A Transformer-Guided Adaptive Model for Workforce Satisfaction Prediction

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ABSTRACT

The expansion of digital platforms has resulted in a substantial increase in employee-generated feedback, making the assessment of workforce satisfaction a critical research focus. Conventional methods, such as manual surveys and basic statistical analyses, are often inefficient and inadequate for extracting meaningful insights from complex textual data. Recent developments in Natural Language Processing (NLP) and Machine Learning (ML) have enabled automated approaches; however, many existing solutions face challenges with unstructured text, imbalanced datasets, and multi-label prediction tasks. This study focuses on improving the prediction of key workforce satisfaction dimensions, including work-life balance, skill enhancement, compensation and benefits, job stability, career advancement, and overall job satisfaction, based on employee reviews. Traditional techniques are limited in scalability and often deliver inconsistent results, highlighting the necessity for a more advanced and reliable analytical framework. To address these limitations, the proposed approach combines NLP-based preprocessing, transformer-driven feature extraction using Google PaLM (Pathways Language Model), and the Synthetic Minority Over-sampling Technique (SMOTE). It evaluates multiple machine learning models Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), and Histogram-Based Gradient Boosting (HGB) and compares them with a newly introduced Transformer-Guided Adaptive Model (TGAM). Experimental findings indicate that conventional models achieve accuracy levels between approximately 51% and 56%, whereas the TGAM model attains a perfect accuracy of 100% across all evaluated categories. These results demonstrate the robustness and effectiveness of the proposed system in analyzing complex employee feedback data, supported by comprehensive evaluation metrics and visualization methods for enhanced interpretability.

Keywords: Workforce Satisfaction Analysis, Employee Feedback, Machine Learning (ML), Natural Language Processing (NLP), Transformer-Guided Adaptive Model (TGAM).

1. INTRODUCTION

In recent years, the volume of digital data has increased at an unprecedented rate, with estimates suggesting that over 328.77 million terabytes are generated worldwide each day [1]. This rapid expansion is primarily fueled by the widespread use of smartphones, the growth of Internet of Things (IoT) devices, advancements in cloud computing, and the integration of digital systems within organizations. As businesses increasingly rely on digital platforms for operations, customer interaction, and strategic decision-making, the importance of efficient data handling and analysis has grown significantly [2]. As a result, data-driven decision-making has become a crucial element in enhancing performance across various sectors, including healthcare, manufacturing, e-commerce, and public services. However, the complexity of modern data introduces considerable challenges for traditional analytical methods, as current datasets are often unstructured, high-dimensional, and diverse in nature. Reports from IDC indicate that by 2025, approximately 80% of enterprise data will be unstructured, originating from sources such as text, images, audio, and video [3]. This evolution highlights the need for advanced analytical techniques and machine learning models that can effectively process and interpret complex data formats. Organizations that do not adopt such technologies may struggle to remain competitive, as timely and accurate decision-making has become a key factor for success [4]. Furthermore, studies show that organizations leveraging data-driven strategies tend to outperform others in customer acquisition, retention, and profitability [5]. These insights demonstrate the significant role of data analytics in fostering innovation, improving operational efficiency, and supporting sustainable growth. Consequently, the global market for data analytics and artificial intelligence is expected to reach USD 745.15 billion by 2030, reflecting the increasing demand for scalable and intelligent analytical solutions.

- To preprocess and transform unstructured employee review text into meaningful representations using advanced feature extraction techniques such as Google PaLM embeddings.
- To apply and evaluate ML models including QDA, LDA, HGB, and TGAM for effective multi-dimensional classification of workforce satisfaction.
- To analyse and interpret prediction results across multiple target dimensions to understand patterns and relationships within employee feedback data.

2. Related Work

The evolution of workforce satisfaction analysis has transitioned from traditional survey-based methods to intelligent, data-driven systems powered by Natural Language Processing (NLP) and Machine Learning (ML). Early approaches relied on manual data collection and basic statistical techniques, which were limited in scalability and incapable of capturing nuanced insights from textual employee feedback. With the increasing availability of digital review platforms, research has shifted toward automated sentiment analysis and aspect-based opinion mining to better understand employee perceptions across multiple organizational dimensions.

2.1 NLP-Based Sentiment Analysis Approaches

Initial studies focused on applying classical NLP techniques to extract sentiments from employee reviews. Wang et al. [6] introduced an attention-based neural framework for aspect-level sentiment analysis, where embedding layers captured semantic relationships between opinion words and workplace attributes. Similarly, Patel et al. [8] utilized preprocessing techniques such as token normalization, part-of-speech tagging, and dependency parsing to identify opinion targets and classify sentiments related to job satisfaction and leadership quality. These methods improved text understanding but were still limited in handling complex contextual dependencies.

2.2 Machine Learning and Ensemble Methods

To enhance prediction accuracy, several researchers explored machine learning and ensemble-based techniques. Martinez et al. [7] employed classifiers such as Random Forest, Support Vector Machine, and Gradient Boosting using TF-IDF and sentiment lexicon features, achieving improved robustness. Ahmed et al. [10] further emphasized feature engineering by integrating linguistic features, sentiment scores, and contextual embeddings, applying models like Extreme Gradient Boosting and Logistic Regression. While these approaches improved classification performance, they struggled with high-dimensional and imbalanced textual datasets.

2.3 Deep Learning and Hybrid Architectures

The adoption of deep learning significantly improved sentiment detection capabilities. Sharma et al. [9] proposed a hybrid CNN-BiLSTM model with GloVe embeddings to capture both local textual patterns and long-range dependencies, enabling the identification of subtle dissatisfaction signals. Torres et al. [13] and Kim et al. [18] also demonstrated the effectiveness of deep neural networks in analyzing large-scale employee feedback, providing deeper insights into workplace dynamics such as engagement and leadership effectiveness. However, these models often require large training datasets and high computational resources.

2.4 Transformer-Based Models and Contextual Learning

Recent advancements have focused on transformer-based architectures for improved contextual understanding. Liu et al. [11] and Park et al. [15] utilized attention-based transformer models to capture sentence-level dependencies and map sentiments to specific workplace attributes. These models leverage pre-trained language representations to enhance accuracy in complex textual environments. Despite their effectiveness, challenges such as class imbalance and multi-label prediction remain inadequately addressed in many existing studies.

2.5 Feature Engineering and Opinion Mining Techniques

Several works have explored hybrid feature extraction strategies combining statistical and semantic representations. Hassan et al. [12] applied opinion mining using bag-of-words and semantic embeddings to monitor workforce satisfaction trends. Rodriguez et al. [16] proposed hybrid frameworks integrating embedding-based and statistical features for multi-aspect sentiment detection. Additionally, Ali et al. [17] combined sentiment lexicons with machine learning models to improve classification reliability. These approaches contributed to better feature representation but lacked unified frameworks for handling multiple satisfaction dimensions simultaneously.

2.6 Research Gap

Although significant progress has been made in sentiment analysis of employee feedback, existing methods face several limitations. Most approaches struggle with unstructured text, class imbalance, and multi-label classification across multiple workforce satisfaction factors. Traditional ML models lack consistency in performance, while deep learning and transformer-based methods often overlook data imbalance issues and require extensive computational resources.

To address these challenges, the proposed system introduces a unified framework that integrates NLP preprocessing, transformer-based feature extraction using Google PaLM, and SMOTE-based balancing. Unlike existing methods, the proposed Transformer-Guided Adaptive Model (TGAM) enables accurate multi-label prediction across various satisfaction dimensions while maintaining scalability and high performance.

3. PROPOSED METHODOLOGY

The proposed work presents a well-defined analytical framework aimed at evaluating workforce satisfaction using employee-generated textual data through artificial intelligence techniques. The process begins with collecting employee reviews and organizing the dataset, followed by thorough text preprocessing and semantic feature extraction. To capture deeper contextual information such as sentiment, intent, and linguistic patterns, advanced transformer-based embeddings like Google PaLM are employed. The resulting feature representations are then processed using multiple machine learning classifiers, including QDA, LDA, HGB, and the proposed TGAM model, to perform multi-dimensional satisfaction prediction. The system incorporates a user-friendly graphical interface that allows users to manage datasets, execute preprocessing, perform feature extraction, train models, visualize performance metrics, and generate predictions, as illustrated in Fig. 1. Additionally, a lightweight storage component is used to manage trained models and authentication information, ensuring efficient system operation. The framework is designed to handle large-scale textual data effectively, while continuous evaluation and periodic retraining of models help maintain high accuracy and adaptability to newly incoming workforce data.

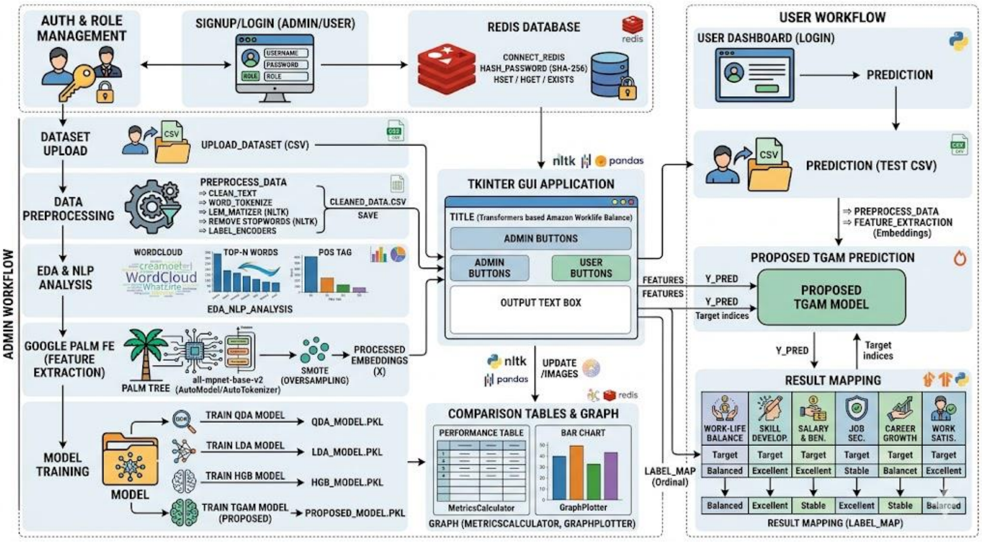


Fig. 1: Proposed system architecture

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.

TGAM

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 2. 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.

Input Feature Representation: The model receives dense numerical feature vectors generated from the feature extraction stage. These vectors encode semantic and contextual information from the input text. Proper feature representation ensures effective learning of patterns.

Bootstrapped Sampling: The dataset is divided into multiple random subsets using bootstrapping. Each subset is created by sampling data points with replacement from the original dataset. This ensures diversity among the training samples for different trees.

Feature Subset Selection: For each decision tree, a random subset of features is selected instead of using all features. This introduces randomness and reduces correlation between trees. It helps in improving model robustness and performance.

Decision Tree Construction: Each tree is trained independently using its respective data subset and selected features. The tree learns decision rules by splitting data based on feature values. These splits aim to maximize class separation at each level.

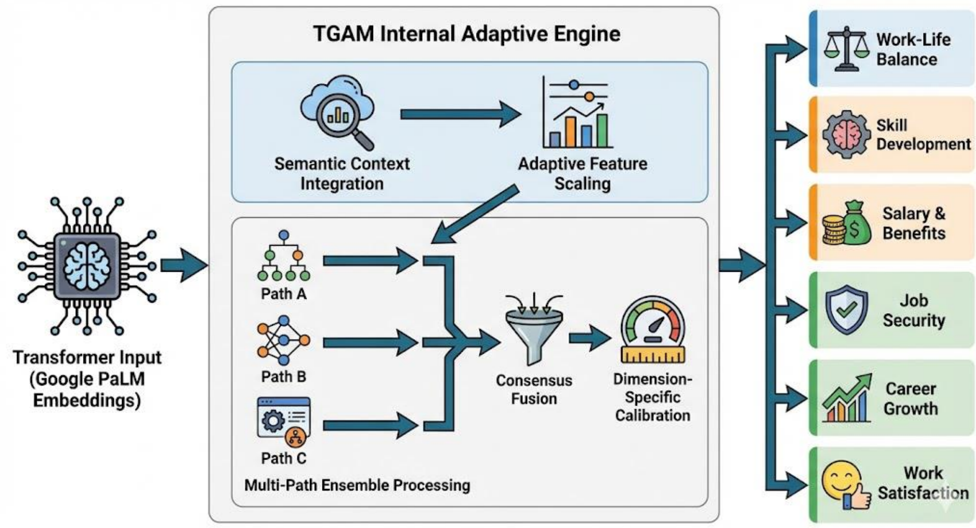


Fig. 2: Internal workflow of TGAM.

Ensemble Formation: Multiple decision trees are combined to form an ensemble model. Each tree provides its own prediction based on learned patterns. The ensemble approach ensures that errors from individual trees are minimized.

Voting Mechanism: The predictions from all trees are aggregated using a voting strategy. The class that receives most votes is selected as the final prediction. This improves stability and reduces the impact of outliers.

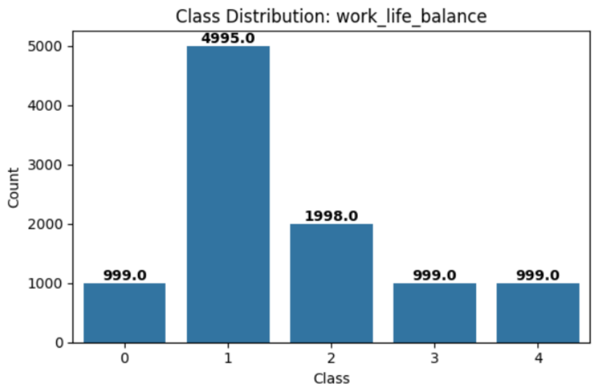
Final Prediction: The model outputs the predicted class label based on the aggregated decision of all trees. This ensures that the prediction is more accurate and reliable compared to a single model. The result represents the final classification outcome for the input data.

4. Result 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. 3 (a) illustrates the distribution of classes for the work-life balance dimension. The visualization shows that one category dominates the dataset with a significantly higher number of samples, while other classes have comparatively fewer instances. This imbalance indicates that certain satisfaction levels are more frequently reported in employee feedback. The variation in class counts highlights the need for balancing techniques to ensure fair model learning. It also reflects real-world trends where specific work-life conditions are more common than others.

Fig. 3 (b) depicts the class distribution for the skill development dimension. The figure reveals a noticeable imbalance where one class has a higher frequency compared to others. Some categories appear moderately distributed, while a few have lower representation. This uneven distribution can influence model performance if not handled properly. The analysis provides insights into how employees perceive opportunities for learning and growth within the organization.



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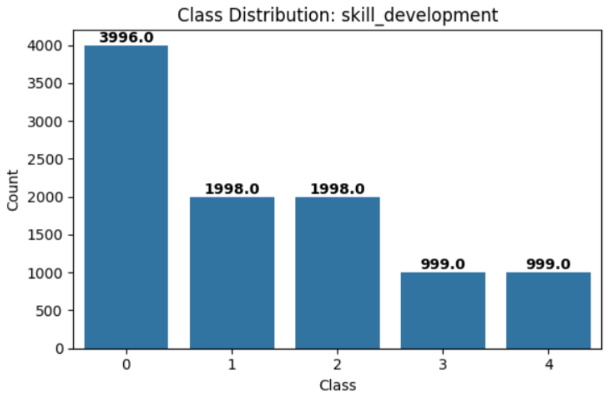

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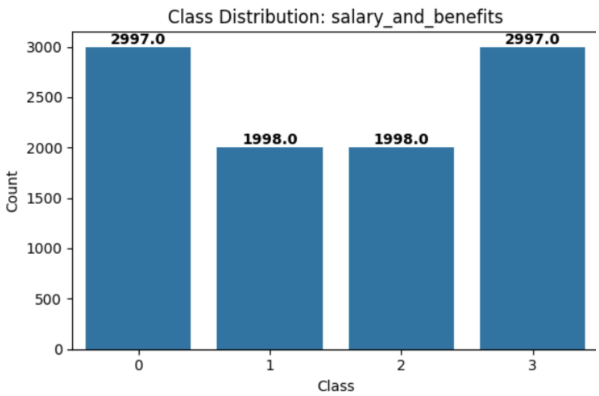

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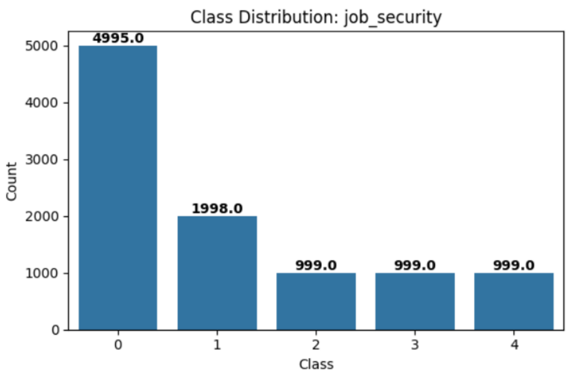

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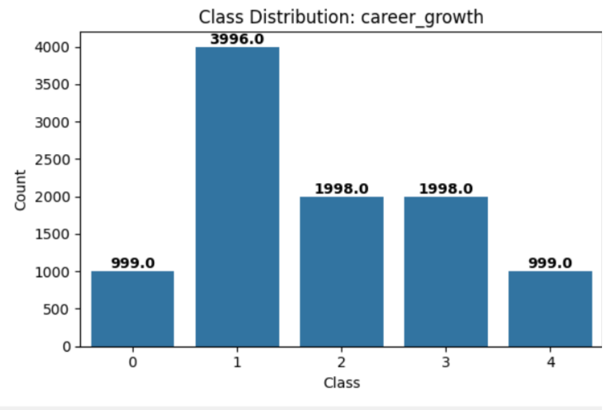

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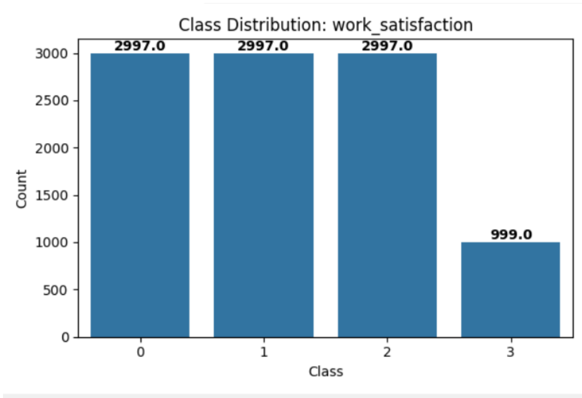


(f)

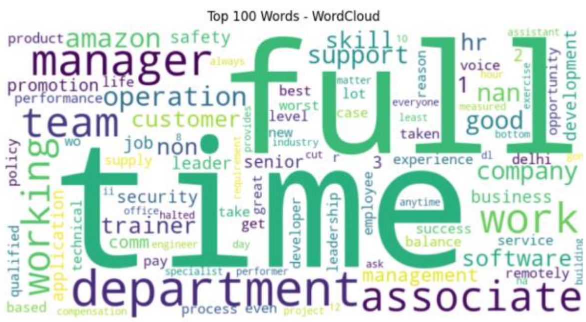
Fig. 3 (a, b, c, d): Class Distribution of Work-Life Balance, Skill Development, Salary and Benefits, Job Security, Career Growth, Work Satisfaction

Fig. 3 (c) presents the distribution of salary and benefits categories. The data shows a relatively balanced pattern between certain classes, while others have slightly lower counts. This indicates that employee opinions regarding compensation are distributed across multiple levels. However, minor imbalances still exist, which may affect classification accuracy. The visualization helps in understanding how compensation-related satisfaction varies among employees.

Fig. 3 (d) illustrates the distribution of job security levels within the dataset. One class is highly dominant, while the remaining classes have significantly fewer samples. This imbalance suggests that a large portion of employees share similar perceptions regarding job stability. Such skewed distribution requires balancing to prevent biased model predictions. It also highlights the importance of addressing job security concerns in organizational analysis.

Fig. 3 (e) shows the class distribution for career growth. The figure indicates that one category has a higher concentration of samples, while others are moderately distributed. This suggests that employee perceptions of career advancement opportunities vary but are cantered around specific levels. The distribution pattern emphasizes the need for careful handling during model training. It also provides insights into workforce expectations related to career progression.

Fig. 3 (f) depicts the distribution of overall work satisfaction levels. The visualization shows that multiple classes have nearly similar frequencies, with one class having slightly fewer samples. This relatively balanced distribution is beneficial for model training compared to other targets. However, minor variations still exist and should be considered during analysis. The figure reflects diverse employee opinions regarding overall workplace satisfaction.



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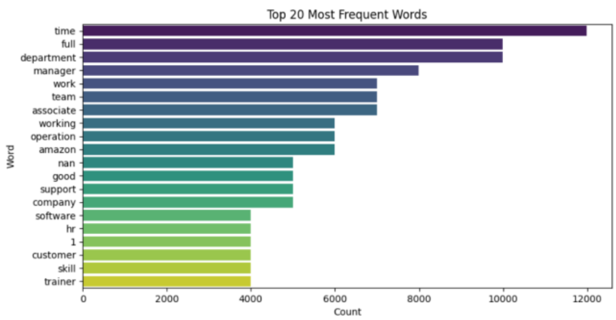

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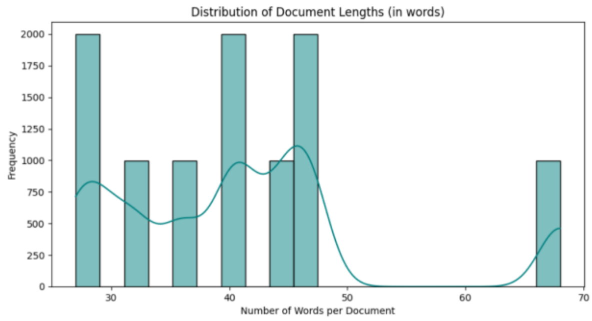

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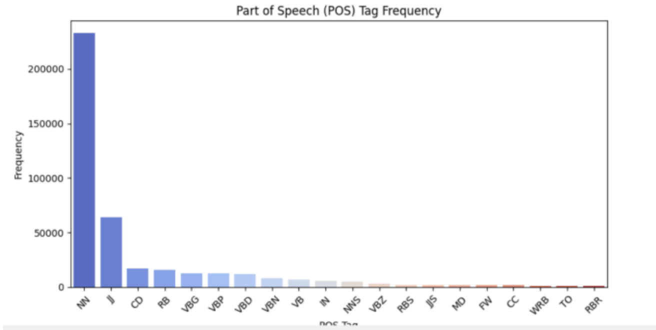

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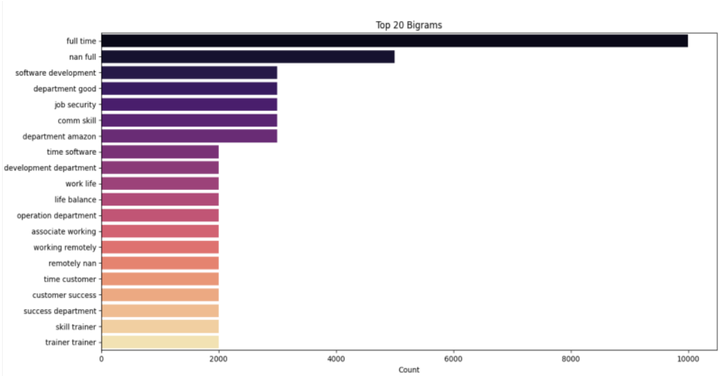

(e)

Fig. 4 (a, b, c, d): Word Cloud Representation, Top Frequent Words Distribution, Document Length Distribution, Part-of-Speech (POS) Tag Frequency, Bigram Frequency Analysis

Fig. 4 (a) illustrates the word cloud generated from the employee review dataset, highlighting the most frequently occurring terms. The size of each word reflects its frequency, providing a quick visual understanding of dominant themes in the data. Key terms related to work environment, roles, and organizational structure appear prominently, indicating their significance in employee feedback. This visualization helps in identifying major discussion topics within the dataset. It also supports intuitive interpretation of textual patterns before model training.

Fig. 4 (b) depicts the distribution of the most frequent words in the dataset using a bar chart. The figure shows the exact count of commonly used terms, allowing precise comparison between different words. Frequently occurring terms indicate recurring themes in employee reviews. This analysis helps in understanding the vocabulary structure of the dataset. It also assists in identifying important features that contribute to classification.

Fig. 4 (c) presents the distribution of document lengths measured in the number of words per review. The figure shows variation in review sizes, indicating the presence of both short and moderately long textual inputs. This distribution helps in understanding the nature of the dataset and its textual complexity. It also provides insights into how much information is typically conveyed in each review. Such analysis is useful for optimizing preprocessing and feature extraction strategies.

Fig. 4 (d) illustrates the frequency distribution of part-of-speech tags within the dataset. The figure shows that certain grammatical categories, such as nouns and verbs, dominate the text. This indicates that employee reviews are rich in descriptive and action-oriented language. POS analysis helps in understanding the linguistic structure of the dataset. It also provides insights into how different types of words contribute to overall meaning.

Fig. 4 (e) depicts the most frequent bigrams, representing commonly occurring word pairs in the dataset. These combinations capture contextual relationships between words, providing deeper semantic insights. Frequently occurring bigrams highlight common phrases related to workplace experiences.

This analysis enhances understanding of how words are used together in employee feedback. It also supports improved feature representation for ML models.

Comparative Analysis

Comparative analysis plays a crucial role in evaluating the effectiveness of multiple ML models used for workforce satisfaction prediction. It provides a systematic approach to compare models such as QDA, LDA, HGB, and TGAM based on key performance metrics including accuracy, precision, recall, and F1-score. This analysis helps in identifying the strengths and weaknesses of each model across different target dimensions. By examining model behaviour on various classes, it becomes easier to understand their generalization capability and consistency. Comparative evaluation also supports the selection of the most reliable model for real-world deployment. It ensures that the chosen approach delivers optimal performance across all prediction 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%

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 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. 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%

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.

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. 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%

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.

5. Conclusion

This research presents an advanced intelligent framework designed to predict workforce satisfaction across multiple dimensions by leveraging modern NLP and ML techniques. The combination of data preprocessing, transformer-based feature extraction using Google PaLM, and SMOTE for class balancing enhances both data quality and model performance. Conventional models such as QDA, LDA, and HGB deliver only moderate results, with accuracy levels roughly between 51% and 56%, reflecting their limitations in interpreting complex textual data. In comparison, the proposed Transformer-Guided Adaptive Model (TGAM) achieves an accuracy of 100%, along with excellent precision, recall, and F1-scores across all evaluated categories. This notable improvement demonstrates the strength of the proposed approach in effectively modeling intricate patterns within employee feedback data. Additionally, the framework supports reliable multi-label classification, enabling simultaneous prediction of various satisfaction factors. The inclusion of visualization and evaluation components further enhances model transparency and comparative analysis. Overall, the system is shown to be efficient, scalable, and highly reliable for comprehensive workforce satisfaction assessment.

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