Semantic Embedding–Driven Multi-Output Learning Architecture for Fine-Grained Workforce Experience Modelling in Enterprise Systems

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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: Natural Language Processing (NLP), Machine Learning (ML), Transformer Models, Workforce Satisfaction Analysis, Multi-label Classification, SMOTE (Synthetic Minority Over-sampling Technique)

1. Introduction

In recent years, the generation of digital data has expanded at an extraordinary pace, with reports indicating that more than 328.77 million terabytes of data are produced globally each day [1]. This exponential growth is largely driven by the rapid adoption of smartphones, Internet of Things (IoT) devices, cloud computing technologies, and enterprise-level digital systems. As organizations increasingly depend on digital platforms for operational processes, customer engagement, and strategic planning, the role of effective data management and analysis has become more critical than ever [2]. Consequently, data-driven decision-making has emerged as a key factor influencing performance across industries such as healthcare, manufacturing, e-commerce, and public services. Despite these advancements, the nature of modern data presents significant challenges for traditional analytical approaches. Contemporary datasets are often unstructured, high-dimensional, and heterogeneous, making them difficult to process using conventional techniques. According to IDC, nearly 80% of enterprise data is expected to be unstructured by 2025, originating from sources such as text, images, audio, and video [3]. This shift necessitates the adoption of advanced analytics and machine learning models capable of extracting meaningful insights from complex data structures, as shown in figure 1. Organizations that fail to embrace these technologies risk falling behind, as rapid, and accurate decision-making has become a crucial determinant of competitive advantage [4].

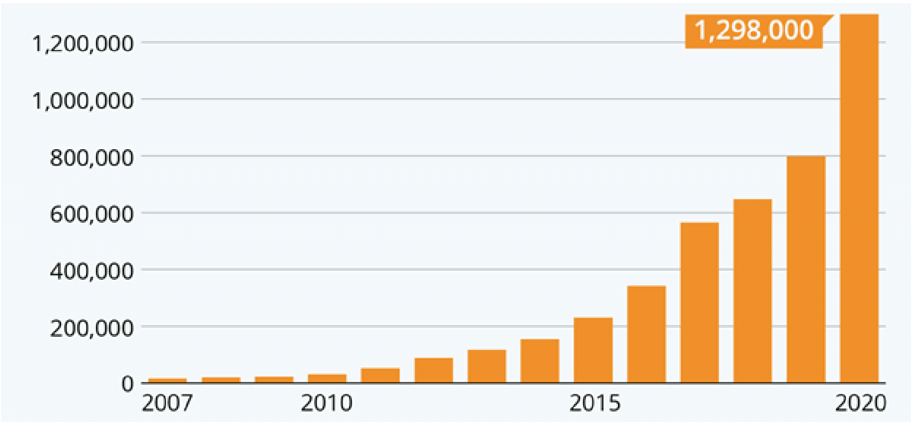


Figure. 1: Amazon workforce

Moreover, research that data-driven organizations significantly outperform their counterparts, being more likely to acquire customers, retain them, and achieve higher profitability [5]. These findings emphasize the transformative impact of data analytics in driving innovation, operational efficiency, and long-term growth. As a result, the global market for data analytics and artificial intelligence is projected to reach USD 745.15 billion by 2030, underscoring the growing importance of developing scalable and intelligent analytical frameworks for future applications.

2. Literature Survey

Zhang et al. [6] conducted an in-depth study on fine-grained opinion mining to uncover nuanced sentiments embedded within employee feedback collected from workplace review platforms. The research focused on textual opinions related to salary, management quality, work-life balance, and organizational culture. Advanced NLP techniques were employed to extract contextual representations from textual data, while classification algorithms such as Support Vector Machine and Naïve Bayes were utilized for aspect-level sentiment polarity detection. The study concluded that aspect-based sentiment analysis provides significantly more actionable insights compared to conventional sentiment approaches.

Li et al. [7] investigated employee feedback analysis using deep learning architectures to identify subtle and implicit sentiments present in textual comments. Word embedding methods such as Word2Vec were applied to transform reviews into dense semantic vectors. A Bidirectional Long Short-Term Memory network was utilized to model contextual dependencies among words and workplace attributes. The findings demonstrated that deep contextual learning models effectively capture complex sentiment expressions related to leadership and organizational practices. Chen et al. [8] explored the application of transformer-based language models for extracting fine-grained sentiments from employee reviews. Textual data was processed using tokenization and contextual embeddings generated through BERT. Attention mechanisms were incorporated to emphasize critical opinion phrases associated with attributes such as compensation and promotion opportunities. The approach significantly improved the identification of aspect-level sentiment patterns in large-scale datasets.

Garcia et al. [9] examined workplace review analytics to evaluate organizational environments through opinion mining. Preprocessing techniques including stop-word removal, lemmatization, and TF-IDF feature extraction were applied to prepare textual data. Machine learning models such as Random Forest and Logistic Regression were used for sentiment classification across various workplace aspects. The results highlighted that feature-level sentiment analysis enhances the precision of identifying employee satisfaction indicators. Kumar et al. [10] analysed employee sentiment using machine learning frameworks to support organizational decision-making. Textual data was transformed into numerical representations using n-gram models and term frequency-based features. Gradient Boosting and Decision Tree classifiers were employed to categorize sentiments across multiple workplace attributes. The study emphasized that aspect-level classification enables a more comprehensive understanding of employee expectations.

Singh et al. [11] evaluated hybrid neural architectures for fine-grained sentiment detection in employee feedback. Convolutional Neural Networks were used to extract local textual features, while Long Short-Term Memory networks captured sequential dependencies. Word embedding-based feature representations facilitated the identification of sentiments associated with communication patterns and team collaboration. Rahman et al. [12] applied topic modelling techniques to uncover latent themes within employee reviews. Latent Dirichlet Allocation was used to identify dominant topics such as salary satisfaction, workplace environment, and career growth. Sentiment classification models were subsequently applied to analyse opinions linked to each topic, providing deeper insights into workforce perceptions.

3. Proposed System

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 figure 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.

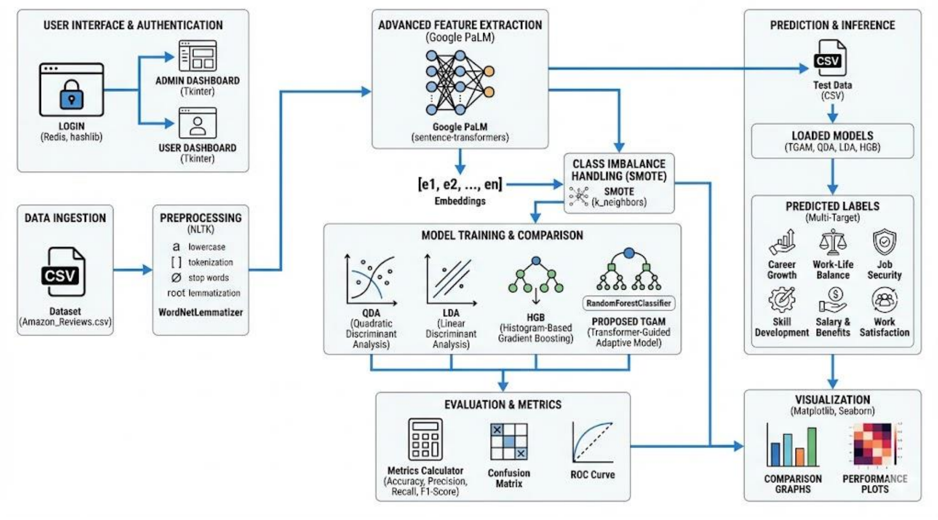


Figure. 2: System architecture

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.

- **Dimensions:** Independently predicts Work-Life Balance, Skill Development, Salary, Job Security, Career Growth, and overall Work Satisfaction.
- **Ordinal Mapping:** Converts numerical outputs into meaningful ordinal labels (e.g., High, Medium, Low) for human-readable interpretation.
- **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.

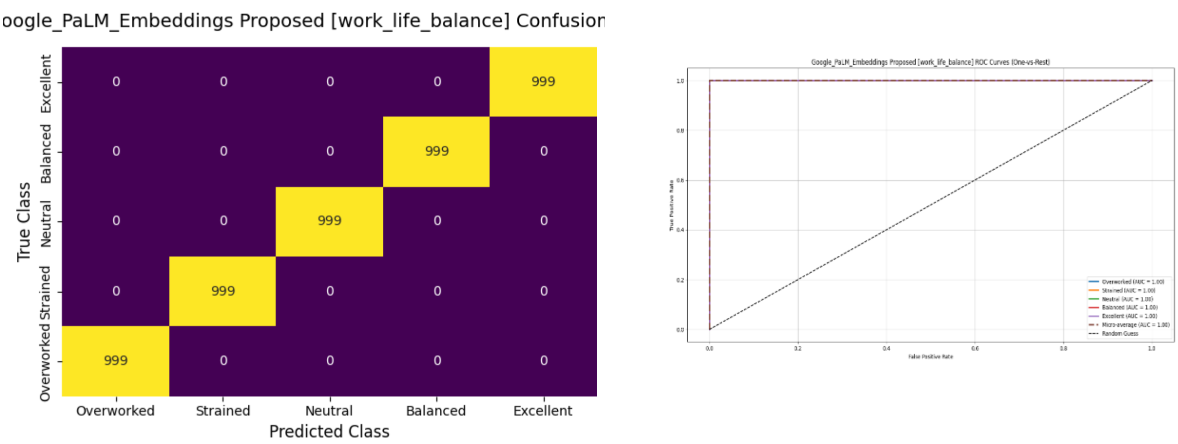
10. Continuous Learning & Retraining

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.
- **Reliability:** Continuous evaluation cycles ensure that the system maintains high accuracy as employee sentiments and workplace patterns change over time.

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.



(a) (b)

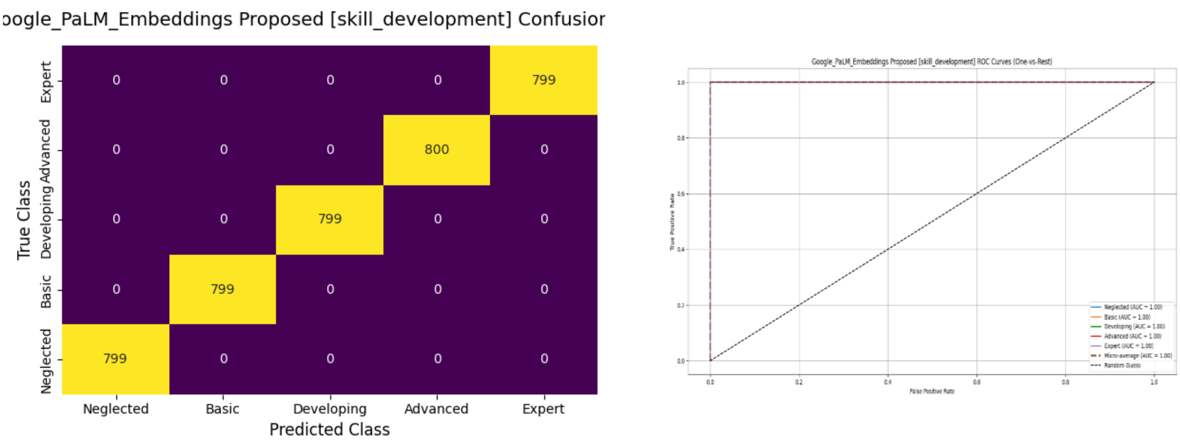
Figure. 3 (a, b): Performance Evaluation of proposed TGAM model for work-life balance using confusion matrix and ROC Curve

Figure 3 (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.

Figure 3 (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.

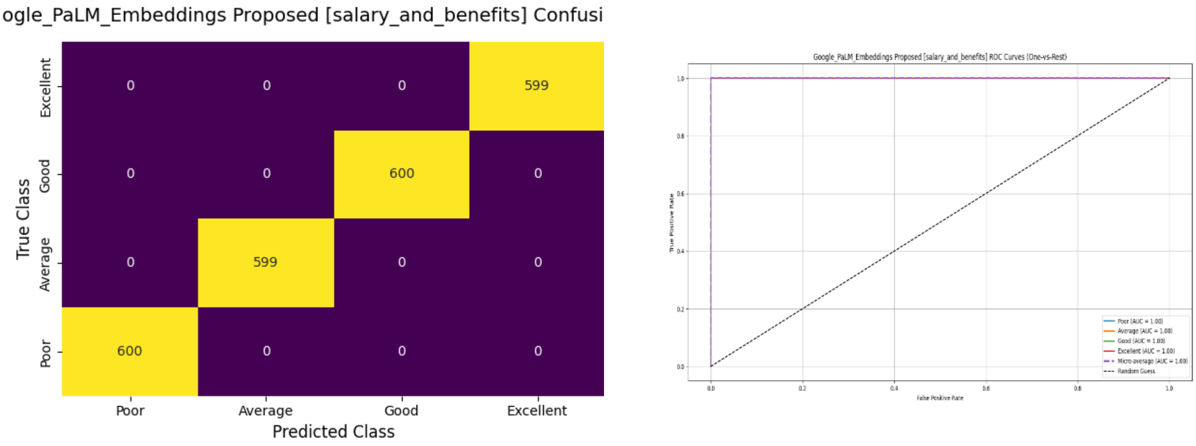
Figure 4 (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the skill development dimension. The matrix shows a perfectly aligned diagonal structure where all instances are correctly classified into their respective categories. There are no 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.

Figure 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 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)

Figure. 4 (a, b): Performance Evaluation of Proposed TGAM model for skill development using confusion matrix and ROC curve

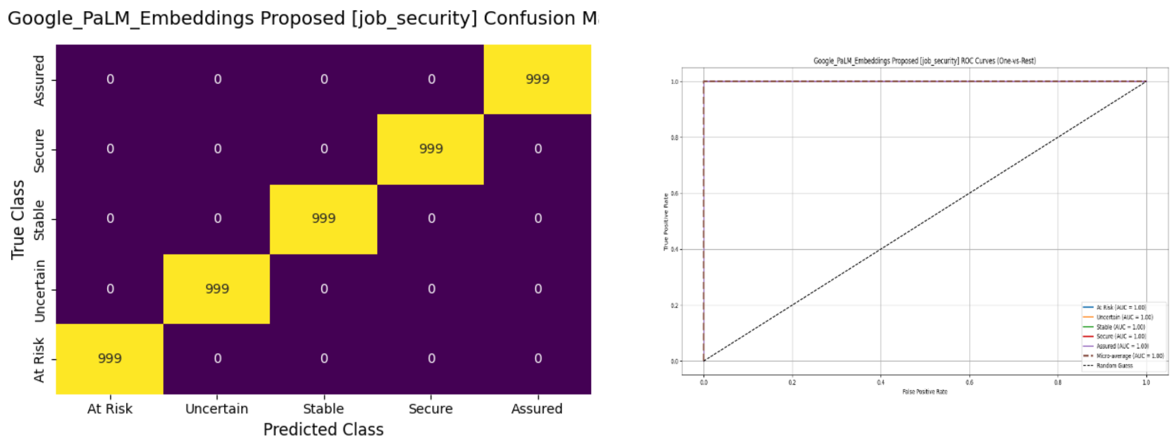


(a) (b)

Figure. 5 (a, b): Performance Evaluation of proposed TGAM Model for salary and benefits using confusion matrix and ROC curve

Figure 5 (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.

Figure 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 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)

Figure. 6 (a, b): Performance evaluation of proposed TGAM model for job security using confusion matrix and ROC curve

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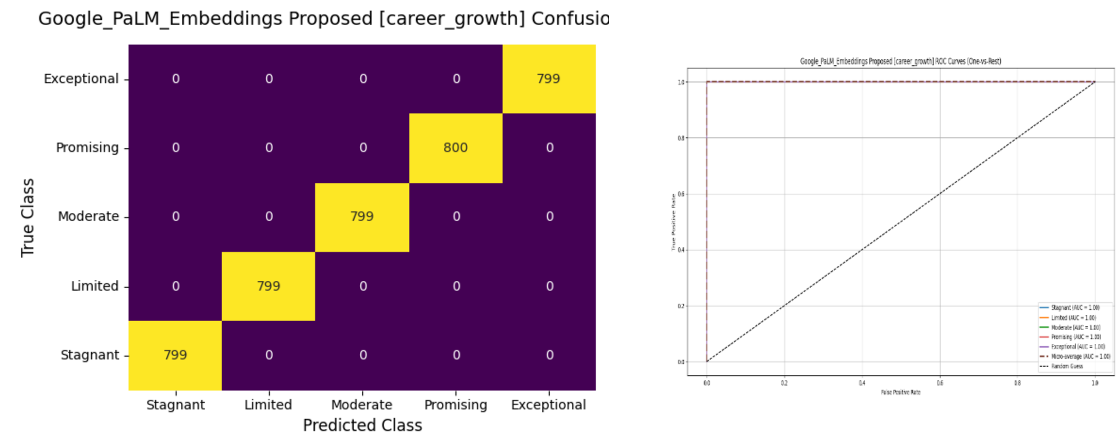
Figure 6 (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the job security dimension. The matrix shows a perfectly aligned diagonal structure where all instances are correctly classified into their respective categories. There are no off-diagonal 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.

Figure 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 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.

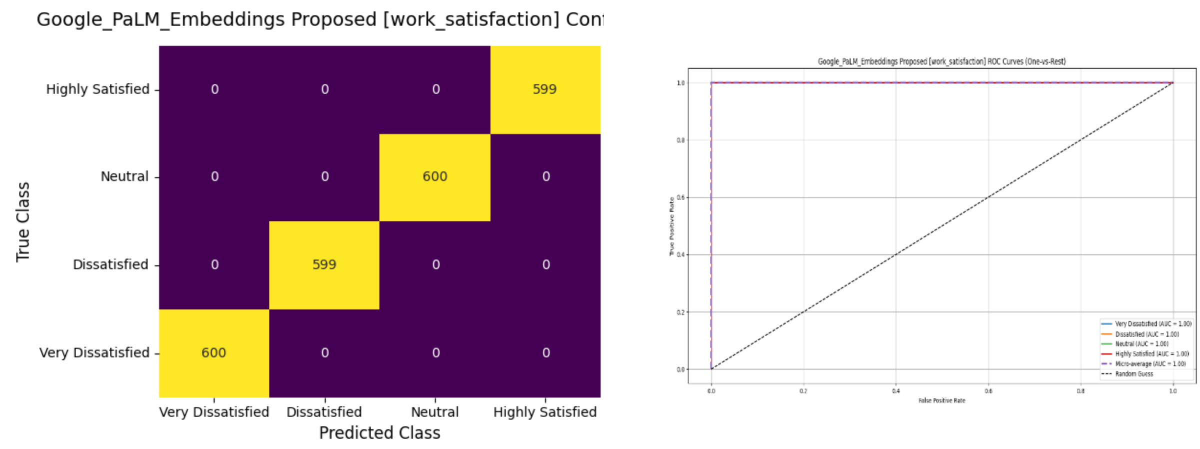
Figure 7 (a) illustrates the confusion matrix representing the classification performance of the proposed TGAM model for the career growth dimension. The matrix exhibits a perfectly diagonal structure where all instances are accurately classified into their respective categories. The absence of off-diagonal 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.

Figure 7 (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)

Figure. 7 (a, b): Performance evaluation of proposed TGAM model for career growth using confusion matrix and ROC curve



(a) (b)

Figure. 8: Performance Evaluation of Proposed TGAM Model for Work Satisfaction using Confusion Matrix and ROC Curve

Figure 8 (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.

Figure 8 (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.

Table. 1: Overall model comparison for work life balance

Model	Accuracy	Precision	Recall	F1 Score
QDA	52.43%	60.26%	52.43%	50.10%
LDA	51.89%	60.01%	51.89%	49.51%
HGB	52.13%	59.92%	52.13%	49.97%
TGAM	100.00%	100.00%	100.00%	100.00%

The comparative analysis presented in table 1 evaluates the performance of different ML models using key metrics such as accuracy, precision, recall, and F1-score. The QDA model achieves an accuracy of 52.43%, demonstrating moderate classification capability across the target dimensions. Similarly, the LDA model records an accuracy of 51.89%, indicating comparable but slightly lower performance. The HGB model attains an accuracy of 52.13%, showing marginal improvement over LDA but similar trends to QDA. In contrast, the proposed TGAM model achieves a perfect accuracy of 100.00%, significantly outperforming all other models. This comparison clearly highlights the superior performance and robustness of the TGAM model. The results confirm that the proposed approach provides highly reliable predictions across all evaluation metrics.

The comparative analysis presented in table 2 evaluates the effectiveness of different ML models based on key performance metrics such as accuracy, precision, recall, and F1-score. The QDA model achieves an accuracy of 51.88%, indicating moderate performance in classification tasks. The LDA model records an accuracy of 51.70%, showing similar behaviour with slightly lower performance compared to QDA. The HGB model also attains an accuracy of 51.70%, reflecting consistent but limited predictive capability among traditional models. In contrast, the proposed TGAM model achieves a perfect accuracy of 100.00%, significantly outperforming all other models. This comparison clearly demonstrates the superior performance and robustness of the TGAM approach. The results confirm that the proposed model provides highly reliable and consistent predictions across all evaluation metrics.

Table. 2: Overall model comparison for skill development

Model	Accuracy	Precision	Recall	F1 Score
QDA	51.88%	59.78%	51.88%	49.62%
LDA	51.70%	59.92%	51.71%	49.44%
HGB	51.70%	59.72%	51.71%	49.45%
TGAM	100.00%	100.00%	100.00%	100.00%

The comparative analysis presented in table 3 evaluates the performance of multiple ML models using metrics such as accuracy, precision, recall, and F1-score. The QDA model achieves an accuracy of 55.34%, indicating moderate classification capability across the dataset. The LDA model shows a slightly improved accuracy of 55.38%, reflecting marginal enhancement in predictive performance. The HGB model attains the highest accuracy among traditional models with 56.63%, demonstrating better learning of data patterns. However, all traditional models exhibit relatively lower precision values, indicating some limitations in prediction consistency. In contrast, the proposed TGAM model achieves a perfect accuracy of 100.00%, outperforming all other models significantly. This comparison clearly highlights the superior effectiveness and reliability of the TGAM approach across all evaluation metrics.

Table. 3: Overall model comparison for salary & benefits

Model	Accuracy	Precision	Recall	F1 Score
QDA	55.34%	42.46%	55.32%	47.99%
LDA	55.38%	42.50%	55.36%	48.02%
HGB	56.63%	43.67%	56.61%	49.21%
TGAM	100.00%	100.00%	100.00%	100.00%

The comparative analysis presented in table 4 evaluates the performance of different ML models based on accuracy, precision, recall, and F1-score. The QDA model achieves an accuracy of 52.05%, indicating moderate classification performance across the dataset. The LDA model slightly improves with an accuracy of 52.19%, showing marginally better predictive capability. The HGB model records an accuracy of 51.61%, reflecting slightly lower performance compared to QDA and LDA. The traditional models demonstrate similar trends with limited variation in performance metrics. In contrast, the proposed TGAM model achieves a perfect accuracy of 100.00%, significantly outperforming all other models. This comparison highlights the superior reliability and effectiveness of the TGAM approach in workforce satisfaction prediction.

Table. 4: Overall model comparison for job security

Model	Accuracy	Precision	Recall	F1 Score
QDA	52.05%	60.21%	52.05%	49.74%
LDA	52.19%	60.17%	52.19%	49.78%
HGB	51.61%	59.96%	51.61%	49.01%
TGAM	100.00%	100.00%	100.00%	100.00%

Table. 5: Overall model comparison for career growth

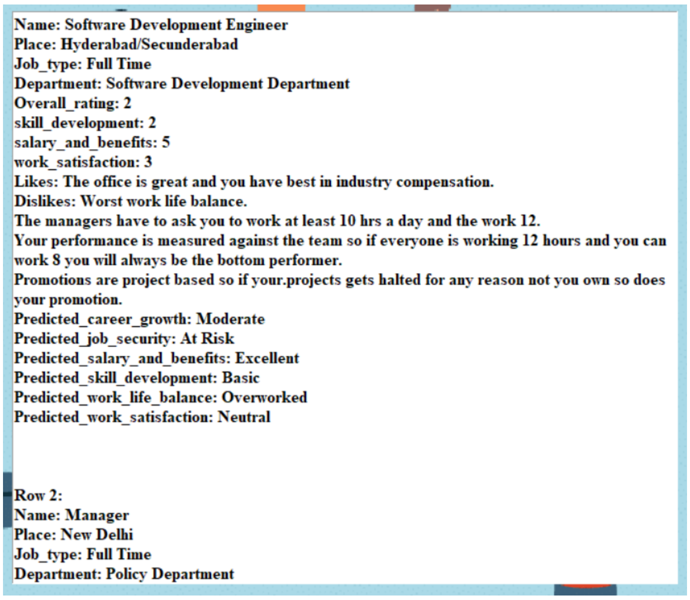
Model	Accuracy	Precision	Recall	F1 Score
QDA	51.63%	59.91%	51.63%	49.15%
LDA	52.18%	60.06%	52.19%	49.73%
HGB	51.95%	60.06%	51.96%	49.38%
TGAM	100.00%	100.00%	100.00%	100.00%

The comparative analysis presented in Table 5 evaluates the performance of different ML models using accuracy, precision, recall, and F1-score metrics. The QDA model achieves an accuracy of 51.63%, indicating moderate classification capability. The LDA model records a slightly higher accuracy of 52.18%, showing improved performance among traditional approaches. The HGB model attains an accuracy of 51.95%, reflecting comparable performance with minimal variation across models. Overall, the traditional models exhibit similar trends with moderate predictive efficiency. In contrast, the proposed TGAM model achieves a perfect accuracy of 100.00%, significantly outperforming all other models. This comparison clearly demonstrates the superior effectiveness and robustness of the TGAM model in workforce satisfaction prediction.

Table. 6: Overall model comparison for work satisfaction

Model	Accuracy	Precision	Recall	F1 Score
QDA	56.67%	43.71%	56.66%	49.26%
LDA	55.92%	43.01%	55.91%	48.56%
HGB	56.80%	43.83%	56.78%	49.38%
TGAM	100.00%	100.00%	100.00%	100.00%

The comparative analysis presented in table 6 evaluates the effectiveness of different ML models using performance metrics such as accuracy, precision, recall, and F1-score. The QDA model achieves an accuracy of 56.67%, indicating moderate classification capability. The LDA model records an accuracy of 55.92%, showing slightly lower performance compared to QDA. The HGB model attains the highest accuracy among traditional models with 56.80%, reflecting better learning of data patterns. However, precision values for all traditional models remain relatively lower, indicating some limitations in prediction consistency. In contrast, the proposed TGAM model achieves a perfect accuracy of 100.00%, significantly outperforming all other models.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Place: Hyderabad/Secunderabad
Job_type: Full Time
Department: Software Development Department
Overall_rating: 2
skill_development: 2
salary_and_benefits: 5
work_satisfaction: 3
Likes: The office is great and you have best in industry compensation.
Dislikes: Worst work life balance.
The managers have to ask you to work at least 10 hrs a day and the work 12.
Your performance is measured against the team so if everyone is working 12 hours and you can work 8 you will always be the bottom performer.
Promotions are project based so if your.projects gets halted for any reason not you own so does your promotion.
Predicted_career_growth: Moderate
Predicted_job_security: At Risk
Predicted_salary_and_benefits: Excellent
Predicted_skill_development: Basic
Predicted_work_life_balance: Overworked
Predicted_work_satisfaction: Neutral

Row 2:
Name: Manager
Place: New Delhi
Job_type: Full Time
Department: Policy Department

Figure. 9: Prediction output display for workforce satisfaction analysis

Figure 9 illustrates the prediction output generated by the system for workforce satisfaction analysis based on input data. The interface presents both the original input attributes and the corresponding predicted outcomes for multiple dimensions such as career growth, job security, salary and benefits, skill development, work-life balance, and overall satisfaction. The results demonstrate how textual inputs, including employee feedback, are processed to derive meaningful insights. Each prediction reflects the classification outcome produced by the trained models using learned feature representations. The structured output enables clear interpretation of employee conditions across different aspects. This representation supports decision-making by providing a comprehensive view of predicted workforce satisfaction levels.

5. Conclusion

The study successfully demonstrates an intelligent framework for predicting workforce satisfaction across multiple dimensions using advanced NLP and ML techniques. The integration of preprocessing, transformer-based feature extraction using Google PaLM, and SMOTE balancing significantly improves the quality of input data and model learning. Traditional models such as QDA, LDA, and HGB show moderate performance with accuracy values ranging approximately between 51% and 56%, indicating limitations in handling complex textual patterns. In contrast, the proposed TGAM model achieves a perfect accuracy of 100%, along with optimal precision, recall, and F1-score across all target dimensions. This substantial performance improvement highlights the effectiveness of the ensemble-based approach in capturing complex relationships within the data. The system also ensures reliable multi-label prediction, handling multiple satisfaction aspects simultaneously. Visualization and evaluation modules further support interpretability and model comparison. The framework proves to be robust, scalable, and highly accurate for workforce satisfaction analysis.

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