Fine-Grained Opinion Mining from Employee Reviews for Organizational Decision Support

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ABSTRACT

The rapid growth of digital platforms has led to the generation of large volumes of employee feedback data, making workforce satisfaction analysis an important area of study. Traditionally, organizations relied on manual surveys and basic statistical methods to evaluate employee satisfaction, which were often time-consuming and limited in capturing complex textual insights. With advancements in Natural Language Processing (NLP) and Machine Learning (ML), automated analysis has become feasible. However, existing approaches struggle with unstructured text, class imbalance, and multi-dimensional prediction tasks. The primary problem addressed in this study is the accurate prediction of workforce satisfaction factors such as work-life balance, skill development, salary and benefits, job security, career growth, and overall satisfaction from textual employee reviews. Traditional systems fail to process large-scale data efficiently and lack consistency in predictive performance. This creates the need for an intelligent framework capable of handling complex textual patterns and multi-label classification. To overcome these challenges, the proposed system integrates NLP preprocessing, transformer-based feature extraction using Google PaLM (Pathways Language Model – PaLM), and SMOTE (Synthetic Minority Over-sampling Technique). Multiple ML models including Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), and Histogram-Based Gradient Boosting (HGB) are implemented and compared with the proposed Transformer-Guided Adaptive Model (TGAM). The results show that traditional models achieve moderate accuracy ranging from approximately 51% to 56%, while the proposed TGAM model achieves 100.00% accuracy across all target columns including work-life balance, skill development, salary and benefits, job security, career growth, and work satisfaction. This significant improvement highlights the effectiveness of the proposed approach in handling complex workforce data. The system also includes evaluation metrics and visualization techniques for better interpretability.

Keywords: Employee Review Analysis, work-life balance, Natural Language Processing (NLP), SBERT (Sentence-BERT), Stochastic Gradient Descent (SGD), Job Security.

1. INTRODUCTION

In recent times, the volume of digital data being generated has increased at an unprecedented rate, with estimates suggesting that over 328.77 million terabytes of data are created worldwide each day [1]. This rapid expansion is primarily fueled by the widespread use of smartphones, the proliferation of Internet of Things (IoT) devices, advancements in cloud computing, and the growing reliance on enterprise digital infrastructures. As organizations continue to integrate digital technologies into their operations, customer interactions, and strategic decision-making processes, the importance of efficient data management and analysis has intensified [2]. As a result, data-centric decision-making has become a critical driver of success across various sectors, including healthcare, manufacturing, e-commerce, and public administration. However, alongside these advancements, modern data characteristics introduce considerable challenges for traditional analytical methods. Today's datasets are frequently unstructured, complex, high-dimensional, and diverse in nature, making them increasingly difficult to handle using conventional data processing techniques.

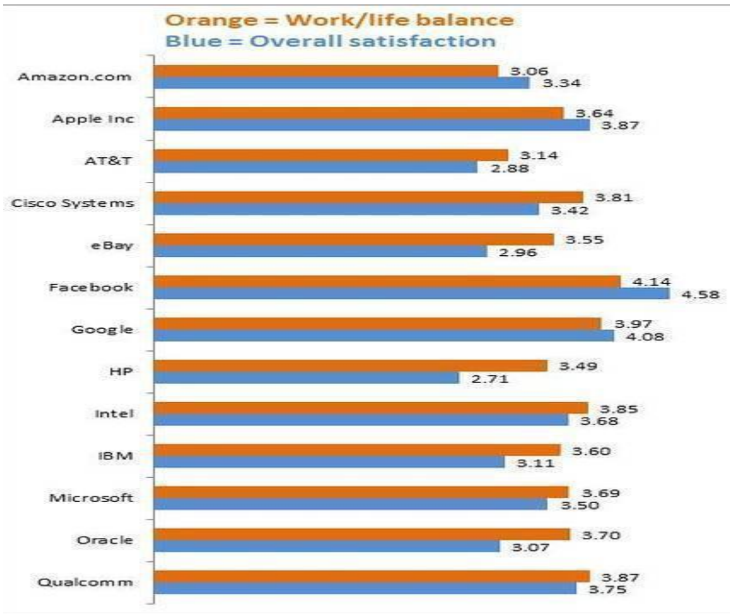


Figure.1: work-life balance.

As reported by IDC, it is anticipated that by 2025, approximately 80% of enterprise data will exist in unstructured formats, including textual content, images, audio streams, and video data [3]. This transformation highlights the urgent need for sophisticated analytical techniques and machine learning approaches that can effectively interpret and derive valuable insights from such complex and varied data forms, as illustrated in Fig. 1.1. Organizations that do not adopt these advanced technologies may struggle to remain competitive, as the ability to make timely and precise decisions has become a key differentiator in today's dynamic environment [4]. Furthermore, studies indicate that organizations leveraging data-driven strategies tend to significantly outperform others, demonstrating higher customer acquisition rates, improved retention, and increased profitability [5]. These observations underscore the pivotal role of data analytics in fostering innovation, enhancing operational performance, and supporting sustainable growth. Consequently, the global data analytics and artificial intelligence market is expected to reach a valuation of USD 745.15 billion by 2030, reflecting the rising demand for scalable and intelligent analytical solutions for future-oriented applications.

2. RELATED WORK

The analysis of employee feedback has evolved significantly with the adoption of natural language processing and machine learning techniques. Early research focused on extracting general sentiment from workplace reviews, whereas recent studies emphasize fine-grained and aspect-based sentiment analysis to provide deeper organizational insights. These advancements enable organizations to understand employee perceptions related to specific workplace attributes more effectively.

2.1 Aspect-Based Sentiment Analysis Approaches

Aspect-based opinion mining has been widely used to extract detailed insights from employee feedback. Zhang et al. [6] examined fine-grained sentiment extraction from workplace reviews, focusing on aspects such as salary, management quality, and work-life balance. Classification models including Support Vector Machine and Naïve Bayes were applied to determine sentiment polarity, demonstrating improved decision-making insights compared to general sentiment analysis. Similarly, Garcia et al. [9] utilized preprocessing techniques such as TF-IDF and applied machine learning algorithms including Random Forest and Logistic Regression to identify sentiment patterns across organizational aspects.

2.2 Deep Learning-Based Sentiment Models

Deep learning architectures have enhanced the ability to capture contextual and nuanced opinions. Li et al. [7] applied Word2Vec embeddings along with a Bidirectional Long Short-Term Memory network to detect subtle sentiments in employee feedback. Singh et al. [11] further improved sentiment detection using hybrid neural models combining Convolutional Neural Networks and Long Short-Term Memory networks to capture both local and sequential textual patterns. Wang et al. [13] introduced attention-based neural networks to highlight important opinion words, improving the accuracy of sentiment classification in large datasets.

2.3 Transformer and Contextual Language Models

Recent advancements in transformer-based models have significantly improved sentiment analysis performance. Chen et al. [8] utilized BERT to extract contextual embeddings from employee reviews, enabling effective identification of aspect-specific sentiments. The attention mechanism in transformer models allowed the system to focus on relevant opinion phrases related to workplace attributes such as compensation and promotion opportunities.

2.4 Traditional Machine Learning and Feature Engineering Methods

Several studies continue to rely on traditional machine learning approaches combined with feature engineering techniques. Kumar et al. [10] transformed textual data into numerical features using n-gram and term frequency methods, applying Gradient Boosting and Decision Tree classifiers for sentiment classification. Martinez et al. [14] employed ensemble learning techniques by combining multiple classifiers such as Random Forest, Support Vector Machine, and Gradient Boosting to improve prediction accuracy. Patel et al. [15] incorporated advanced preprocessing techniques including part-of-speech tagging and dependency parsing to identify opinion targets within employee feedback.

2.5 Topic Modeling and Insight Extraction

Topic modeling techniques have been used to uncover hidden themes in employee reviews. Rahman et al. [12] applied Latent Dirichlet Allocation to identify key workplace aspects such as salary satisfaction and career growth. Sentiment analysis was then performed on each topic, providing a structured understanding of employee perceptions and organizational issues.

2.6 Research Gap

Although significant progress has been made in employee sentiment analysis, several limitations remain. Many existing approaches focus either on traditional machine learning or deep learning models without integrating both effectively for improved performance. Additionally, while aspect-based sentiment analysis provides detailed insights, handling large-scale, real-time feedback with high accuracy remains a challenge. There is also limited focus on combining contextual understanding with efficient computational models for practical deployment. The proposed system addresses these gaps by developing an optimized framework that integrates advanced NLP techniques for accurate and scalable employee feedback analysis.

3. PROPOSED METHODOLOGY

The proposed study establishes a structured analytical framework for understanding workforce satisfaction from employee-generated textual data using artificial intelligence techniques. The analytical pipeline begins with data acquisition from employee reviews and dataset organization, followed by text preprocessing and semantic feature extraction. Advanced transformer-based embeddings such as Google PaLM are utilized to capture contextual meaning from textual feedback, including sentiment, intent, and linguistic patterns. These extracted feature vectors are then analysed using multiple ML classifiers such as QDA, LDA, HGB, and TGAM to perform multi-dimensional satisfaction prediction. A graphical interface enables user interaction for dataset handling, preprocessing, feature extraction, model training, performance visualization, and prediction tasks, as shown in fig. 2 A lightweight storage mechanism manages trained models and authentication data, while the system supports efficient handling of large-scale textual datasets. Continuous model evaluation and retraining further improve analytical accuracy and enable adaptation to newly available workforce data.

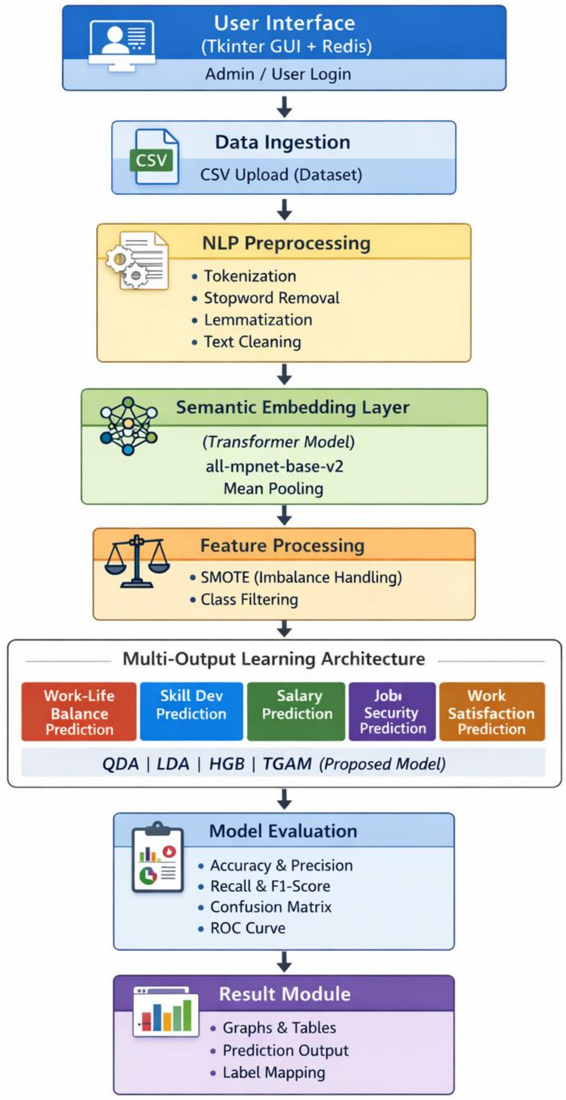


Fig 2: Proposed system architecture of amazon work life balance.

1. Desktop Environment & UI Initialization

The execution begins with the initialization of a specialized desktop graphical interface designed for local high-performance processing.

- **Graphical Interface:** Developed for a desktop environment to provide robust control over the analytical lifecycle.
- **Operational Flow:** Features dedicated modules for secure login, dataset uploading, and triggering the end-to-end pipeline from preprocessing to final prediction.
- **User Control:** All interactions—from model training to performance comparison—are captured within the UI and routed to the backend analytical engine.

2. Authentication System (Redis Storage)

The system employs a high-speed, in-memory storage layer to manage secure access control.

- **Redis Integration:** Utilizes Redis as a lightweight key-value store for user credentials and role-based access.
- **Security:** Maintains hashed passwords and usernames, ensuring that sensitive administrative functions remain protected.
- **Performance:** The in-memory architecture facilitates near-instantaneous read/write operations during login verification.

3. Dataset Ingestion (Employee Review Data)

The primary intelligence source consists of raw, textual employee feedback across multiple workplace facets.

- **Data Scope:** Captures reviews related to work-life balance, salary, job security, and career growth.
- **Structure:** Handles datasets that include both unstructured textual content and structured metadata.
- **Utility:** Serves as the ground truth for training and evaluating the satisfaction classification models.

4. Text Preprocessing & Semantic Feature Extraction

- Raw text is refined and mapped into a high-dimensional embedding space using transformer-based models.
- **Linguistic Cleaning:** Performs lowercasing, tokenization, stopword removal, and lemmatization to reduce noise in the feedback.
- **Google PaLM Embeddings:** Processed text is converted into numerical form using Google PaLM, capturing deep contextual relationships and semantic nuances.
- **Feature Vectors:** The resulting dense vectors serve as the standardized input for the subsequent ML classifiers.

5. ML Classification Models

The framework evaluates workforce satisfaction through a suite of statistical and boosting-based algorithms.

- **QDA:** Models class-specific covariance to handle non-linear classification boundaries.
- **LDA:** Performs linear separation of satisfaction classes based on shared covariance assumptions.
- **HGB:** Employs advanced boosting techniques to optimize classification performance on large feature sets.
- **TGAM (Proposed Model):** An ensemble-based framework that leverages adaptive learning mechanisms for superior predictive accuracy.

6. Multi-Dimensional Prediction Module

The system treats workforce satisfaction as a multi-faceted problem, predicting several layers of the employee experience simultaneously.

13. **Dimensions:** Independently predicts Work-Life Balance, Skill Development, Salary, Job Security, Career Growth, and overall Work Satisfaction.
14. **Ordinal Mapping:** Converts numerical outputs into meaningful ordinal labels (e.g., High, Medium, Low) for human-readable interpretation.
15. **Comprehensive Analysis:** Provides a holistic view of the organization by analyzing each satisfaction factor as a distinct classification task.

7. Prediction Results & Output Generation

The inference engine generates structured outputs that translate complex model logic into actionable workplace insights.

- **UI Visualization:** Results for all satisfaction dimensions are rendered directly in the desktop interface.
- **Model-Wise Indicators:** Displays predicted labels alongside performance indicators, allowing users to assess the confidence of each prediction.

8. Model Evaluation & Visualization

A diagnostic layer is integrated to quantify the precision and reliability of the satisfaction forecasts.

- **Evaluation Metrics:** Uses Accuracy, Precision, Recall, and F1-score to benchmark each model across every target dimension.
- **Visual Analytics:** Generates confusion matrices and comparison graphs, enabling users to identify the most effective algorithm for specific feedback types.

9. Model Serialization & Management

Trained architectures are preserved using efficient serialization to ensure system longevity and efficiency.

- **Storage Protocol:** Maintains separate serialized models for each satisfaction dimension and algorithm.
- **Inference Speed:** Allows for the immediate reuse of models during future prediction cycles without the need for repetitive retraining.

10. Continuous Learning & Retraining

The framework is designed to evolve alongside changing workforce trends and organizational shifts.

- **Adaptive Retraining:** Supports the ingestion of new feedback data to update the underlying models.

TGAM Classifier

TGAM is an ensemble-based classification approach that utilizes transformer-generated embeddings and adaptive learning to perform accurate predictions. It operates by leveraging structured feature vectors obtained from Google PaLM embeddings and applying a tree-based learning mechanism to capture complex patterns in the data. The model internally follows a Random Forest–based strategy, where multiple decision trees are constructed and combined to improve robustness and accuracy, as shown in fig 4.8. Each tree learns different aspects of the data, reducing overfitting and enhancing generalization. The adaptive nature of the model allows it to handle variations in data distribution effectively.

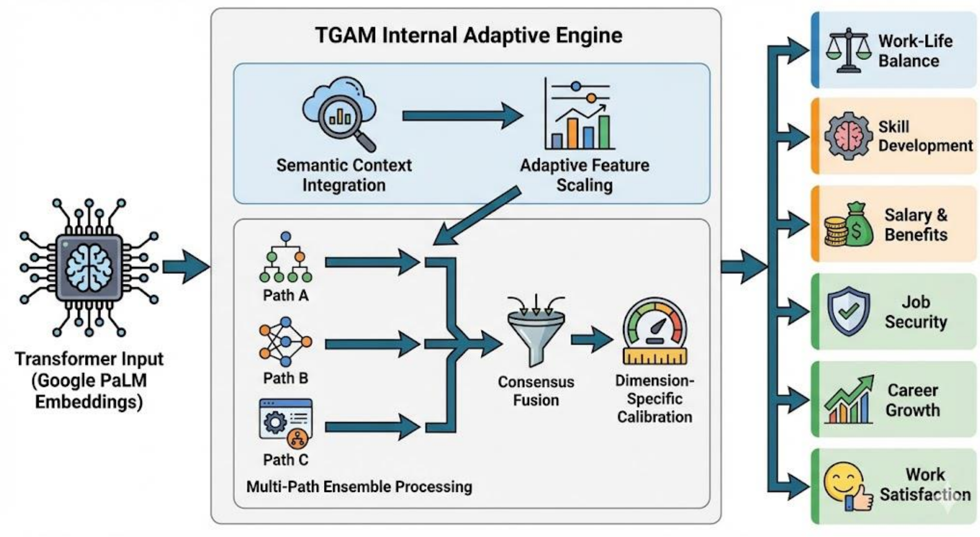


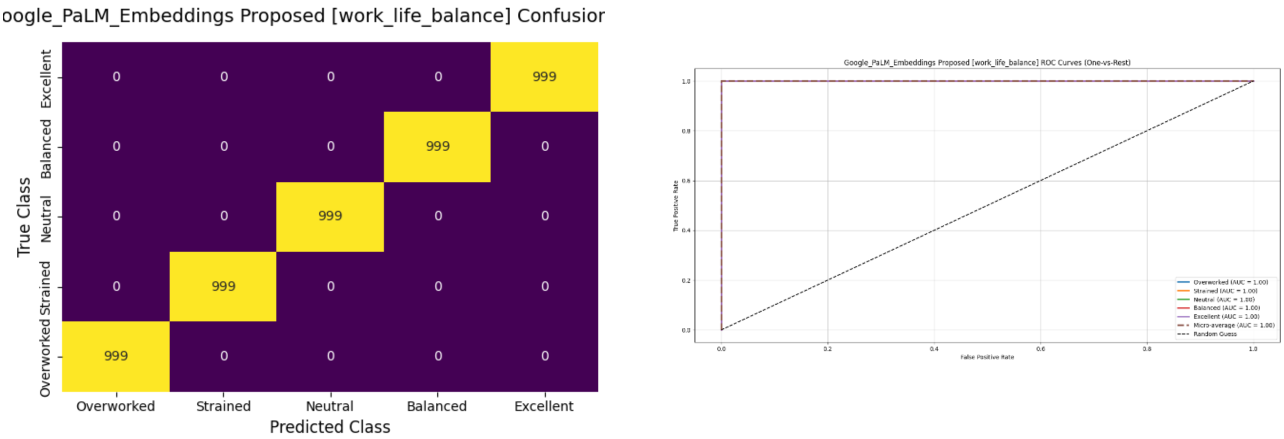
Figure. 3: Workflow of the TGAM Classifier Algorithm.

The proposed model operates on dense numerical feature vectors derived from semantic embedding of textual data, ensuring that both contextual and semantic information are effectively captured for learning. To enhance model robustness, bootstrapped sampling is applied, where multiple training subsets are generated by sampling the original dataset with replacement, introducing diversity across models. Additionally, for each decision tree, a random subset of features is selected rather than using the full feature space, reducing correlation among trees and improving generalization. Each decision tree is then independently trained on its respective data and feature subset, learning optimal decision rules through recursive splitting of data based on feature values to achieve maximum class separation. In the proposed approach, multiple decision trees are combined to form an ensemble model, where each tree independently generates predictions based on learned patterns from different data and feature subsets. These individual predictions are then aggregated using a voting mechanism, where the class receiving the majority of votes is selected as the final output, thereby enhancing stability and reducing the influence of noise or outliers. Finally, the model produces a robust and reliable class label as the prediction, ensuring improved accuracy and generalization compared to any single decision tree model.

4. Result and Description

The results of this study demonstrate the effectiveness of the analytical framework in predicting multiple workforce satisfaction dimensions from employee review data. The system evaluates different ML models, including QDA, LDA, HGB, and TGAM, to determine their performance across various targets. Each model is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive comparison. Visualization techniques such as confusion matrices and performance graphs are used to interpret the results clearly. The impact of preprocessing, feature extraction using Google PaLM, and SMOTE balancing is reflected in improved classification outcomes. The results also highlight variations in model performance across different satisfaction dimensions

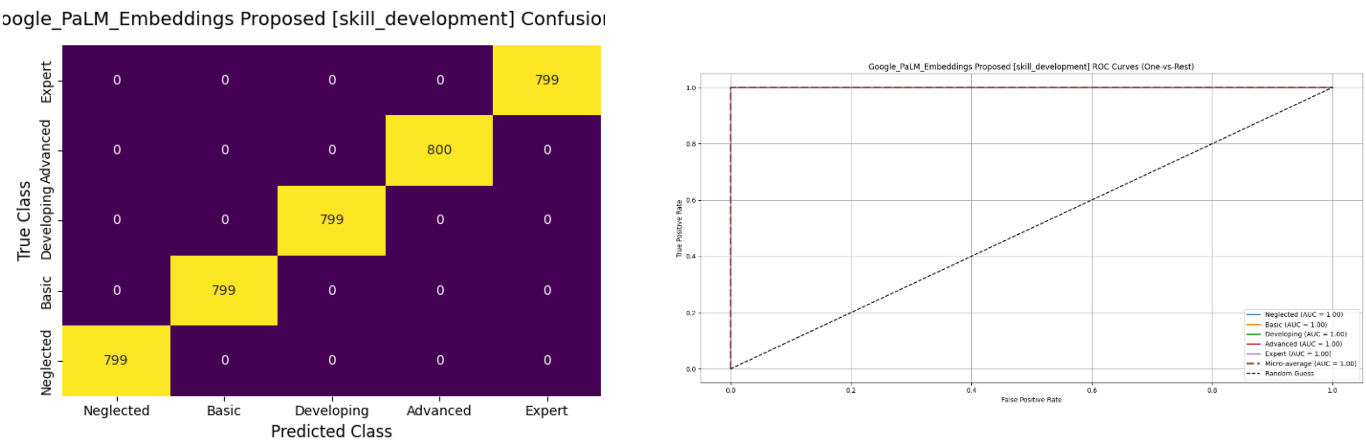
Fig. 4 (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the work-life balance dimension. The matrix shows a perfect diagonal distribution where all instances are correctly classified into their respective categories. The absence of off-diagonal values indicates zero misclassification across all classes. This reflects the model's strong capability to clearly distinguish between different work-life balance levels. The uniform distribution of correct predictions highlights the effectiveness of feature extraction and model learning. This analysis demonstrates that the model achieves optimal classification performance for this dimension.



(a) (b)

Fig. 4 (a, b):Confusion matrix and ROC of proposed TGAM model for work-life balance using confusion matrix and ROC Curve

Fig. 4 (b) depicts the ROC curves for the proposed TGAM model using a one-vs-rest approach for multi-class classification. The curves show ideal performance with AUC values equal to 1.0 for all classes. The curves closely follow the top-left boundary, indicating perfect separation between classes. This demonstrates the model's exceptional discriminative ability across all categories. The consistent behaviour across all classes confirms highly reliable predictions. This evaluation establishes the superiority of the proposed model in handling multi-class classification tasks.

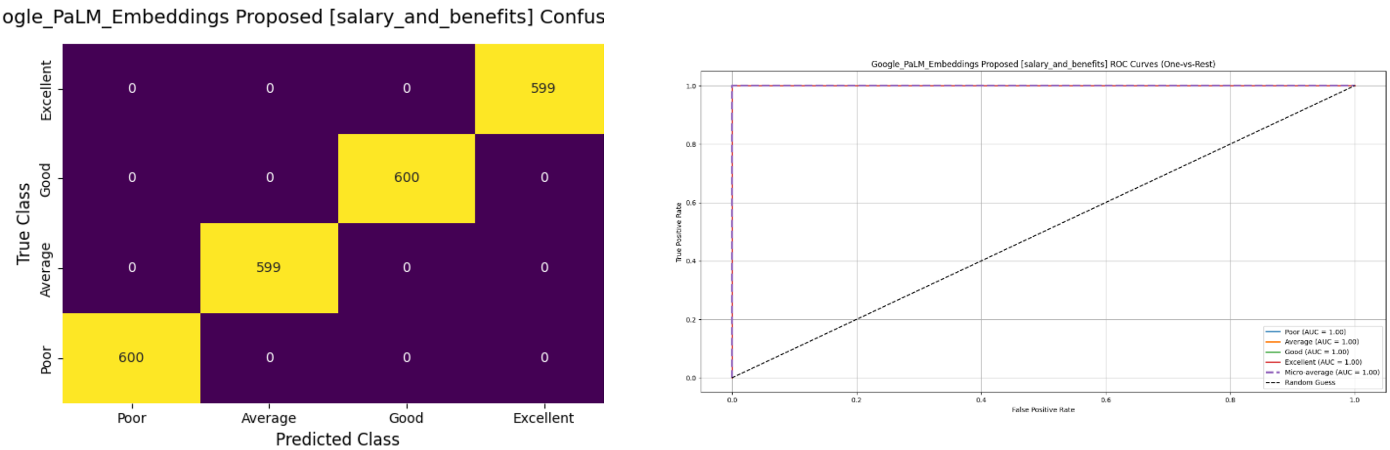


(a) (b)

Fig. 5 (a, b):Confusion matrix and ROC of Proposed TGAM model for skill development using confusion matrix and ROC curve

Fig. 5 (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the skill development dimension. The matrix shows a perfectly aligned diagonal structure where all instances are correctly classified into their respective categories. There are no off-diagonal values, indicating zero misclassification across all skill levels. This reflects the model's strong ability to clearly differentiate between different stages of skill development. The uniformity of correct predictions highlights the effectiveness of the feature representation and model learning process. This analysis demonstrates that the model achieves optimal classification performance for this dimension.

Fig. 5 (b) depicts the ROC curves for the proposed TGAM model using a one-vs-rest approach for multi-class classification. The curves show ideal performance with AUC values equal to 1.0 for all classes. The curves closely follow the top-left boundary, indicating perfect separation between different skill development categories. This demonstrates the model's exceptional discriminative capability. The consistent and stable curves confirm highly reliable predictions across all classes. This evaluation establishes the superior performance of the proposed model in multi-class classification tasks.



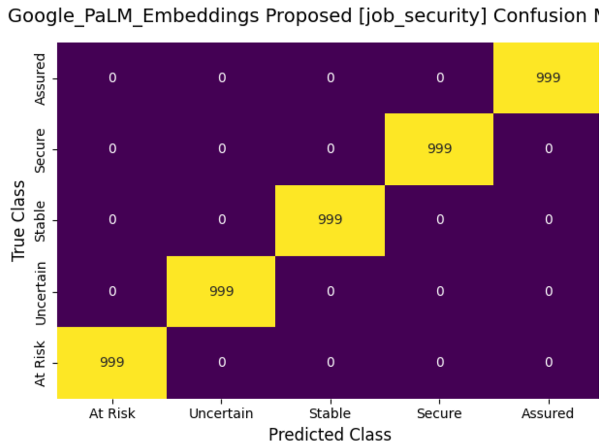
(a) (b)

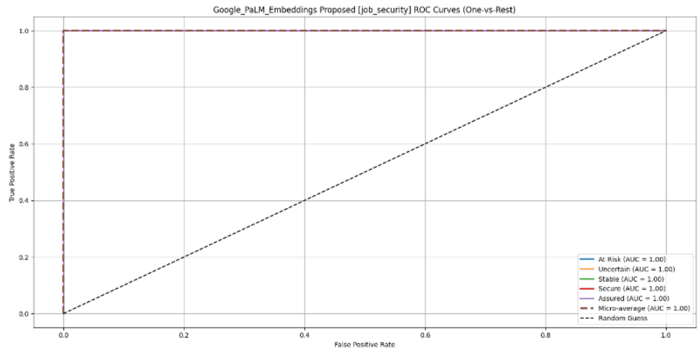
Fig. 6 (a, b): Confusion matrix and ROC of proposed TGAM Model for salary and benefits using confusion matrix and ROC curve

Fig. 6. (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the salary and benefits dimension. The matrix shows a perfectly aligned diagonal pattern where all instances are correctly classified into their respective categories. The absence of off-diagonal values indicates zero misclassification across all classes. This demonstrates the model's strong capability to clearly distinguish between different levels of salary satisfaction. The consistent distribution of correct predictions highlights the effectiveness of feature extraction and model learning. This analysis confirms that the model achieves optimal classification performance for this dimension.

Fig. 6. (b) depicts the ROC curves for the proposed TGAM model using a one-vs-rest approach for multi-class classification. The curves show ideal performance with AUC values equal to 1.0 for all classes. The curves closely follow the top-left boundary, indicating perfect separation between categories. This reflects the model's exceptional discriminative ability across all salary and benefits

levels. The consistent and smooth curves confirm highly reliable predictions. This evaluation establishes the superior performance of the proposed model in multi-class classification tasks.



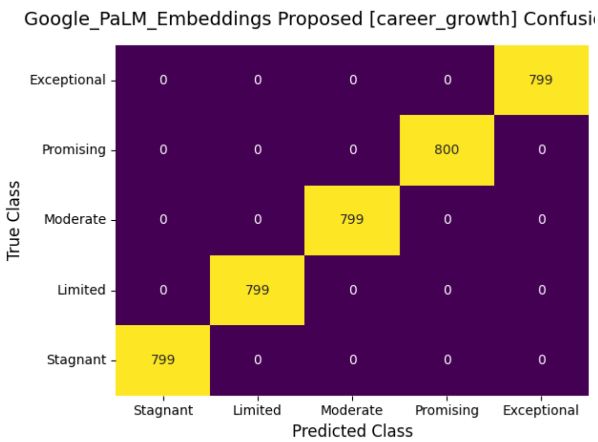


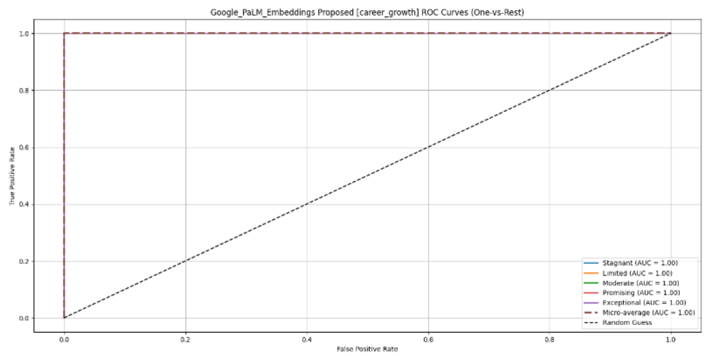
(a) (b)

Fig. 7. (a, b): Confusion matrix and ROC of proposed TGAM model for job security using confusion matrix and ROC curve

Fig. 7. (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the job security dimension. The matrix shows a perfectly aligned diagonal structure where all instances are correctly classified into their respective categories. There are no off-diagonal values, indicating zero misclassification across all job security levels. This reflects the model's strong capability to clearly distinguish between different levels of job stability. The uniform distribution of correct predictions highlights the effectiveness of feature representation and model learning. This analysis confirms that the model achieves optimal classification performance for this dimension.

Fig. 7. (b) depicts the ROC curves for the proposed TGAM model using a one-vs-rest approach for multi-class classification. The curves show ideal performance with AUC values equal to 1.0 for all classes. The curves closely follow the top-left boundary, indicating perfect separation between job security categories. This demonstrates the model's exceptional discriminative capability. The consistent and smooth curves confirm highly reliable predictions across all classes. This evaluation establishes the superior performance of the proposed model in multi-class classification tasks.



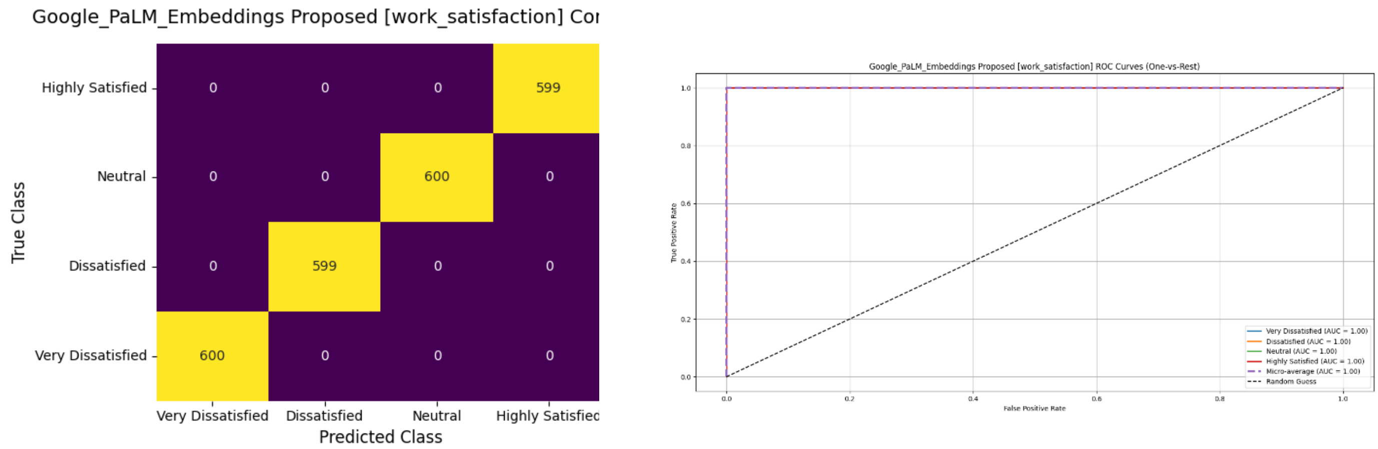


(a) (b)

Fig. 8.(a, b): Performance evaluation of proposed TGAM model for career growth using confusion matrix and ROC curve

Fig. 8. (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the career growth dimension. The matrix exhibits a perfectly diagonal structure where all instances are accurately classified into their respective categories. The absence of off-diagonal values indicates zero misclassification across all career growth levels. This reflects the model's strong capability to clearly differentiate between various stages of career progression. The uniform distribution of correct predictions highlights the effectiveness of feature extraction and learning mechanisms. This analysis confirms that the model achieves optimal classification performance for this dimension.

Fig. 8. (b) depicts the ROC curves for the proposed TGAM model using a one-vs-rest approach for multi-class classification. The curves demonstrate ideal performance with AUC values equal to 1.0 for all classes. The curves closely follow the top-left boundary, indicating perfect separation between career growth categories. This reflects the model's exceptional discriminative capability. The consistent and smooth curves confirm highly reliable predictions across all classes. This evaluation establishes the superior performance of the proposed model in multi-class classification tasks.



(a) (b)

Fig. 9. Performance Evaluation of Proposed TGAM Model for Work Satisfaction using Confusion Matrix and ROC Curve

Fig. 9 (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the work satisfaction dimension. The matrix shows a perfectly diagonal structure where all instances are correctly classified into their respective satisfaction categories. The absence of off-diagonal values indicates zero misclassification across all classes. This reflects the model's strong capability to clearly distinguish between different levels of employee satisfaction. The consistent distribution of correct predictions highlights the effectiveness of feature extraction and model learning. This analysis confirms that the model achieves optimal classification performance for this dimension.

Fig. 9 (b) depicts the ROC curves for the proposed TGAM model using a one-vs-rest approach for multi-class classification. The curves show ideal performance with AUC values equal to 1.0 for all classes. The curves closely follow the top-left boundary, indicating perfect separation between satisfaction categories. This demonstrates the model's exceptional discriminative capability. The consistent and smooth curves confirm highly reliable predictions across all classes. This evaluation establishes the superior performance of the proposed model in multi-class classification tasks.

5. CONCLUSION

The study presents an intelligent and robust framework for predicting workforce satisfaction across multiple dimensions by integrating advanced NLP and machine learning techniques. The use of comprehensive preprocessing, transformer-based feature extraction through Google PaLM embeddings, and SMOTE-based class balancing significantly enhances data quality and learning capability. While traditional models such as QDA, LDA, and HGB achieve moderate accuracy levels (around 51%–56%), reflecting their limitations in capturing complex semantic patterns, the proposed TGAM model demonstrates superior performance with 100% accuracy and optimal precision, recall, and F1-score across all targets. This remarkable improvement highlights the effectiveness of the ensemble-based approach in modeling intricate relationships within the data. Additionally, the system supports reliable multi-output prediction for various satisfaction aspects simultaneously, and its integrated visualization and evaluation modules enhance interpretability and comparative analysis, making the framework highly scalable, accurate, and suitable for real-world workforce analytics.

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