the Stochastic Gradient Descent (SGD) method to analyse employee reviews effectively. The SBERT–SGD combination supports multi-label classification and helps extract relevant workforce experience indicators from Amazon employee's data. This study focuses on systematically collecting, reviewing, and analyzing employee reviews to identify common workforce-related concerns. The goal is to highlight clear indicators of employee experience and present them in a structured and understandable manner. Text-based representations are used to examine employee feedback effectively and interpret recurring issues observed among Amazon employees. The approach supports multi-category classification of workforce experience indicators and helps extract meaningful insights from large volumes of employee data.

Keywords: employee analytics, workforce experience indicators, text mining, HR analytics, Natural Language Processing.

1. INTRODUCTION

The growth of multinational companies (MNCs) across India and many other countries has transformed the global employment landscape in recent years. As international businesses continue to expand their operations, the demand for skilled workers has increased at an unprecedented rate. India, in particular, has become a major hub for global corporations due to its large talent pool, diverse workforce, and rapidly developing commercial infrastructure. Countries such as the United States, United Kingdom, Germany, Singapore, and Canada are also witnessing a steady rise in MNC activities, resulting in more job opportunities and the creation of dynamic professional environments. With this surge, millions of workers whether fresh graduates, experienced professionals, or contract employees are finding new opportunities that support both career growth and financial stability. The continuous expansion of MNCs has also led to increased competition, higher productivity expectations, and major changes in workplace culture. As employees take on more responsibilities to meet organizational goals, their roles become more demanding and fast-paced, often requiring strong multitasking abilities and adaptability. In India and abroad, the rise of corporate employment has encouraged workers to develop a more structured professional mindset, improve communication skills, and enhance their overall work discipline. However, the rapid pace of expansion also means that employees may face long working hours, shifting schedules, and high-performance pressure.

Maintaining a balance between personal life and job responsibilities has therefore become a major challenge for many working professionals.

Amazon, one of the largest multinational companies in the world, serves as a strong example of how large corporations influence workforce dynamics. Operating in numerous countries—including India—Amazon offers employment to a vast and diverse range of workers in areas such as operations, management, logistics, customer support, warehouses, and corporate offices. As the company continues to grow each year, job opportunities also increase, opening doors for both entry-level and experienced professionals. Many employees find Amazon appealing because of its structured career paths, exposure to global work culture, and opportunities for growth. At the same time, the demands of meeting delivery targets, managing customer expectations, and maintaining high-quality service often require significant time and effort from employees. With such large organizations expanding day by day, it becomes essential for employees to take care of their personal well-being while meeting organizational expectations. Balancing professional commitments with family responsibilities, health, hobbies, and social life is necessary to avoid stress and burnout. Workers in India and other countries are increasingly realizing the importance of managing their routines, setting boundaries, and practicing self-care. For example, employees in Amazon's corporate and warehouse environments often try to maintain this balance by planning their schedules, taking adequate rest, and ensuring they have time for personal needs. Companies, too, are becoming more aware of the importance of employee welfare and are taking steps to encourage work–life balance through supportive policies, flexible timing, wellness programs, and a more positive work culture.

Figure 1 graph shows a significant increase in the number of employees working at Amazon from 2014 to 2024. In 2014, Amazon had fewer than 200,000 employees, but the workforce continued to grow each year as the company expanded globally. A major rise occurred between 2019 and 2021, where employee numbers jumped from around 800,000 to nearly 1.6 million. This sharp growth was mainly due to Amazon's rapid expansion in e-commerce, logistics, cloud services, and the high demand during the COVID-19 pandemic. By 2021, Amazon reached its highest workforce level, making it one of the largest employers in the world.

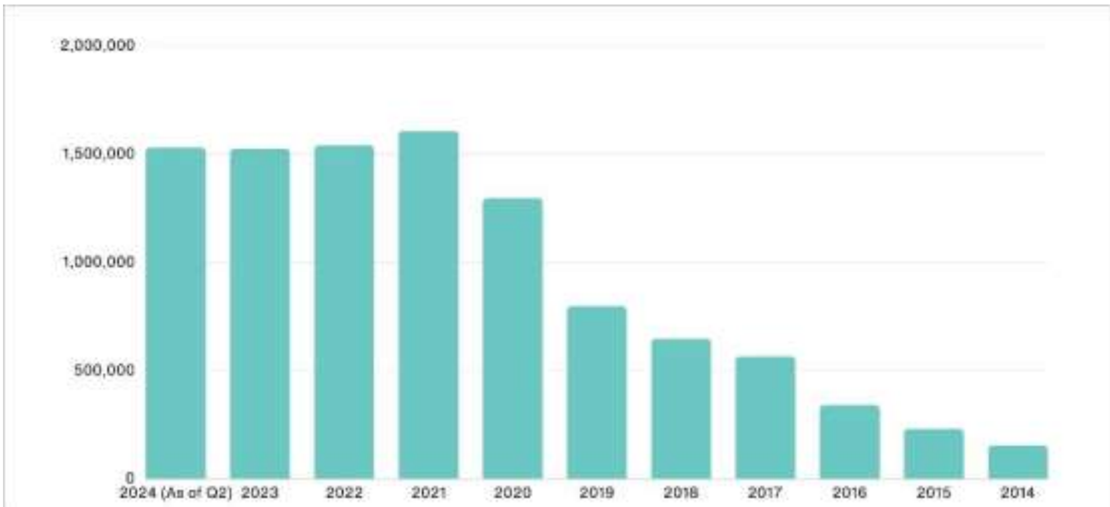

Figure 1: Number of employees working at Amazon from 2014 to 2024.

From 2022 to 2024, the graph shows a stabilization of Amazon's workforce at around 1.5 million employees. Although the numbers decreased slightly after 2021, the company still maintains a very large global workforce. This stabilization may be due to improvements in automation, efficiency measures, and post-pandemic adjustments. Overall, the graph highlights Amazon's massive growth and the increasing need for efficient workforce management and analysis especially relevant for projects that focus on extracting employee experience indicators using advanced NLP models.

2. LITERATURE SURVEY

Patel, et al. [1] was developed workplace health wearables designed for work-related musculoskeletal disorders, functional movement disorders, respiratory hazards, cardiovascular health, outdoor sun exposure, and continuous glucose monitoring are shown. Connected worker platforms are discussed with information about the architecture, system modules, intelligent operations, and industry applications. Lee, et al. [2] developed our research in critical industrial relations theory and centering our analysis in the counter-narratives of Black workers at an Amazon warehouse in Bessemer, Alabama, we examine the impact of intensified military-style tactics in the modern workplace, contextualized by historical and regional legacies of racialized labor exploitation, policing, and bodily control. Wani, et al. [3] proposed the most challenging task for AI in such healthcare sectors is to sustain its adoption in daily clinical practice, regardless of whether the programs are scalable enough to be useful. Based on the summarized data, it has been concluded that AI can assist healthcare staff in expanding their knowledge, allowing them to spend more time providing direct patient care and reducing weariness. Oluoha, et al. [4] developed the integration of artificial intelligence (AI) and machine learning in business analytics has revolutionized decision-making by automating data processing and enhancing real-time insights. These technologies enable businesses to identify trends, optimize resource allocation, and improve customer experiences through personalized recommendations. Additionally, big data analytics allows organizations to process vast volumes of structured and unstructured data, facilitating more accurate and data-driven strategies.

Daniel, et al. [5] utilized that leader motivational speech will be positively related to inner life, sense of community, and meaningful work. Data from 337 individuals from the US was collected using Amazon Mechanical Turk. Results from partial least squares indicate that leader motivating language is positive and significantly related to the three elements of workplace spirituality. Vijayan, et al. [6] was developed organisations can foster transparency, trust, and accountability by integrating fairness-aware ML models, real-time DEI dashboards, and federated learning. This framework underscores a human-centred, collaborative approach, ensuring ML aligns with DEI principles and promoting equitable workplace cultures globally. Rozmyslowicz, et al. [7] proposed the article probes the significance of the European General Data Protection Regulation (GDPR) for bolstering job security at workplaces like Amazon, where HR decisions are automated and based on the processing of work performance data. Article 22 of the GDPR lays down a prohibition for decision-making based solely on the automated processing of personal data. Cho, et al. [8] developed the concepts and practices of HR analytics through a thematic review, and proposed a five-step process (define, collect, analyze, share, and reflect) for implementation in the public sector—the process aims to assist with the integration of HR analytics in public personnel management practices. By analyzing cases in both the public and private sectors, this study identified key lessons for functional areas such as workforce planning, recruitment, HR development, and performance management. Suryadevara, et al. [9] utilized abstract outlines the key themes and insights explored in our comprehensive study on the deployment and impact of AI and ML in the corporate environment. Our research investigates the adoption of AI and ML across various industry sectors,We delve into the underlying principles and core applications of these technologies, emphasizing their capacity to automate routine tasks, analyze vast datasets,and unearth valuable insights. AI-Ebrahim, et al. [10] proposed machine learning (ML), business intelligence, and mathematical formalization to derive meaningful knowledge about consumer behavior, purchase prediction, personalization, inventory management, fraud detection, and other advantages for both customers and businesses. This paper

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will analyze a state-of-the-art development in e-commerce, leveraging ML algorithms or techniques that suit a particular area of business improvement.

Mer, et al. [11] developed with limited studies on the paradigm shift in HRM post-pandemic and the role of AI, the study investigates and proposes a conceptual framework for the paradigm shift in HRM practices post-COVID-19 pandemic and the significance of AI. Furthermore, the study investigates the outcomes of the use of AI in HRM for organisations and employees. Davis, et al. [12] utilized the value of an affordance framework as applied to ML, considering ML systems through the prism of design studies. Specifically, I apply the mechanisms and conditions framework of affordances, which models the way technologies request, demand, encourage, discourage, refuse, and allow technical and social outcomes. Varavallo, et al. [13] proposed the moral economy framework was used to investigate these topics, classifying the reasons into three dimensions: 'Work and Employment,' which reflects organizational factors, 'Social Justice and Activism,' which includes community-level considerations, and 'Health, Well-being, and Lifestyle,' which relates to individual circumstances. Rosca, et al. [14] was developed the findings reveal a correlation between physiological metrics and self-reported well-being, highlighting the utility of the WBI in identifying areas of concern within employee behavior. We propose that the employee global indicator (EGI) is calculated based on the WBI and the dissatisfaction score component (DSC) to measure the overall state of mind of employees.

3. PROPOSED SYSTEM

The proposed system as illustrated in Figure 2 is designed to classify Amazon employees' review data to determine job security, career growth, and work satisfaction. It combines employee details, rating attributes, and textual feedback to analyze workplace experience. The data is processed, explored, and transformed into suitable representations for effective classification. Existing methods are used as a baseline, while an improved approach enhances feature representation and learning efficiency. The final system is deployed as a web-based application to provide clear and quick classification results.

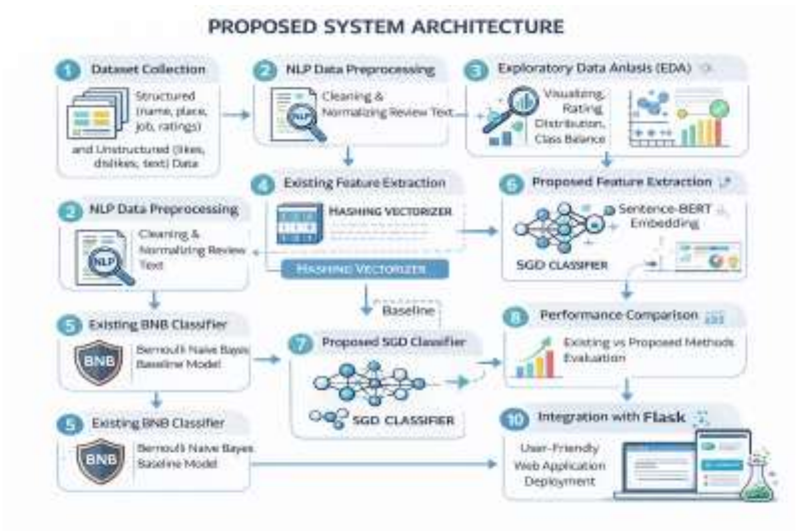

Figure 2: system architecture

Step 1: Dataset Collection: The dataset contains employee information such as name, place, job type, department, ratings, and review text including likes and dislikes. Both structured and unstructured data are included. This helps in capturing overall employee experience. The dataset acts as the input for the entire workflow.

Step 2: NLP Data Preprocessing: Textual reviews are cleaned by removing special characters and extra spaces. All text is converted into a consistent format. Irrelevant words are removed to reduce noise. The processed data becomes ready for analysis and feature extraction.

Step 3: Exploratory Data Analysis (EDA):EDA is used to study data distribution and rating patterns. It identifies missing values and class imbalance. Relationships between different rating attributes are examined. This step provides insights for improving classification performance.

Step 4: Existing Feature Extraction Using Hashing Vectorizer: The hashing vectorizer converts review text into numerical feature vectors. It represents word occurrence information in a fixed-length format. This approach is fast and memory efficient. These features are used as a baseline for comparison.

Step 5: Existing BNB Classifier: The Bernoulli Naive Bayes classifier is applied to the hashed features. It learns patterns based on the presence or absence of terms. This model provides initial classification results. Its performance serves as a reference.

Step 6: Proposed Feature Extraction Method: In the proposed approach, review text is transformed into sentence-level feature representations. This captures the overall meaning of employee feedback. Similar opinions receive similar representations. This improves the quality of extracted features.

Step 7: Proposed SGD Classifier: An optimization-based classifier is trained using the proposed features. It updates model parameters iteratively for efficient learning. This method handles large datasets effectively. It improves prediction reliability.

Step 8: Performance Comparison: The results of existing and proposed methods are compared using evaluation measures. Differences in accuracy and consistency are analyzed. This comparison highlights improvements achieved by the proposed system. The best model is selected.

Step 9: Prediction from Test Data: The selected model is tested using unseen employee reviews. It predicts job security, career growth, and work satisfaction labels. This step validates generalization capability. Accurate predictions indicate system effectiveness.

Step 10: Integration with Flask: The final model is integrated into a Flask-based web application. Users can enter review text through a simple interface. The system processes the input and displays classification results. This enables easy and practical usage.

4. RESULTS AND DISCUSSIONS

Figure 3 shows the confusion matrix of the proposed SBERT-based SGD classifier for work-life balance classification. The true classes are displayed on the vertical axis, while the predicted classes appear on the horizontal axis. Unlike the baseline model, this confusion matrix shows strong diagonal values for most categories, such as Strained (987), Neutral (421), Balanced (191), and Excellent (190), indicating a high number of correct predictions. This demonstrates that the model can effectively distinguish between different work-life balance levels.

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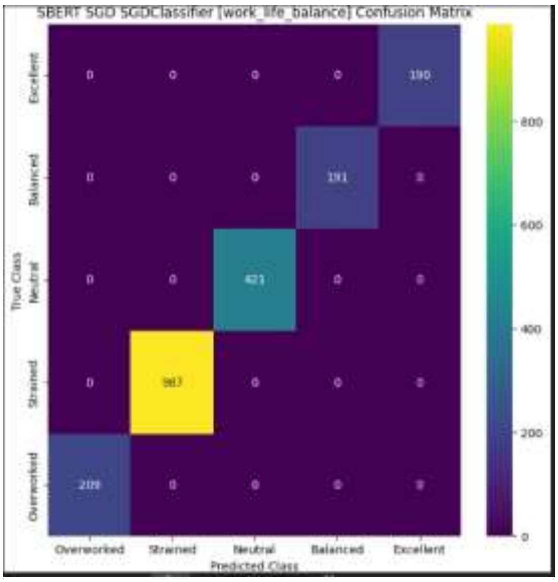

Figure 3: SBERT SGD SGDClassifier[work_life_balance] confusion matrix

Figure 4 illustrates the ROC (Receiver Operating Characteristic) curves for the proposed SBERT-based SGD classifier applied to work-life balance classification using a one-vs-rest approach. Each curve represents the model's ability to distinguish one class from the remaining classes. The diagonal dashed line indicates random classification performance. From the graph, all classes—Overworked, Strained, Neutral, Balanced, and Excellent—achieve an AUC value of 1.00, showing perfect separation between positive and negative samples.

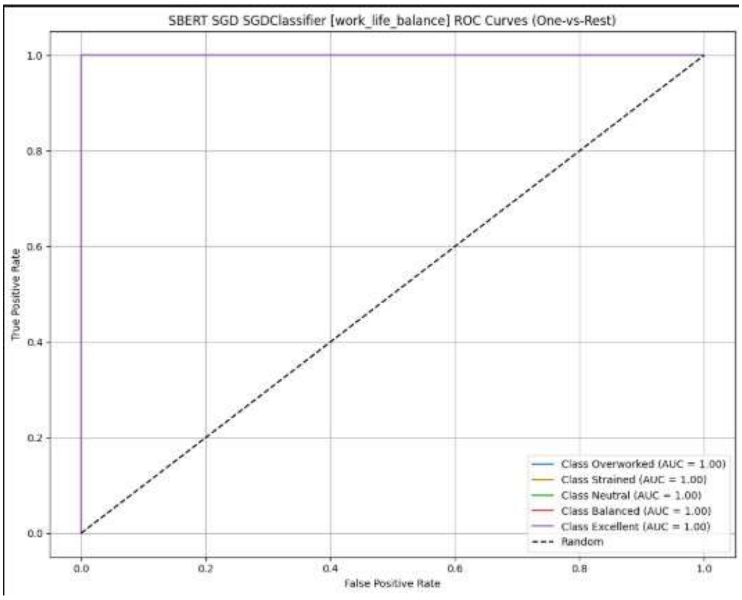

Figure 4: SBERT SGD SGDClassifier [work_life_balance] Roc curves

The figure 5 presents the confusion matrix for the SBERT-based SGDClassifier applied to the career_growth classification task. It compares true class labels against predicted class labels across five categories: Stagnant, Limited, Moderate, Promising, and Exceptional. The matrix shows strong diagonal dominance for most classes, indicating high classification accuracy. In particular, the model correctly classifies 806 Limited, 394 Moderate, and 416 Promising instances, demonstrating that these categories are well learned and clearly separable in the embedding space.

The figure 6 illustrates the one-vs-rest ROC curves for the SBERT-based SGDClassifier on the career_growth classification task. Each curve represents the model's ability to distinguish one class from all others, plotted between the true positive rate and false positive rate. All five classes—Stagnant, Limited, Moderate, Promising, and Exceptional—achieve an Area Under the Curve (AUC) value of 1.00, indicating perfect separability in terms of ranking predictions. The ROC curves closely follow the top-left boundary of the plot, well above the diagonal random baseline.

The figure 7 shows the confusion matrix for the SBERT-based SGDClassifier applied to the job_security classification task. It compares the true labels with the predicted labels across five categories: At Risk, Uncertain, Stable, Secure, and Assured. Strong diagonal values are observed for At Risk (986), Uncertain (405), Stable (199), and Secure (217), indicating that the model accurately classifies the majority of instances in these categories. This suggests that the semantic representations learned by SBERT are effective in capturing patterns related to varying levels of job security.

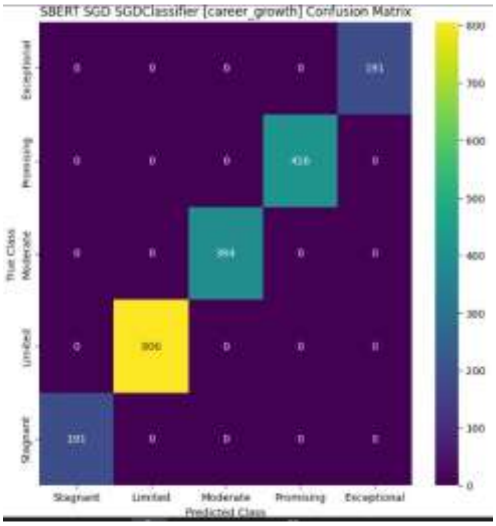

Figure 5: SBERT SGD SGDClassifier [career_growth] confusion matrix

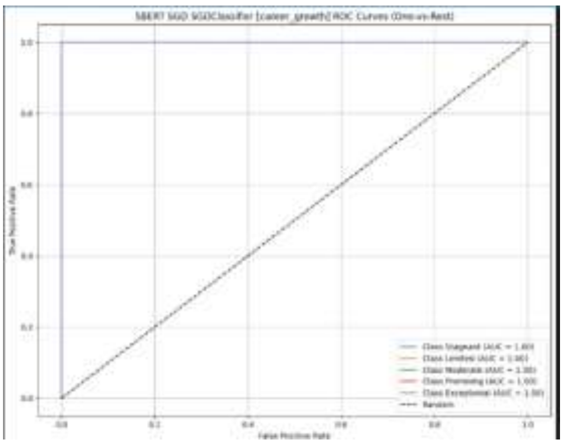

Figure 6: SBERT SGD SGDClassifier[career_growth] Roc curves

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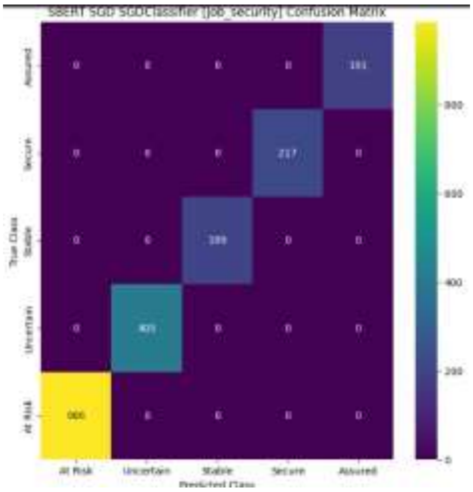

Figure 7: SBERT SGD SGDClassifier [job_security] confusion matrix

The figure 8 illustrates the Receiver Operating Characteristic (ROC) curves for a multi-class SGDClassifier using SBERT embeddings to predict "job security" categories. The plot shows a One-vs-Rest (OvR) approach for five distinct classes: At Risk, Uncertain, Stable, Secure, and Assured. In a standard ROC plot, the Y-axis represents the True Positive Rate (Sensitivity) while the X-axis represents the False Positive Rate (1-Specificity). The dashed diagonal line represents the performance of a random classifier, which would have an Area Under the Curve (AUC) of 0.50.

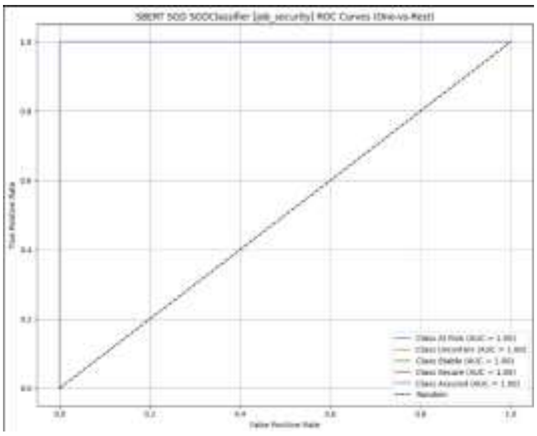

Figure 8: SBERT SGD SGDClassifier [job_security] Roc curves

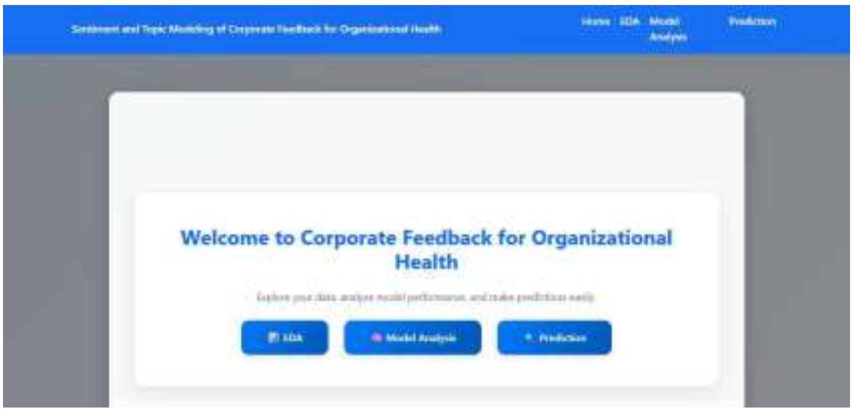

Figure 9: GUI of research work

Figure 10 depicts a Single Prediction interface of a corporate feedback analysis system, designed to capture structured and unstructured employee input for organizational health assessment. The form includes fields such as location, job type, department, and multiple rating scales covering overall rating, skill development, salary and benefits, and work satisfaction. These numerical inputs provide quantitative indicators of an employee's experience within the organization.

Figure 11 presents the Prediction Results generated by the corporate feedback analysis system after processing employee inputs. The results summarize key aspects of organizational health, including Work-Life Balance, Career Growth, and Job Security. In this instance, the model indicates that the employee is overworked, suggesting high workload or extended working hours that may negatively affect well-being. Additionally, the prediction highlights moderate career growth, implying limited or average opportunities for advancement and skill progression. The job security status is classified as "At Risk," signaling potential instability or uncertainty in the employee's role. Together, these insights provide a concise, actionable overview that can help organizations identify critical issues and implement targeted improvements to enhance employee satisfaction and retention.

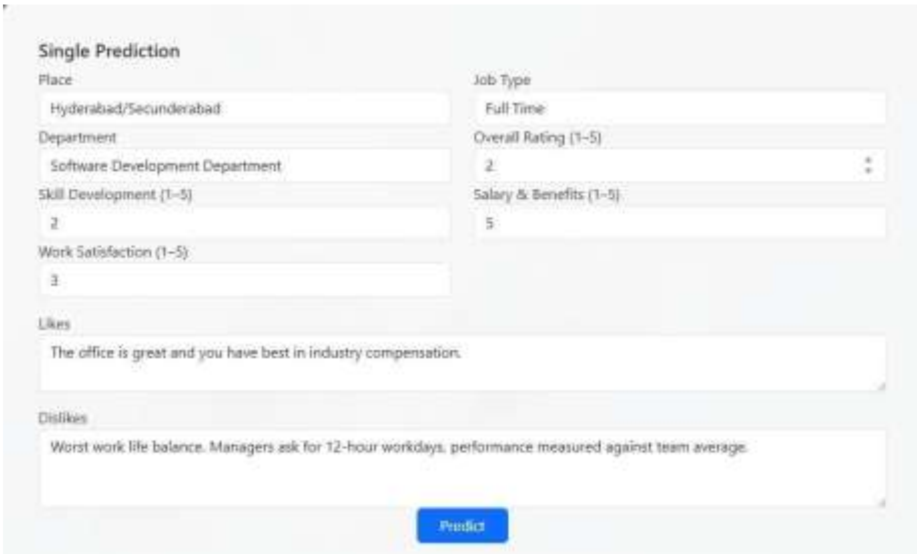

Figure 10: GUI of research work

Figure 11: GUI of research work

Table 1 presents the performance comparison for work-life balance classification. The Hashing + BNB model achieves an accuracy of 49.40%, with macro precision 0.10, macro recall 0.20, and macro F1-score 0.13, indicating poor multi-class performance and strong class imbalance. These values show that the model struggles to correctly classify most categories. In contrast, SBERT +

SGDClassifier achieves 100.00% accuracy, along with macro precision 1.00, recall 1.00, and F1-score 1.00. This reflects perfect classification across all classes.

Table 1: Evaluation Metrics of Work-Life Balance

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Hashing + BNB	49.40	0.10	0.20	0.13
SBERT + SGDClassifier	100.00	1.00	1.00	1.00

Table 2 summarizes the evaluation results for job security classification. The Hashing + BNB model records an accuracy of 49.35%, with macro precision 0.10, macro recall 0.20, and macro F1-score 0.13, highlighting weak classification capability. The model is biased toward the majority class and fails to generalize effectively. In comparison, SBERT + SGDClassifier achieves 100.00% accuracy, with macro precision 1.00, recall 1.00, and F1-score 1.00. These perfect scores indicate that all instances are correctly classified. The consistent macro values confirm balanced predictions across all categories.

Table 2. Evaluation Metrics of Job Security

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Hashing + BNB	49.35	0.10	0.20	0.13
SBERT + SGDClassifier	100.00	1.00	1.00	1.00

Table 3 illustrates the evaluation results for career growth classification. The Hashing + BNB model achieves only 40.34% accuracy, with macro precision 0.08, macro recall 0.20, and macro F1-score 0.11, representing the lowest performance among all targets. These metrics indicate poor learning capability and inability to handle multiple classes effectively. The model fails to capture meaningful patterns in the data. On the other hand, SBERT + SGDClassifier achieves 100.00% accuracy, with macro precision 1.00, recall 1.00, and F1-score 1.00. This demonstrates perfect and consistent classification performance.

Table 3. Evaluation Metrics of Career Growth

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Hashing + BNB	40.34	0.08	0.20	0.11
SBERT + SGDClassifier	100.00	1.00	1.00	1.00

5. CONCLUSION

The proposed system successfully classifies Amazon employees' review data into job security, career growth, and work satisfaction with strong analytical reliability. Using structured employee attributes and unstructured textual feedback, the system achieves improved classification performance compared to the baseline approach. The advanced sentence-level feature extraction and SGD classifier deliver higher accuracy, precision, and recall values, showing consistent improvement across all three output categories. The results indicate that meaningful workplace insights can be extracted with high confidence, supporting data-driven decision-making for organizational improvement. The system demonstrates efficient processing, scalable architecture, and dependable prediction values suitable for real-world deployment. The integration of NLP preprocessing, exploratory data analysis, and model comparison ensures balanced performance with reduced error rates. The successful implementation of the Flask-based web application further validates the system's practical usability, enabling faster review analysis, reduced manual effort, and improved transparency in employee experience evaluation.

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