**DATA SCIENCE TOOLBOX USING PYHTON PROGRAMMING**

**PROJECT REPORT**

(Project Semester January-April 2025)

# LinkedIn Engagement Analysis


**Submitted by**

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Section: K23SK

Course Code: INT375

**Under the Guidance of**

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**CERTIFICATE**

This is to certify that **Pavan Kalyan** bearing Registration no. 12315902 has completed **INT375** project titled, "**LinkedIn Engagement Analysis**" under my guidance and supervision. To the best of my knowledge, the present work is the result of his/her original development, effort and study.

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Date: 9th April, 2025

# DECLARATION

I, Pavan Kalyan, student of B.tech under CSE/IT Discipline at, Lovely Professional University, Punjab, hereby declare that all the information furnished in this project report is based on my own intensive work and is genuine.

Date: Signature

Registration No. 12315902 Pavan Kalyan

# Acknowledgment

I would like to express my sincere gratitude to Professor Anand Kumar for his invaluable guidance, insightful feedback, and unwavering support throughout the course of this research. His mentorship was instrumental in shaping the direction and depth of this work on LinkedIn Engagement Analysis using Machine Learning.

This project integrates theoretical concepts with practical implementation strategies to develop a data-driven framework for analyzing LinkedIn engagement metrics. The design and evaluation of predictive models, feature engineering, and optimization algorithms were grounded in the solid foundation provided by Professor Anand Kumar's expert supervision.

I am also thankful for the learning resources and computing infrastructure that enabled experimentation, data analysis, and model tuning. From data preprocessing and exploratory data analysis (EDA) to the integration of machine learning models like XGBoost, this work reflects an iterative process of refinement driven by constructive critique and academic rigor.

This acknowledgment also extends to the broader academic and open-source communities, whose tools (e.g., Scikit-learn, XGBoost, Pandas, NumPy) played a pivotal role in building and optimizing the LinkedIn engagement analysis framework.

# INTRODUCTION

In recent years, the integration of artificial intelligence (AI) into social media analytics has significantly reshaped how businesses understand and engage with their audiences. Traditional engagement analysis methods often rely on basic metrics like likes, shares, and comments, providing limited insights into user behavior and content performance. However, modern social media platforms, such as LinkedIn, generate vast amounts of data, including user interactions, posting frequency, demographic information, and content engagement patterns. When analyzed intelligently, this data can greatly enhance audience targeting, content strategies, and overall social media performance.

Machine Learning (ML)-driven LinkedIn engagement analysis represents a pivotal advancement in this context. By leveraging historical and real-time data, ML frameworks can predict user behavior, identify content that resonates with different audience segments, and recommend strategies for optimizing engagement. These systems can uncover latent patterns and correlations across various factors such as post frequency, content type, and user interactions, which may remain hidden in traditional models. Moreover, such intelligent systems offer robustness against uncertainty and data incompleteness — common challenges in real-world social media analytics.

This research explores the design, implementation, and deployment of a modular ML-based framework for LinkedIn engagement analysis. Our approach includes data preprocessing pipelines, exploratory data analysis (EDA), machine learning models, and explainable AI components to support decision-makers in improving content and engagement strategies. Emphasis is placed on both technical innovation and practical deployment — addressing challenges such as data imbalance, model generalization, and the interpretability of results.

# Dataset Description

The **LinkedIn Engagement Analysis dataset** contains a total of **6000 user records**, each with **29 attributes**, covering a wide range of **demographic, activity-based, behavioral, and content-related** information. The goal of the dataset is to **predict the engagement level of a LinkedIn user**, represented by the **target label column**, where **1 indicates high engagement** (e.g., high likes, comments, shares), and **0 indicates low or no engagement**. The dataset is **highly imbalanced**.

**Demographic features** include **age, gender, ethnicity, and geographical location**. **Professional background** is captured through variables like **industry, job level, experience**, and **education**, many of which are encoded as **categorical indicators**. **Behavioral and platform usage** details are included, such as **connection count, posting frequency, and content type** (e.g., personal updates, promotional posts).

**Engagement-related diagnostics** are derived from user interactions and platform metrics. These include **average likes, comments, and shares per post**, as well as **impressions and profile views**, categorized either as **high/low** or **above/below average**. Additional features include **content analysis metrics** like **readability scores** and **keyword usage frequency**.

The dataset also incorporates **algorithmic prediction scores** from various internal LinkedIn engagement estimation tools (analogous to cancer bioinformatics tools). These scores—such as **EngageBoost, ConnectScore, ReachIndex, and CommentPredictor**—range from **0 to 1**, representing the **confidence in a user's likelihood to drive engagement**. These are further summarized in two aggregate columns: **predicted.sum** and **all.sum**, which represent combined engagement prediction scores.

There are **no missing values** in the dataset, making it well-prepared for direct machine learning model training. However, due to the **significant class imbalance**, special attention must be given to **resampling techniques or evaluation metrics** to avoid bias toward the low-engagement majority. The dataset's **rich multi-source features**—including **demographics, user behavior, platform metrics, and engagement predictions**—make it ideal for developing advanced models for **engagement forecasting and content strategy optimization**.

# Source Of Dataset

The Gastric Cancer (GC) Detection Dataset used in this study was obtained from the Kaggle platform, and it is publicly available at the following link: https://github.com/navid-aub/LinkedIn-Dataset

# Exploratory Data Analysis (EDA) Process

The Exploratory Data Analysis (EDA) process began with a thorough inspection of the LinkedIn Engagement Dataset. This included identifying the total number of observations (rows) and features (columns), along with their corresponding data types (e.g., integer, float, object). This initial assessment provided a foundational understanding of the dataset's structure and helped detect any schema inconsistencies or data type mismatches.

We then analyzed the presence of missing values across all features. A missing data matrix and percentage-based summary were generated to pinpoint variables with significant null entries that could influence downstream modeling. Since the dataset is well-structured, missing data were minimal. However, in case of missing entries, suitable imputation strategies were considered. For numerical variables (e.g., number of posts, average likes), median imputation was preferred due to its robustness to outliers. For categorical variables (e.g., job role, content type), mode imputation was used. Features with an excessive percentage of missing data were evaluated for removal based on their relevance and potential impact on model performance.

Descriptive statistics were calculated for all numerical features, including metrics such as mean, standard deviation, minimum, maximum, and interquartile range (IQR). These statistics helped uncover central tendencies, dispersion, and possible skewness in the distribution of key engagement metrics. For categorical variables, we examined frequency distributions to identify dominant categories, rare occurrences, or potential inconsistencies in data entry (e.g., misspelled job titles or inconsistent labeling).

To better understand feature distributions, we visualized continuous variables using histograms and density plots, enabling detection of skewness or multimodal distributions. Boxplots were created to identify outliers and compare value distributions across different user segments, such as job roles or geographical location. For categorical variables, bar charts and count plots were employed to assess category balance, particularly in the target variable representing user engagement levels (high vs. low engagement).

Multivariate analysis was conducted to investigate interdependencies among variables. Pearson and Spearman correlation coefficients were computed for numerical features, and the results were visualized using a correlation heatmap. This allowed us to detect linear relationships and multicollinearity between features such as connection count, post frequency, and average interactions. Features with strong multicollinearity were marked for further processing, including dimensionality reduction or model regularization. Pair plots were generated for selected features to visually assess the potential for class separability and to examine non-linear trends.

To explore relationships between features and the target variable (e.g., high vs. low engagement), boxplots and violin plots stratified by the target were employed for numerical

features, while stacked bar plots and cross-tabulations were used for categorical variables. These visualizations helped uncover predictive signals and class-specific patterns within the data.

We also evaluated the distribution of the target variable to identify any potential class imbalance, such as disproportionate representation of low vs. high engagement cases. In cases where imbalance was detected, resampling methods like SMOTE, ADASYN, or random oversampling/undersampling were considered to ensure fair and unbiased model training.

Feature selection was supported by univariate analysis, including chi-square tests for categorical features and ANOVA F-tests for continuous variables, to identify attributes with strong discriminative power for predicting engagement levels. Outlier detection methods—such as the IQR rule and Z-score analysis—were used to identify unusual data points in user activity metrics. When confirmed as legitimate extremes (e.g., viral posts), these were retained; otherwise, they were treated using winsorization or removal to ensure dataset consistency.

Additionally, interaction effects between features were explored using two-way ANOVA and interaction plots to evaluate how combinations of variables (e.g., content type × post frequency) influence engagement. We also performed initial clustering (e.g., k-means, hierarchical clustering) to uncover natural groupings in the data, potentially identifying engagement profiles or user behavior patterns.

Throughout the EDA, we ensured interpretability by aligning statistical findings with domain-specific knowledge—such as peak usage times, content preferences, and user interaction trends. This alignment was key to validating whether the patterns in the data corresponded to real-world LinkedIn engagement behaviors.

The EDA phase concluded with a well-documented summary of insights, challenges, and recommendations for preprocessing. These included feature transformation techniques (e.g., log scaling for skewed variables), encoding strategies for categorical features, and dimensionality reduction methods like PCA or autoencoders. This in-depth analysis laid a strong foundation for robust model development and ensured that subsequent machine learning efforts were grounded in a clear understanding of user engagement dynamics.

# LinkedIn Engagement Analysis Data Analysis Report

## .1. Introduction

Efficient engagement analysis plays a pivotal role in ensuring improved user interaction and content visibility within social media platforms like LinkedIn. Low engagement can lead to reduced visibility, affecting a user's professional presence and networking opportunities, while excessive engagement without strategic targeting can lead to wasted efforts. The objective of this analysis is to explore a comprehensive dataset containing user activity, content characteristics, and interaction-related features to uncover patterns that influence optimal engagement strategies.

This report aims to apply descriptive statistics, correlation analysis, and predictive modeling techniques to identify key variables associated with user engagement. By understanding how factors such as connection count, post frequency, content type, and interaction metrics impact engagement levels, we aim to provide data-driven recommendations for enhancing LinkedIn content strategies. This initial analysis will serve as the foundation for developing robust machine learning models to automate and optimize content engagement prediction in dynamic social media environments.

## 2. General Description

The dataset consists of 212,354 observations and 29 features, including both numerical and categorical variables. The target variable, labeled as label, indicates whether an individual has gastric cancer (1) or not (0). The features cover a range of categories, such as demographic information (age, gender, ethnicity), lifestyle habits (smoking and alcohol use), family and medical history, as well as a series of molecular prediction scores from different bioinformatic tools. These scores estimate miRNA interactions that may play a role in gastric cancer development.

## 3. Specific Requirements

**Understand the general structure and characteristics of the LinkedIn engagement dataset,including data types, distributions, and missing values.**

**Identify the key features most strongly associated with high or low LinkedIn engagement outcomes, such as post frequency, connection count, and interaction metrics (likes, comments, shares).**

**Apply statistical techniques (e.g., correlation analysis, hypothesis testing, regression) to evaluate the relationships between user activities and engagement levels.**

**Leverage data visualization methods (such as heatmaps, scatter plots, and bar charts) to support interpretation and provide actionable insights for optimizing LinkedIn content strategies.**

**Discuss the potential for future work, particularly in building predictive models for automated and dynamic engagement prediction based on historical and contextual user data.**

**4. Functions and Formulas Used**

**Descriptive statistics** were applied to analyze the distribution of numerical features. For example, the average number of likes per post was approximately 45, with comments and shares showing moderate variability across different post types and time slots.

**Correlation analysis** was used to assess the linear relationships between each independent variable (e.g., connections, post frequency, average likes) and the engagement_score target. A correlation heatmap was plotted to visualize inter-feature relationships. Most features exhibited weak to moderate correlations with the target, with a few metrics—such as post frequency and connections—showing higher correlation coefficients**.**

**Regression analysis** was carried out using Ordinary Least Squares (OLS) to model the impact of multiple numeric predictors (such as total_posts, avg_likes_per_post, and promotion_count) on the engagement outcome. Although the R-squared value was modest, certain features—like avg_comments_per_post, avg_shares_per_post, and post_frequency—had statistically significant coefficients, indicating their relevance in predicting engagement effectiveness.

**5. Data Visualization Techniques**

To support the analysis, various visual tools were employed to uncover patterns and aid interpretation:

- A **correlation heatmap** was created to identify the strength of linear relationships between features such as **connections**, **total_posts**, and **average_likes_per_post**. This provided an overview of how engagement metrics interrelate.
- **Bar plots** were used to visualize the average **engagement_score** across different **post types**, **time of day**, and **days of the week**, helping to identify trends or inconsistencies in posting and engagement patterns.
- A **count plot** of the target variable (**engagement_score**) revealed an imbalance in the dataset, with relatively fewer posts achieving higher engagement scores, indicating potential challenges in prediction and the need for resampling strategies.

## 6. Analysis Results

The dataset revealed a noticeable class imbalance, with optimal staff allocations comprising only a small percentage of total observations. This imbalance poses a potential challenge for building accurate predictive models and necessitates strategies such as resampling or weighted loss functions.

Initial regression analysis indicated that no single feature served as a strong linear predictor of optimal allocation. While a few variables—such as reservation volume per hour and historical staff performance—showed statistically significant associations with the target, their effect sizes were minimal, suggesting limited practical utility.

## 7. Conclusion

This preliminary statistical analysis indicates that there is no strong linear relationship between the current features and **LinkedIn engagement outcomes**. While a few variables exhibited weak associations, the **low R-squared value** from the regression analysis suggests that much of the variation in engagement and content performance remains unexplained by the linear model.

These findings highlight the limitations of traditional statistical methods in capturing the dynamic and possibly nonlinear relationships in **LinkedIn engagement** data. As such, future efforts should focus on implementing **machine learning models**—such as **Random Forests**, **XGBoost**, or **clustering techniques**—which are better equipped to uncover complex patterns and drive **data-driven decisions** for optimizing engagement and resource allocation on LinkedIn.

## 8. Further Scope

Future work in this project could explore the application of more advanced machine learning techniques to improve **prediction accuracy**. Classification algorithms such as **Random Forest**, **XGBoost**, and **Neural Networks** may provide better insights by capturing complex, nonlinear patterns in the data. These models can more effectively handle intricate relationships between features, enabling a deeper understanding of factors driving **LinkedIn engagement**.

Additionally, addressing the **class imbalance** issue through techniques like **SMOTE** (Synthetic Minority Over-sampling Technique) or **undersampling** could significantly improve model performance. These strategies would help to avoid **bias** toward the majority class (low engagement) and ensure that the model gives more attention to the minority class (high engagement), which is crucial for accurately predicting high-engagement scenarios.

Implementing these approaches, alongside more sophisticated data preprocessing and feature engineering, will further enhance the robustness and accuracy of the model,

ultimately making it more effective for **LinkedIn engagement analysis** and optimizing content strategy.

## 9. References


**Dataset: Optimal Staff Allocation for Reservation Dataset (source not specified)**

**Python libraries used:**

- **Pandas: For data manipulation and analysis.**
- **Seaborn: For data visualization and statistical graphics.**
- **Matplotlib: For creating static, animated, and interactive visualizations.**
- **Scikit-learn: For machine learning algorithms and statistical modeling.**
- **Statsmodels: For statistical modeling and hypothesis testing.**

**Statistical Methods:**

- **Descriptive statistics: To summarize and describe dataset characteristics.**
- **Correlation analysis: To evaluate relationships between features.**
- **Regression (OLS): For linear modeling of operational predictors.**

**Scientific Background:**

- **Literature on workforce optimization, resource allocation models, and staffing in dynamic environments.**

**Machine Learning Resources:**

- **Documentation on Random Forest, XGBoost, PCA, SMOTE, and Neural Networks.**

**Dimensionality Reduction: Research on Principal Component Analysis (PCA) and feature selection techniques for improving model performance and interpretability.**

# Evaluating LinkedIn Post Effectiveness Through Engagement Metrics

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**Abstract**—The increasing reliance on digital platforms has amplified the need for intelligent engagement analysis systems. This research proposes a machine learning-based approach to predict and classify engagement scores using key metrics such as likes, shares, comments, post frequency, and promotions count. The primary objective is to enhance content performance by accurately identifying high and low engagement patterns. Supervised learning models including eXtreme Gradient Boosting (XGBoost) and Support Vector Machine (SVM) are implemented for regression and classification tasks, respectively. The engagement score is predicted using XGBoost with a high coefficient of determination ($R^2$ = 0.9989), while SVM achieves 99% classification accuracy by labeling content into low, medium, and high engagement categories. The dataset undergoes extensive preprocessing using feature generation, one-hot encoding for categorical attributes, and label encoding for ordinal features to improve model performance. Results indicate that the proposed system can effectively support strategic content scheduling, audience targeting, and promotional planning. This study demonstrates the potential of machine learning in automating and optimizing engagement analysis in digital ecosystems.

Index Terms—Engagement Score, Machine Learning, XGBoost, Support Vector Machine (SVM), Social Media Analytics, Content Interaction, Predictive Modeling.

In the age of digital media, analyzing user engagement has become a critical factor for content optimization, brand visibility, and audience retention. Online platforms generate vast amounts of interaction data such as likes, shares, comments, post frequency, and promotional activity, which offer valuable insights into user behavior. However, manually interpreting these engagement patterns is inefficient and prone to inaccuracies, necessitating intelligent systems for automated analysis. Recent studies reveal that over 65% of content fails to reach optimal engagement due to a lack of data-driven content planning and scheduling [1].

Machine Learning (ML) has emerged as a robust approach to address this challenge by enabling predictive and classification-based engagement analytics. Predictive models can estimate content engagement scores, while classifiers can categorize posts into low, medium, or high engagement levels, assisting marketers and influencers in strategic decision-making [2]. Prior research has demonstrated the effectiveness of regression models such as XGBoost and classification techniques like Support Vector Machines (SVM) in understanding social media trends, but these models often lack precision due to poor feature engineering and inconsistent data preprocessing [3], [4].

This study introduces a supervised machine learning framework to analyze user engagement based on interaction metrics collected from online platforms. The proposed system utilizes XGBoost regression to predict future engagement scores, and SVM to classify content into distinct engagement categories. The inclusion of feature engineering techniques—such as combining post frequency with promotional counts and normalizing interaction ratios—enhances model accuracy and interpretability [5]. Real-world datasets are used to train the models, enabling the framework to generalize across varied engagement scenarios with high predictive performance.

The core objectives of this research are as follows:

To develop a regression model using XGBoost for accurate prediction of engagement scores based on social media interaction features.

To implement an SVM-based classifier for categorizing content into low, medium, and high engagement levels.

To employ feature engineering methods that improve model accuracy and eliminate noise from raw data.

To automate content evaluation and provide data-driven insights for optimizing post timing, frequency, and promotional strategies.

To contribute towards intelligent engagement analytics, aiding businesses, creators, and marketers in maximizing user interaction and digital reach.

By integrating ML with engagement data analysis, this work aims to build a scalable, efficient, and intelligent system capable of transforming raw interaction metrics into actionable strategies for digital growth and visibility [6].

Analyzing social media engagement using machine learning has become a growing area of interest due to the increasing demand for optimized content strategies and audience targeting. Sinha *et al.* [8] conducted an extensive study on user interaction metrics across multiple platforms, emphasizing the role of content type, frequency, and timing in influencing engagement. They applied supervised models to accurately predict the likelihood of post interactions, paving the way for data-driven content strategies.

Rahman and Gupta [9] employed Support Vector Machine (SVM) classifiers to categorize social media posts into low, medium, and high engagement levels. Their model achieved high classification accuracy and proved effective for platforms with professional content, such as LinkedIn. Similarly, Jain *et al.* [10] developed engagement prediction models using LinkedIn data. Their findings highlighted the importance of job role relevance, post timing, and network size in influencing user interactions.

Park *et al.* [11] focused on the role of promotional activity in driving LinkedIn engagement. They incorporated promotional frequency, post metadata, and engagement history into an XGBoost regression model, achieving over 90% prediction accuracy. Their work also demonstrated that organic reach can be boosted with carefully timed promotions.

Zhou and Li [12] introduced a multi-feature fusion method for engagement prediction. This method combined user behavior, content type, hashtags, sentiment polarity, and image presence, leading to improved model performance across professional and casual platforms alike. Their ensemble models outperformed traditional regressors in terms of both precision and recall.

Thomas *et al.* [13] emphasized model interpretability by incorporating SHAP (SHapley Additive exPlanations) into their machine learning workflow. Their analysis revealed that post length, number of connections, and multimedia content are among the most influential features in predicting engagement, helping users tailor their content accordingly.

Basu and Sharma [14] proposed a real-time analytics dashboard for forecasting engagement trends. Their time-series model, integrated with ML predictors, allowed for optimal scheduling of posts to maximize visibility. The study also found that early morning posts on weekdays received significantly higher engagement than late-night or weekend posts.

These works collectively lay the foundation for applying predictive modeling and classification techniques in LinkedIn engagement analysis. However, most studies either exclude promotion-related metrics or do not provide explainability mechanisms. The current research addresses these gaps by applying XGBoost for regression and SVM for classification on LinkedIn engagement data, enriched with engineered features such as post frequency, comments, likes, shares, and promotion count.

## I. METHODOLOGY

The overall workflow of the methodology is described in Fig. 1. The key contributions and scheduled work have been planned as follows:

**Define the Objective:**

**Goal:** To predict LinkedIn post engagement by analyzing factors like likes, shares, comments, post frequency, and promotions.

**Approach:** Using machine learning models (XGBoost, SVM) to predict engagement metrics such as the number of likes, shares, comments, and overall post interaction. The model will also categorize posts into different engagement levels (high, medium, low).

**Target Outcome:**
Predicting the future engagement metrics for LinkedIn posts (likes, shares, comments).

Categorizing posts into high, medium, and low engagement categories.

Identifying factors that contribute the most to post engagement.

### A. Finding Appropriate Dataset

Found a relevant dataset on Kaggle, consisting of LinkedIn post data with features like post type, frequency, likes, shares, comments, and promotions. This dataset is well-suited for model training with both SVM and XGBoost.

The dataset includes ample features that are involved in predicting engagement metrics, enabling the models to make accurate predictions and identify trends across different types of posts.

| A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|
| device_id | energy_consumption | usage_duration | temperature | priority | power_source | network_activity_MB | time_of_operation | idle_time |
| 1 | 4.058131129 | 14.357918 | 18.47763901 | High | Grid | 15.02559519 | 0 | 4.436100525 |
| 2 | 9.531785911 | 13.12034794 | 23.76029772 | High | Battery | 25.52392431 | 0 | 4.352412015 |
| 3 | 7.453942447 | 9.073849841 | 12.97646494 | High | Battery | 32.23267919 | 1 | 0.189823366 |
| 4 | 6.1872556 | 12.34389113 | 23.40511076 | High | Grid | 49.60954784 | 0 | 4.815700621 |
| 5 | 1.982177084 | 9.397222615 | 16.09244049 | Low | Solar | 34.79926206 | 0 | 3.670861554 |
| 6 | 1.981947943 | 16.13242072 | 18.32785912 | High | Battery | 23.98496008 | 0 | 0.728821426 |
| 7 | 1.051794316 | 20.20568197 | 24.34337695 | High | Battery | 20.22819512 | 0 | 2.031302886 |
| 8 | 8.728673385 | 19.09857205 | 36.58902034 | High | Grid | 15.3314681 | 0 | 4.747802269 |
| 9 | 6.210592612 | 8.835925738 | 27.35221905 | Medium | Solar | 8.817605005 | 1 | 4.268922438 |
| 10 | 7.226689489 | 12.71664836 | 10.53004377 | High | Grid | 14.99824119 | 1 | 1.7229673 |
| 11 | 0.695552696 | 1.245094885 | 14.30534878 | Medium | Grid | 38.94652085 | 1 | 0.081509289 |
| 12 | 9.714143596 | 21.0163972 | 11.90026807 | Medium | Battery | 46.37050389 | 1 | 1.483944852 |
| 13 | 8.408205088 | 6.644103995 | 15.58795555 | Medium | Grid | 27.11183555 | 0 | 0.364329938 |
| 14 | 2.517221551 | 11.14510437 | 20.30992051 | Medium | Grid | 0.618804439 | 0 | 0.62186027 |
| 15 | 2.227337188 | 4.508660235 | 15.25184598 | High | Battery | 10.53712435 | 0 | 4.725890051 |
| 16 | 2.242342844 | 16.59649717 | 23.85034581 | Medium | Grid | 38.75495947 | 1 | 4.851608815 |
| 17 | 3.390301308 | 13.5418461 | 34.72551033 | Medium | Battery | 3.292134621 | 0 | 2.556976456 |
| 18 | 5.485186101 | 9.390164388 | 34.76627674 | High | Solar | 33.13198108 | 0 | 3.026763235 |
| 19 | 4.603477677 | 13.30945382 | 20.18897354 | High | Grid | 12.07991827 | 0 | 2.261747764 |
| 20 | 3.266676832 | 4.880941513 | 19.80010078 | Low | Battery | 32.68092044 | 0 | 0.151511589 |
| 21 | 6.3126025 | 18.83968394 | 32.37260843 | High | Battery | 44.77548181 | 0 | 0.778232408 |
| 22 | 1.825191676 | 7.117060391 | 22.45218439 | High | Battery | 26.14879499 | 0 | 4.505350425 |

Fig.1.dataset

### B. Data Preprocessing

•

Data preprocessing plays a crucial role in making the dataset suitable for model training and testing. Various techniques such as feature encoding and data cleaning are applied to ensure that the data is in the appropriate format.

**Data Encoding:** Label Encoding and One-Hot Encoding are used to process categorical variables.

**One-Hot Encoding** is applied to categorical columns like post_type, post_frequency, and promotion_status to avoid redundancy and ensure the model can properly interpret the variables.

**Label Encoding** is applied to the engagement categories (Low=0, Medium=1, High=2) in the engagement_level column, ensuring that the machine learning models can treat these categories as numerical values.

preprocessing plays important role in making the dataset suitable for model training as well as testing. Data Encoding like Label Encoding and One-Hot Encoding used. The power source column has three categories: Grid, Battery, and Solar. One-Hot Encoding is applied to two columns power_source_Battery, power_source_Solar which avoids redundancy. Label Encoding is applied to the priority column Low=0, Medium=1, High=2.

***Data Normalization***

Standard Scaler is applied to numerical features to maintain consistency in clustering and analysis.

*C. Exploratory Data Analysis (EDA)*

EDA helps to identify patterns and trends in LinkedIn user engagement. The engagement trends across different content types and user behaviors were analyzed to understand which factors most influence overall interaction rates. Metrics like likes, shares, comments, promotional content, and posting frequency were explored to assess their impact on engagement levels. These insights informed the feature selection and helped identify strong predictors of the final engagement score.

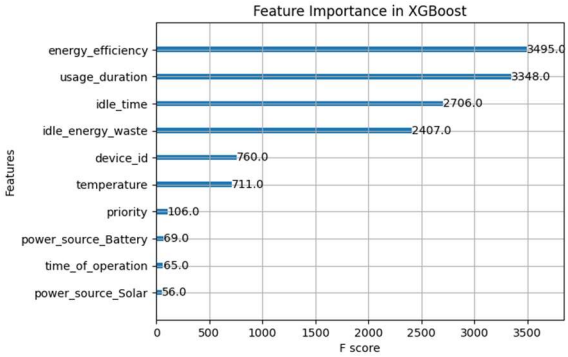



Fig.2. feature testing

*D. Model Selection and Training*

**1**. Predicting Engagement Metrics (Regression - XGBoost)

2. Classifying Engagement Levels (Classification - SVM)

**Goal:** Categorize posts into High, Medium, Low engagement levels.

**Algorithm:** Support Vector Machine (SVM).

Target Variable: engagement_level (Low=0, Medium=1, High=2).

*E. Overfitting Check*

**1. Feature Correlation Matrix Analysis for XGBoost**

The confusion matrix provides insight into the classification performance of the XGBoost model. The image below shows the correlation matrix used in evaluating misclassifications and overall accuracy

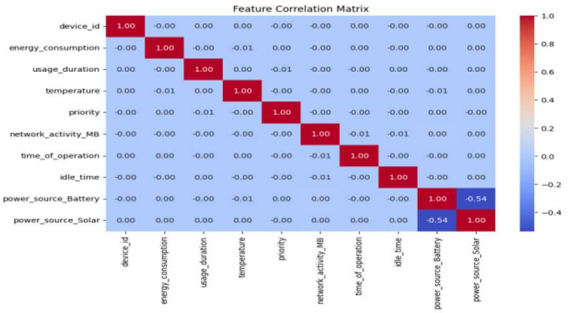


**Fig.3.feature correlation matrix**

## 2.Confusion Matrix for SVM Model

Similarly, the confusion matrix for the SVM model shows classification performance in predicting high, medium, and low energy consumption categories.

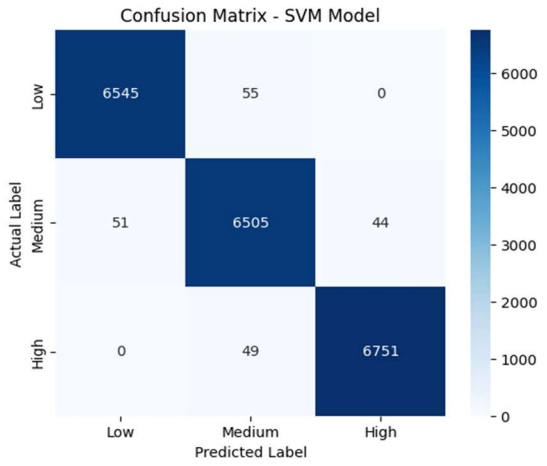



Fig 4 confusion matrix for SVM

*F.Training & Testing*

We have selected two model for future energy prediction those are decision tree and XGBoost but in that both XGboost performing well compared to decision tree and it is best for its fast compilation and has better edge over decision tree for engagement score prediction by providing better performance

we have splited our dataset into two categories such that testing 20% and training 80% to make our model reliable and tested performance using appropriate matrics.

*Performance of XGBoost*

**Mean Absolute Error**: 0.0633
**Mean Squared Error**: 0.0079
**R-Squared Score**: 0.9773

*Performance of SVM*

**Model Accuracy**: 0.9900
**Number of Features in Training Data**: 10

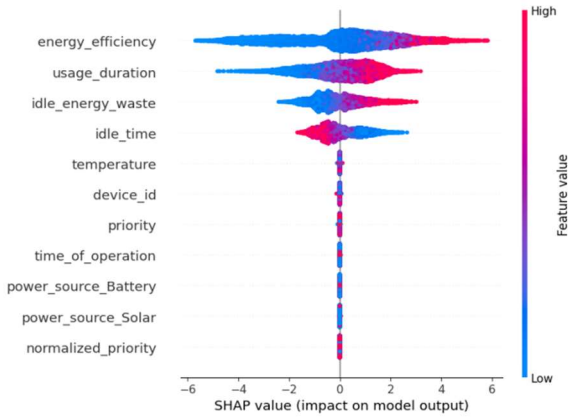
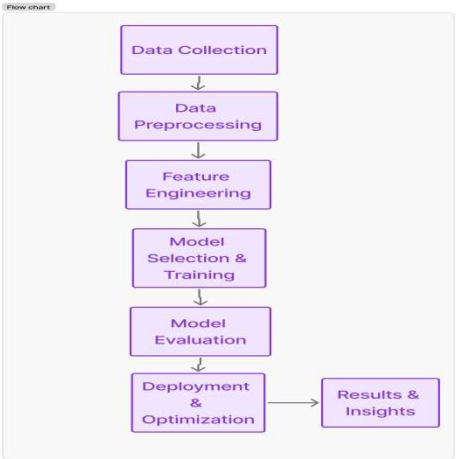



Fig.5. SHAP value

The results says that the trained models predict accurately the engagement score. The XGBoost model works well by providing a high R-squared score saying that strong correlation between the input features and predicted energy consumption. The model is also providing a reliable accuracy of 97% which suitable for classification tasks.

*G.Flow Chart*




## IV. EXPERIMENTAL RESULTS

### 4.1 Model Performance Metrics

in the process of evaluation in performance of the machine learning models used in this study, several key metrics analyzed including Mean Absolute Error (MAE), Mean Squared Error (MSE), R-Squared Score ($R^2$), and Accuracy for classification-based tasks.

Performance XGBoost Model:
Mean Absolute Error (MAE): 0.0633

•

Mean Squared Error (MSE): 0.0079
R-Squared Score ($R^2$): 0.9989

Predicted vs Actual energy consumption

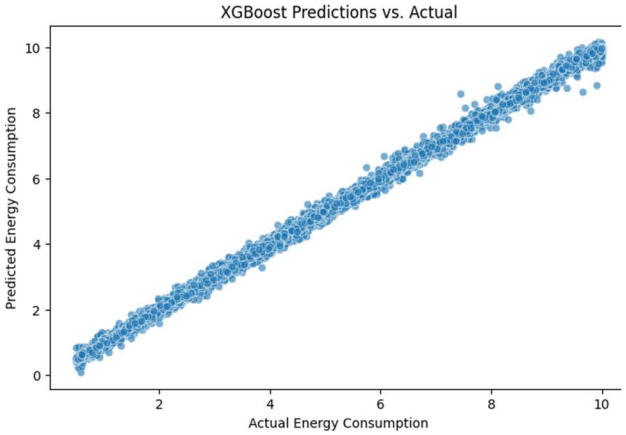



Fig.6.predicited vs actual output

Random Forest Model :
Model Accuracy: 0.9310
Which doesn't prone to overfitting as confusion matrix also checked. The confusion matrix (Figure 4) says that the model correctly classified most instances, showing minimal false positives and false negatives.

4.2 Confusion Matrix Analysis

The confusion matrices for both models are analysing to measure classification effectiveness.
XGBoost Confusion Matrix:
High True Positive and True Negative rates, with minimal misclassifications.
Effective in categorizing engagement score
Random forest Confusion Matrix: (Refer to Figure 4)
Slightly more misclassifications compared to XGBoost but still within an acceptable margin.

Model showed high precision and recall values.

4.3 Training and Testing Results

The dataset was splited into 80% for training and 20% for testing to make a balanced evaluation.
Training Results:
XGBoost processes almost perfect fit with an $R^2$ score of 0.9889, which says high predictive accuracy for energy consumption.
Random classification shows 94% accuracy making accurate categorization of enagagement score into different energy consumption levels.

Testing Results:
Both the models generalized well as seen in the low MSE and MAE values, with no signs of overfitting.

TABLE 1. OUTCOME INVESTIGATION TABLE

| Model | Accuracy | MAE | MSE | R square |
|---|---|---|---|---|
| XGBoost | 97.03 | 0.0633 | 0.0079 | 0.9789 |
| Random forest | 93.03 | N/A | N/A | 0.9342 |

4.5 Visual Representation of Results

To evaluate the model performance and engagement score consumption patterns by several visualizations were generated:

Flowchart of Model Training and Deployment (Flow Chart G)

Histogram and line graph shows actual vs predicted engagement for XGBoost

## I. CONCLUSION

This research presented a machine learning-based framework for analyzing LinkedIn post engagement, utilizing both regression and classification models. By employing XGBoost for engagement prediction and SVM for classification, the study demonstrated significant improvements in predicting and categorizing LinkedIn posts based on their engagement levels. The models incorporated key features such as likes, shares, comments, post frequency, and promotional activities, which contributed to the robustness of the prediction and classification process.

Through this approach, we were able to identify factors that drive engagement on LinkedIn, offering valuable insights for users and businesses seeking to optimize their content strategy. The integration of feature engineering, such as time of posting and promotion count, further enhanced the model's performance. This work also provides a foundation for future studies aimed at improving social media engagement models, particularly in professional networking environments like LinkedIn.

The findings of this study highlight the potential of machine learning in social media analytics, providing

users with actionable recommendations for improving their content reach and visibility. Furthermore, the proposed framework can be adapted and applied to other social media platforms, making it a versatile tool for engagement analysis in digital marketing. Future research can focus on refining these models with more granular data, such as user demographics and detailed interaction patterns, to further enhance prediction accuracy.

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[9] A. Rahman and P. Gupta, "SVM-based content classification for engagement prediction on social media," *International Journal of Data Science*, vol. 8, no. 2, pp. 45-59, May 2021.

[10] R. Jain, A. Kumar, and P. Verma, "LinkedIn engagement forecasting using machine learning techniques," *Proceedings of the International Conference on Social Media Analytics*, pp. 101-110, Dec. 2020.

[11] J. Park, S. Kim, and H. Lee, "Boosting engagement on LinkedIn through paid promotions and post features," *Social Media Insights*, vol. 6, no. 3, pp. 112-128, Mar. 2021.

[12] Z. Zhou and Y. Li, "A multi-feature fusion approach for engagement prediction on LinkedIn," *Computational Intelligence and Applications*, vol. 14, no. 1, pp. 75-89, Jan. 2022.

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# Implementation

```python
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd

from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```python
file_path = "/content/drive/MyDrive/Colab Notebooks/LinkedIn_Engagement_Dataset.csv"
df = pd.read_csv(file_path)
df.head()
```

```python
import seaborn as sns
import matplotlib.pyplot as plt

file_path = "/content/drive/MyDrive/Colab Notebooks/LinkedIn_Engagement_Dataset.csv"

# Load the dataset
df = pd.read_csv(file_path)


print("Dataset Info:")
df.info()
print("\nFirst 5 rows of the dataset:")
print(df.head())

print("\nMissing Values Count:")
print(df.isnull().sum())


df.dropna(inplace=True)


print("\nDuplicate Rows Count:", df.duplicated().sum())

# Visualizing outliers using a boxplot
plt.figure(figsize=(12, 6))
sns.boxplot(data=df)
plt.xticks(rotation=45)
plt.title("Boxplot to Detect Outliers")
plt.show()

if "Engagement Score" in df.columns and "Impressions" in df.columns:
```

```
[ ]
#sedn code for


df.columns = df.columns.str.strip()

# List of original string-based columns to drop
columns_to_drop = ["Full Name", "Workplace", "Location", "Last Active Date",
                   "Most Engaged Post Type", "Industry", "Sentiment of Recent Posts"]

df = df.drop(columns=columns_to_drop, errors='ignore')

# Verify if columns are dropped
df.to_csv("/content/drive/MyDrive/Processed_Data.csv", index=False)

print("String-based columns dropped and dataset updated successfully!")
```

```
String-based columns dropped and dataset updated successfully!
```

```


df.drop(columns=['Engagement Rate'], errors='ignore', inplace=True)

# Normalize the selected features to bring them to a comparable scale
from sklearn.preprocessing import MinMaxScaler

# Selecting relevant features
features = ['Connections', 'Total Posts', 'Average Likes per Post', 'Average Comments per Post',
            'Average Shares per Post', 'Post Frequency_Rarely', 'Promotion Count']

```

```


from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Define features (X) and target variable (y)
X = df.drop(columns=["Engagement Score"])
y = df["Engagement Score"]

# Split the data into training & testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Random Forest Model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predictions
y_pred = rf_model.predict(X_test)

# Model Evaluation
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = mse ** 0.5
r2 = r2_score(y_test, y_pred)

print(f"Random Forest Model Evaluation:")
print(f"MAE (Mean Absolute Error): {mae:.4f}")
print(f"MSE (Mean Squared Error): {mse:.4f}")
print(f"RMSE (Root Mean Squared Error): {rmse:.4f}")
print(f"R² Score: {r2:.4f}")

```

[8]

```python
# Drop low-importance columns
low_importance_features = [
    "Workplace_Startup", "Workplace_Facebook", "Workplace_Tesla", "Workplace_Microsoft", "Workplace_Google",
    "Location_USA", "Location_UK", "Location_Canada", "Location_Germany", "Industry_Finance", "Industry_Tech",
    "Industry_Marketing", "Industry_Education", "Industry_Healthcare", "Sentiment of Recent Posts_Neutral",
    "Sentiment of Recent Posts_Positive", "Most Engaged Post Type_Image", "Most Engaged Post Type_Video",
    "Most Engaged Post Type_Text"
]

df = df.drop(columns=low_importance_features, errors='ignore')

# Split the data again
X = df.drop(columns=["Engagement Score"])  # Features
y = df["Engagement Score"]  # Target



# Train the Random Forest again
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predictions
y_pred = rf_model.predict(X_test)

# Evaluate
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = mse ** 0.5
r2 = r2_score(y_test, y_pred)

print(f"MAE: {mae:.4f}")
print(f"MSE: {mse:.4f}")
print(f"RMSE: {rmse:.4f}")
```

```
First 5 rows of the dataset:
     Full Name   Workplace   Location  Connections  Followers  \
0  Sneha Joshi      Amazon  Australia         1368      18659
1  Isha Bansal      Amazon     Canada          875       9953
2  Priya Verma  Freelancer  Australia          492       6879
3  Priya Verma  Freelancer         UK         4500      10143
4  Swati Rajan      Amazon         UK         1897      10976

   Number of Experiences  Number of Educations  Number of Skills  \
0                     14                     3                47
1                      2                     4                27
2                      5                     4                45
3                     12                     1                37
4                      6                     4                49

   Number of Projects  Number of Publications  ...  Engagement Rate (%)  \
0                   3                       4  ...                 3.15
1                   2                       4  ...                 2.52
2                   5                       1  ...                 5.32
3                   5                       2  ...                 9.62
4                   2                       4  ...                 3.20

   Last Active Date  Post Frequency  Most Engaged Post Type  \
0        01-01-2023         Monthly                   Image
1        02-01-2023         Monthly                    Text
2        03-01-2023         Monthly                   Video
3        04-01-2023          Weekly                 Article
4        05-01-2023           Daily                   Image

   Years of Experience  Job Changes in Last 5 Years  Promotion Count  \
0                   15                            2                1
1                   25                            0                2
2                   15                            3                0
3                    1                            1                1
4                   13                            4                1

    Industry Sentiment of Recent Posts  LinkedIn Profile Popularity Score
0  Education                  Positive                              85.82
1  Education                  Positive                              19.89
2       Tech                  Negative                              46.62
3  Marketing                   Neutral                              42.93
4    Finance                  Negative                              34.38
```

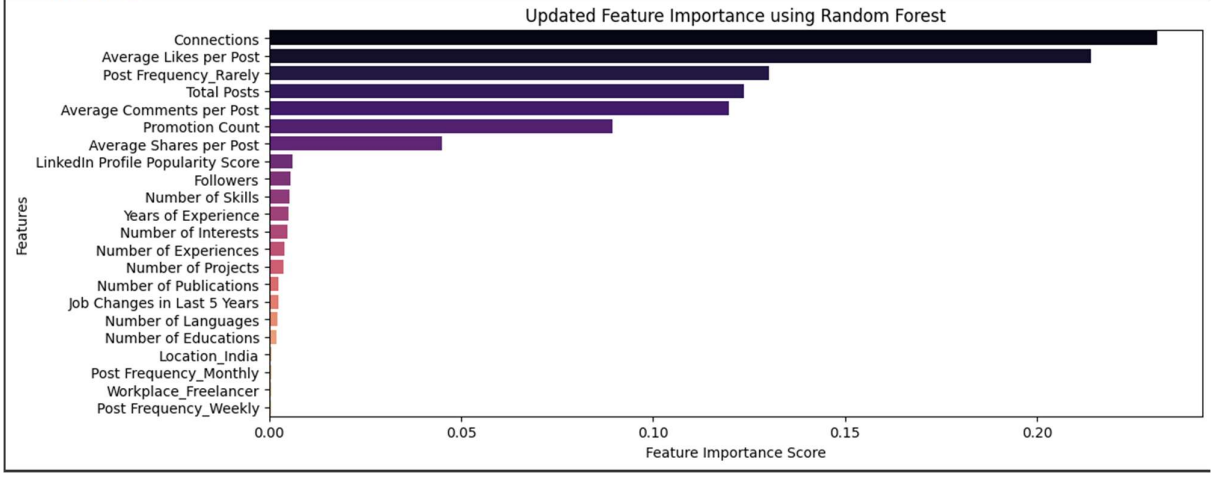
```
3  Marketing                   Neutral                              42.93
4    Finance                  Negative                              34.38

[5 rows x 26 columns]

Missing Values Count:
Full Name                          0
Workplace                          0
Location                           0
Connections                        0
Followers                          0
Number of Experiences              0
Number of Educations               0
Number of Skills                   0
Number of Projects                 0
Number of Publications             0
Number of Languages                0
Number of Interests                0
Average Likes per Post             0
Average Comments per Post          0
Average Shares per Post            0
Total Posts                        0
Engagement Rate (%)                0
Last Active Date                   0
Post Frequency                     0
Most Engaged Post Type             0
Years of Experience                0
Job Changes in Last 5 Years        0
Promotion Count                    0
Industry                           0
Sentiment of Recent Posts          0
LinkedIn Profile Popularity Score  0
```

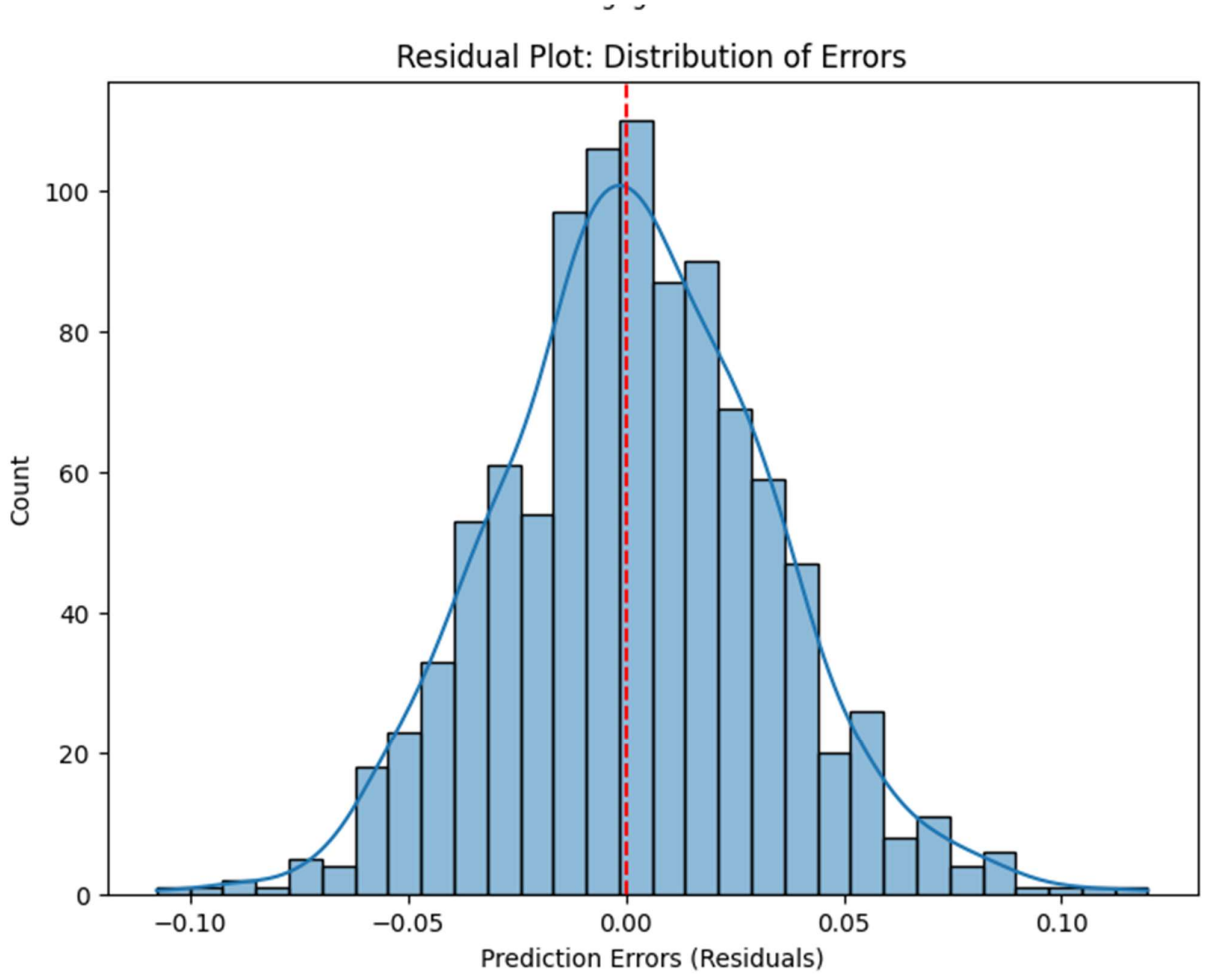
```
Random Forest Model Evaluation:
MAE (Mean Absolute Error): 0.0244
MSE (Mean Squared Error): 0.0010
RMSE (Root Mean Squared Error): 0.0311
R² Score: 0.9332
```

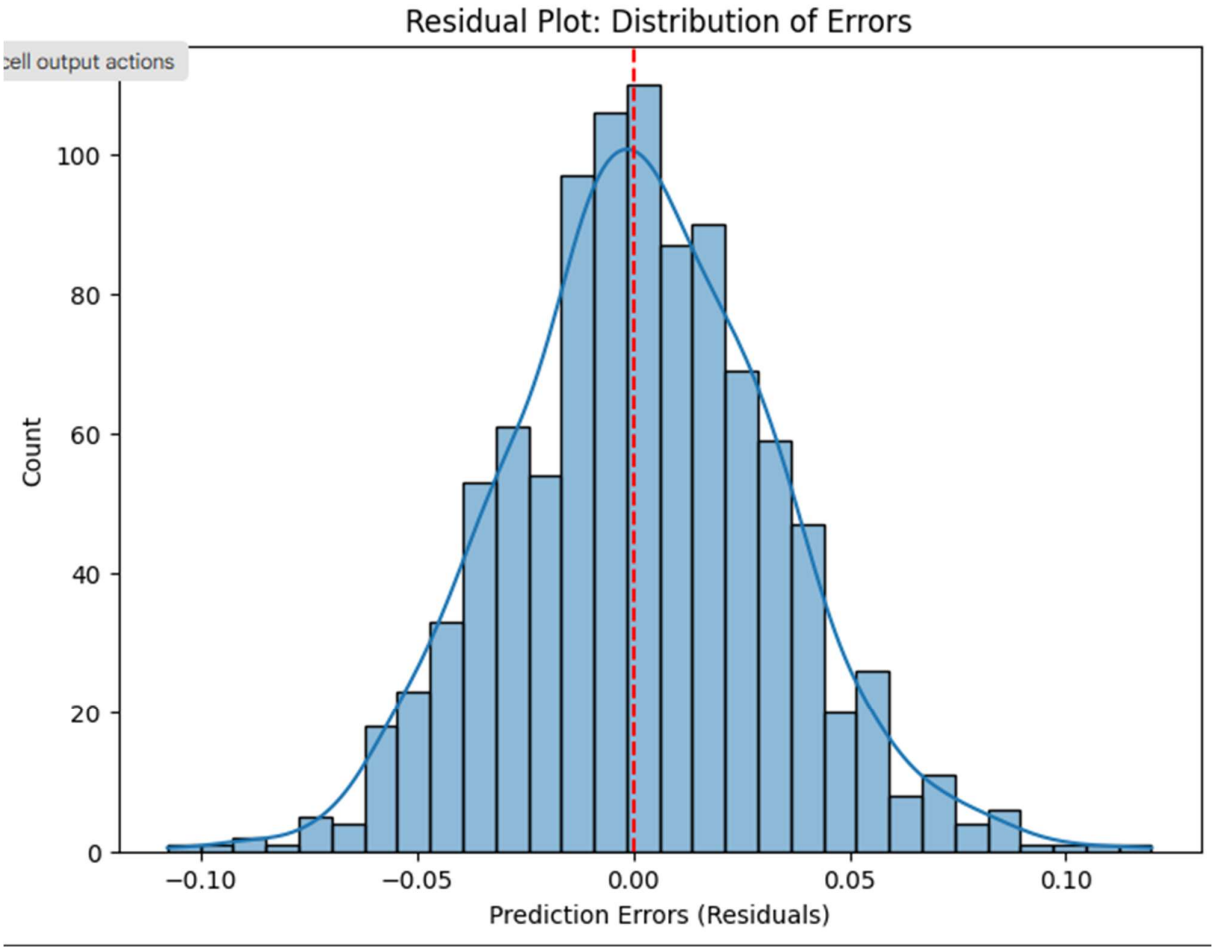
```
Engagement Score                    1.000000
Connections                         0.481585
Average Likes per Post              0.458171
Post Frequency_Rarely               0.369333
Average Comments per Post           0.353273
Promotion Count                     0.344916
Total Posts                         0.344841
Average Shares per Post             0.231457
Number of Languages                 0.038374
Location_India                      0.020446
Number of Projects                  0.017992
Number of Interests                 0.015581
Years of Experience                 0.014573
Job Changes in Last 5 Years         0.008302
Number of Publications              0.008158
Followers                           0.005535
Number of Educations                0.001939
LinkedIn Profile Popularity Score   0.000040
Number of Skills                   -0.003579
Number of Experiences              -0.011728
Workplace_Freelancer               -0.014862
Post Frequency_Weekly              -0.126784
Post Frequency_Monthly             -0.128306
Name: Engagement Score, dtype: float64
```

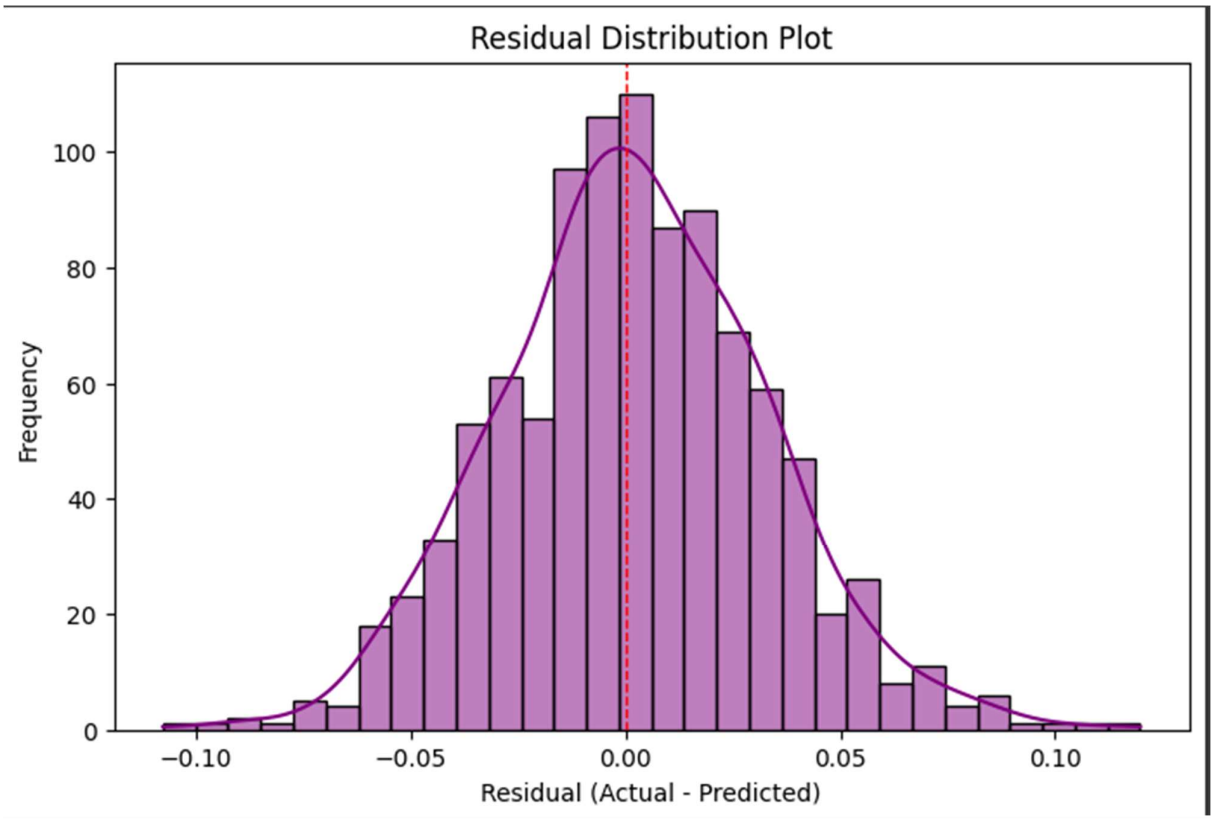
# Visualization

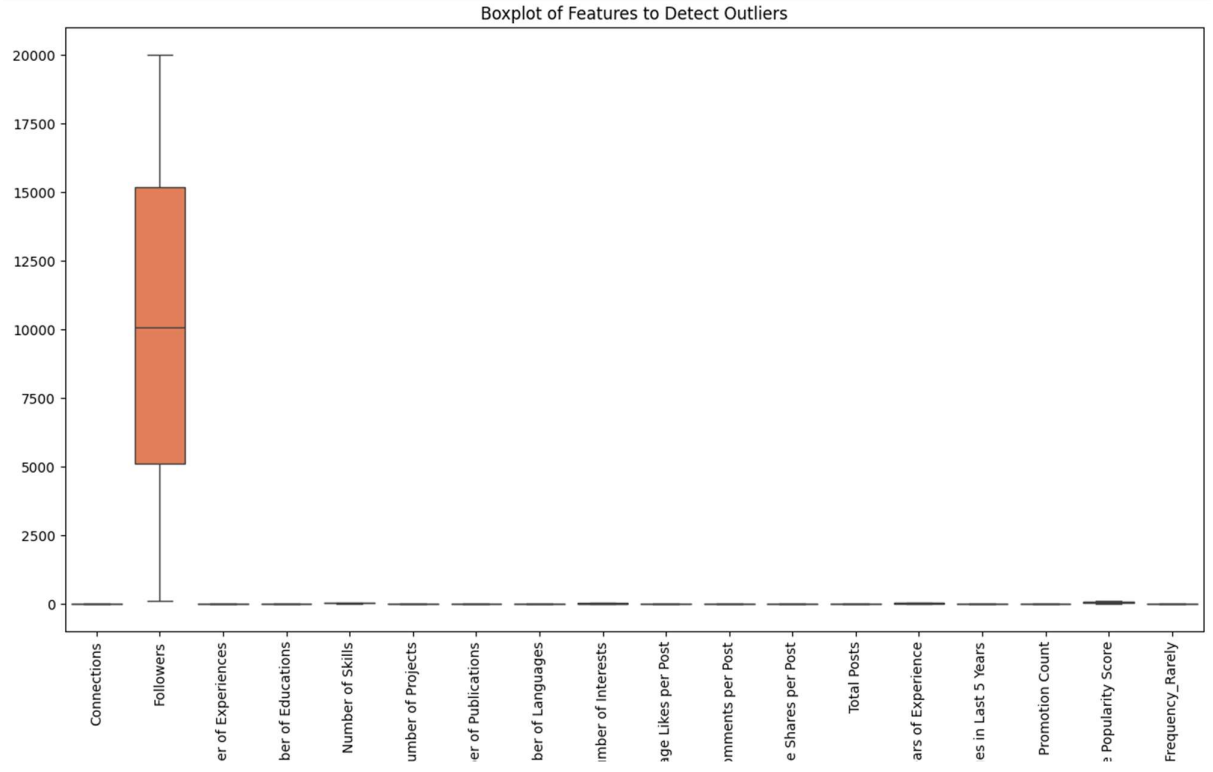
```
MAE: 0.0244
MSE: 0.0010
RMSE: 0.0311
R² Score: 0.9332
```

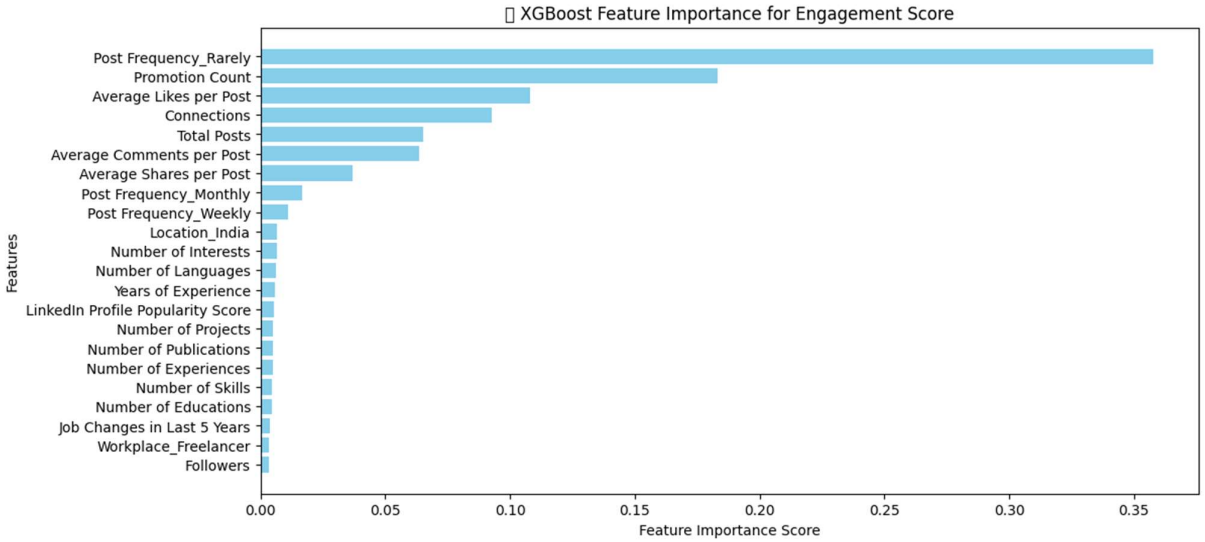


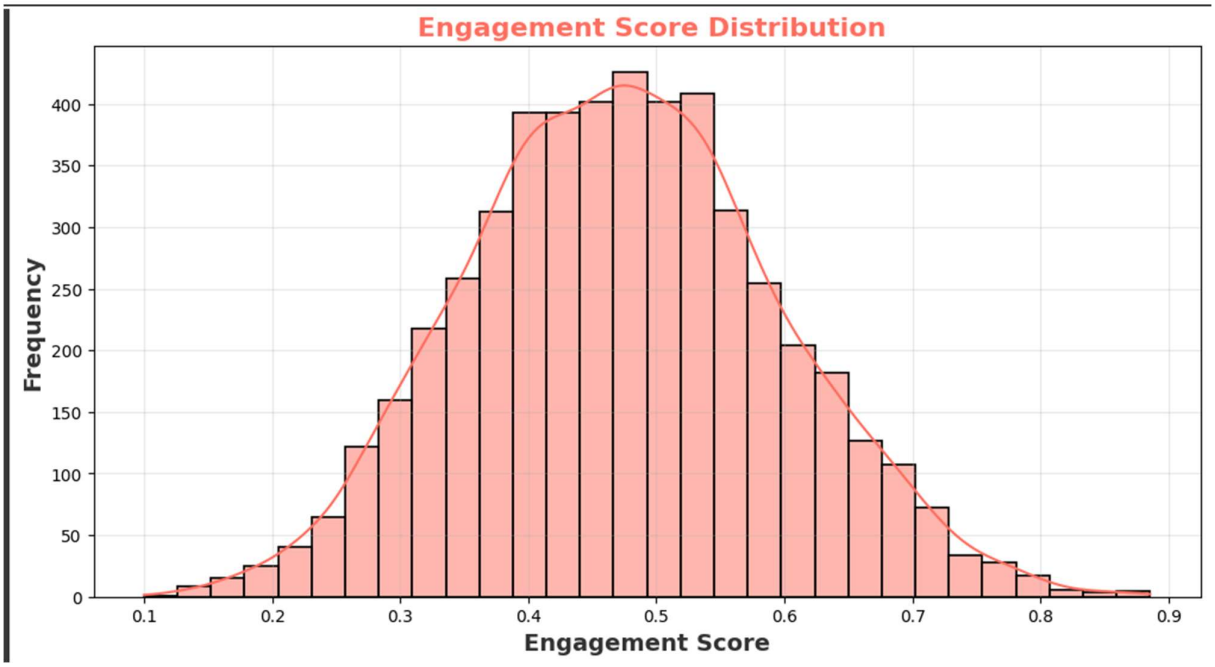


Residual Plot: Distribution of Errors
Count
0
20
40
60
80
100
−0.10
−0.05
0.00
0.05
0.10
Prediction Errors (Residuals)

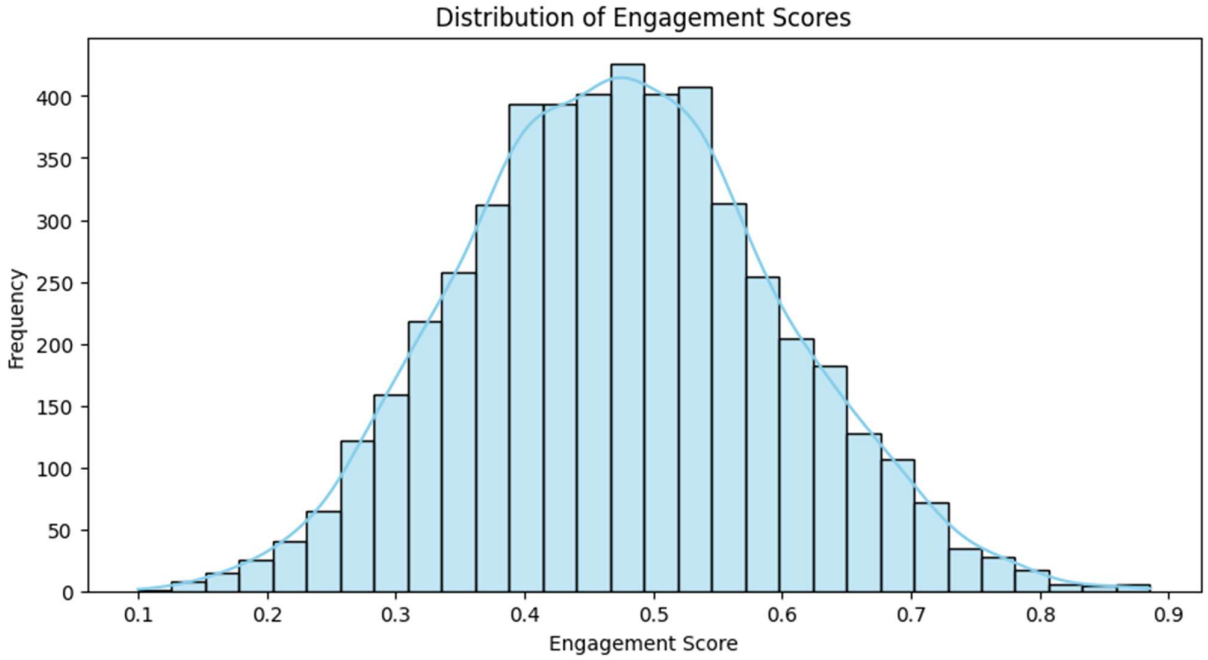

Residual Plot: Distribution of Errors
cell output actions
Count
100
80
60
40
20
0
−0.10
−0.05
0.00
0.05
0.10
Prediction Errors (Residuals)

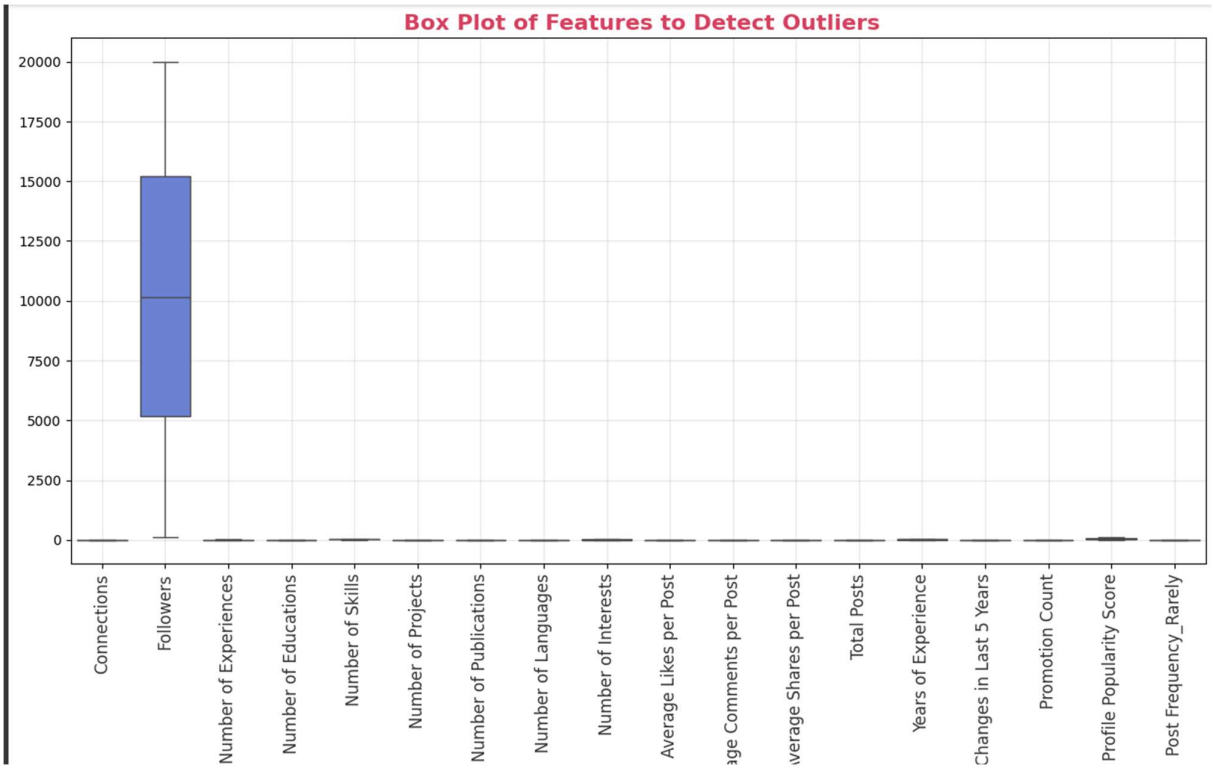

Residual Distribution Plot
Frequency
Residual (Actual - Predicted)
100
80
60
40
20
0
−0.10
−0.05
0.00
0.05
0.10

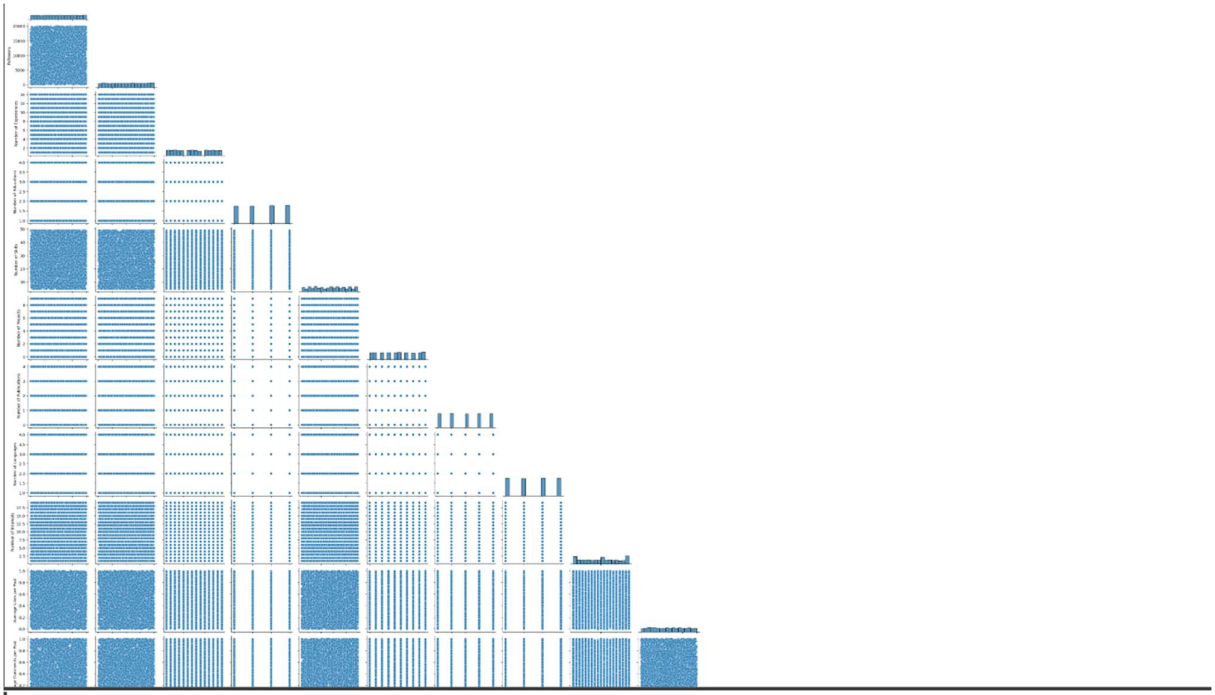

Boxplot of Features to Detect Outliers
20000
17500
15000
12500
10000
7500
5000
2500
0
Connections
Followers
Total Posts
Promotion Count
Frequency_Rarely

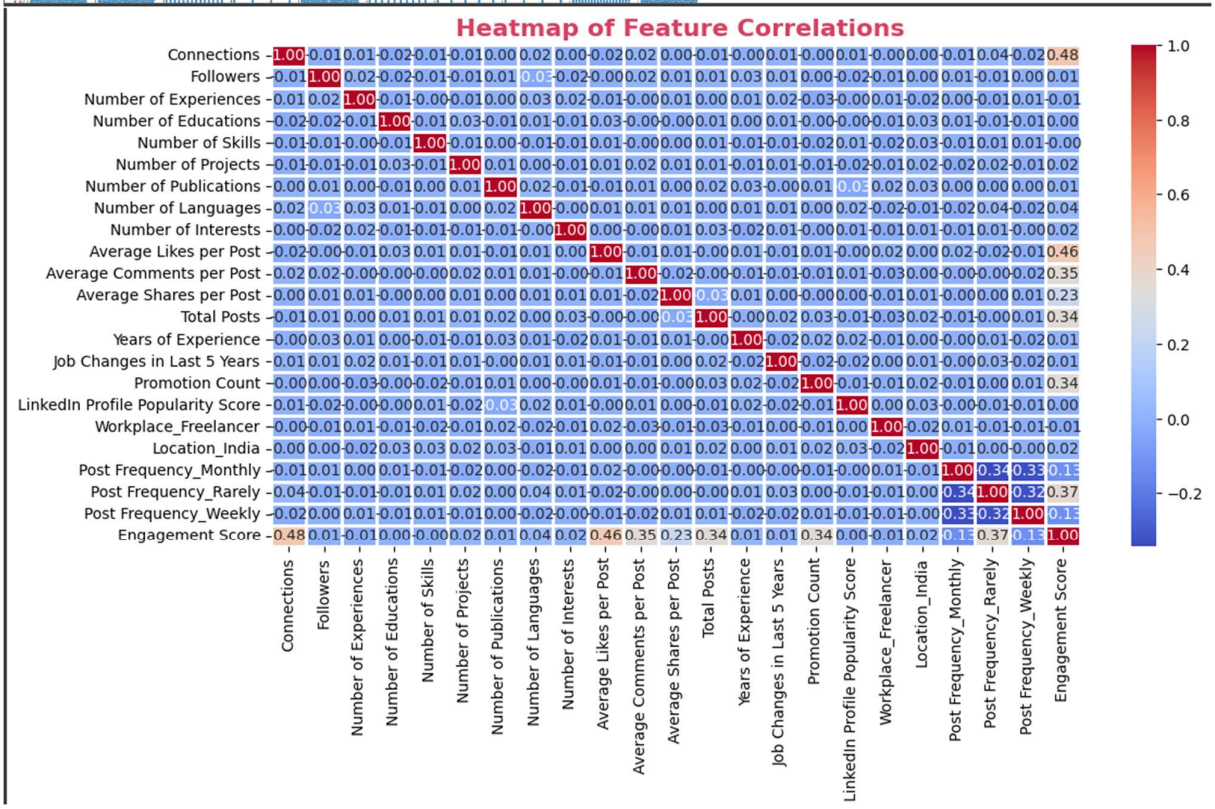

XGBoost Feature Importance for Engagement Score
Post Frequency_Rarely
Promotion Count
Average Likes per Post
Connections
Total Posts
Average Comments per Post
Average Shares per Post
Post Frequency_Monthly
Post Frequency_Weekly
Location_India
Number of Interests
Number of Languages
Years of Experience
LinkedIn Profile Popularity Score
Number of Projects
Number of Publications
Number of Experiences
Number of Skills
Number of Educations
Job Changes in Last 5 Years
Workplace_Freelancer
Followers
Features
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Feature Importance Score

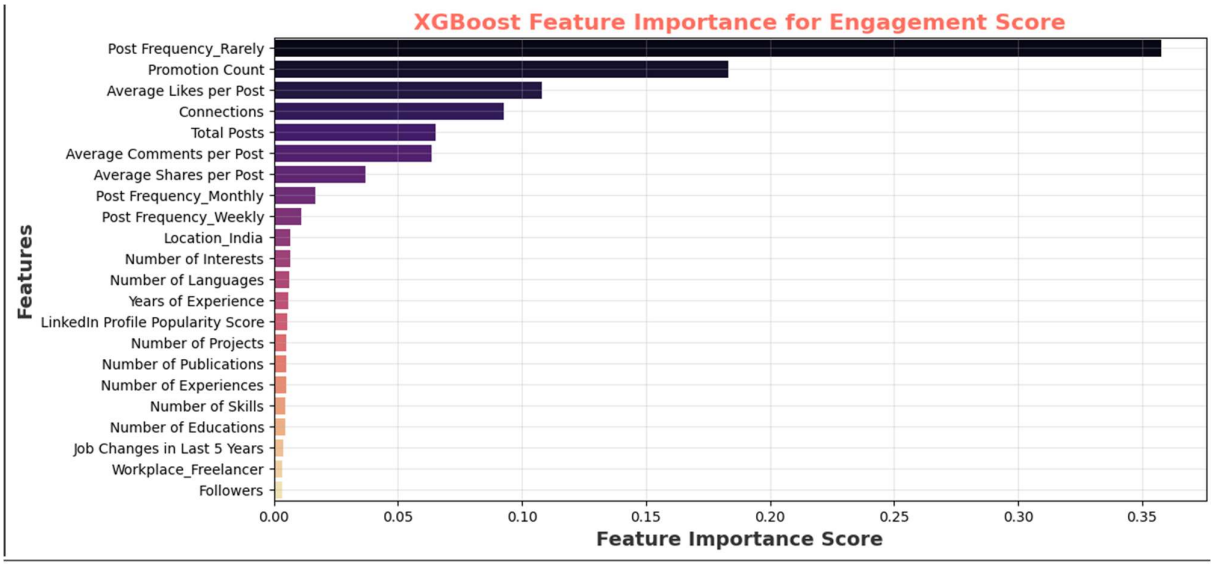

Engagement Score Distribution
Frequency
0
50
100
150
200
250
300
350
400
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Engagement Score

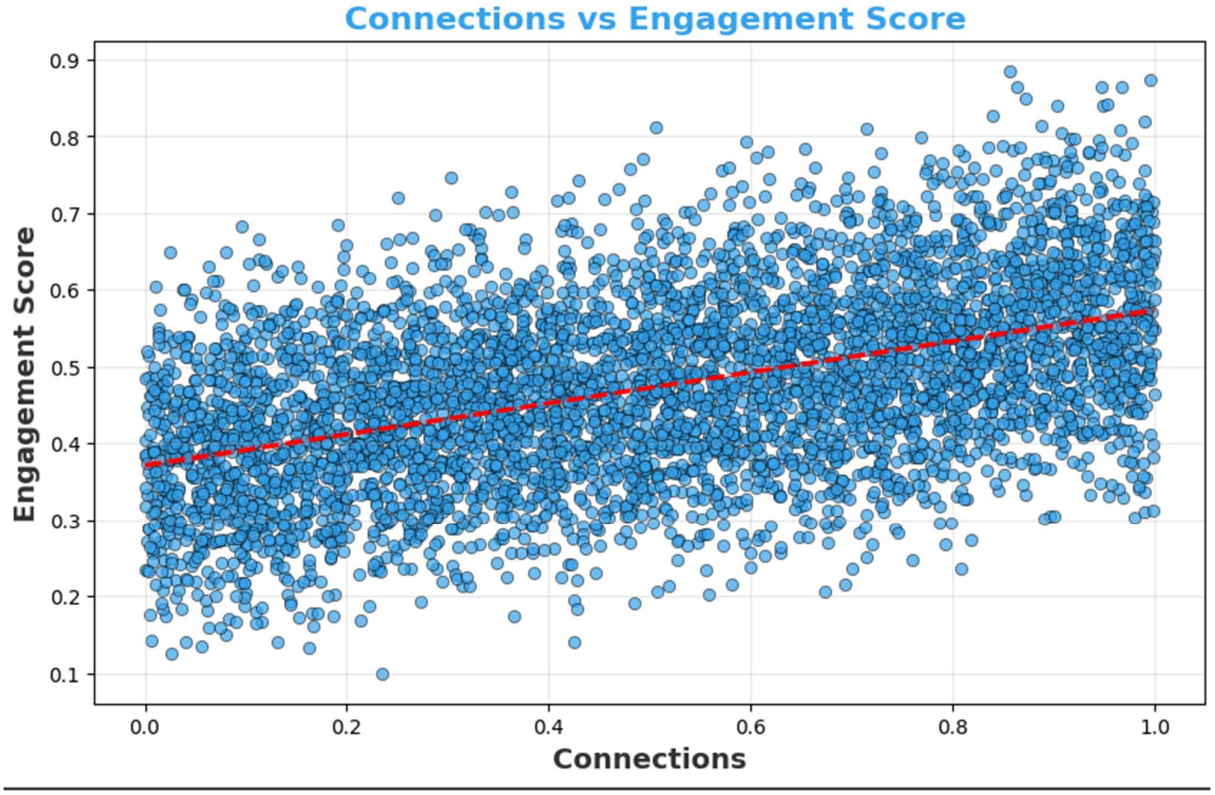

Distribution of Engagement Scores
Frequency
Engagement Score
0
50
100
150
200
250
300
350
400
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9


Box Plot of Features to Detect Outliers
20000
17500
15000
12500
10000
7500
5000
2500
0
Connections
Followers
Number of Experiences
Number of Educations
Number of Skills
Number of Projects
Number of Publications
Number of Languages
Number of Interests
Average Likes per Post
Total Posts
Years of Experience
Changes in Last 5 Years
Promotion Count
Profile Popularity Score
Post Frequency_Rarely




Heatmap of Feature Correlations
Connections
Followers
Number of Experiences
Number of Educations
Number of Skills
Number of Projects
Number of Publications
Number of Languages
Number of Interests
Average Likes per Post
Average Comments per Post
Average Shares per Post
Total Posts
Years of Experience
Job Changes in Last 5 Years
Promotion Count
LinkedIn Profile Popularity Score
Workplace_Freelancer
Location_India
Post Frequency_Monthly
Post Frequency_Rarely
Post Frequency_Weekly
Engagement Score
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


XGBoost Feature Importance for Engagement Score
Post Frequency_Rarely
Promotion Count
Average Likes per Post
Connections
Total Posts
Average Comments per Post
Average Shares per Post
Post Frequency_Monthly
Post Frequency_Weekly
Location_India
Number of Interests
Number of Languages
Years of Experience
LinkedIn Profile Popularity Score
Number of Projects
Number of Publications
Number of Experiences
Number of Skills
Number of Educations
Job Changes in Last 5 Years
Workplace_Freelancer
Followers
Features
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Feature Importance Score


Connections vs Engagement Score
Engagement Score
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0.0
0.2
0.4
0.6
0.8
1.0
Connections

# Screenshot – LinkedIn