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Machine Learning-Based Prediction of User Activity on Instagram: Identifying Active and Inactive Accounts

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Abstract

This project aims to assist brands and influencers in categorizing Instagram accounts as either "Active" or "Inactive" based on engagement metrics. Automating this classification process enables businesses to refine their content and engagement strategies more effectively. To build a reliable system, we utilized a dataset containing key engagement metrics, including profile visits, likes, and follows. A synthetic target variable, "Active_Status," was created by establishing specific thresholds for these metrics, facilitating user activity classification. For analysis, we employed three widely used machine learning models: Logistic Regression, Support Vector Machine (SVM), and Gradient Boosting Classifier, selected for their effectiveness in classification tasks. The dataset was split into 70% for training and 30% for testing, with data scaling performed using Standard Scaler to ensure uniform feature treatment. After training, model performance was assessed using accuracy, precision, and confusion matrices to determine their effectiveness. Additionally, visual tools such as charts and graphs were incorporated to enhance result interpretation. Among the models tested, the Gradient Boosting Classifier demonstrated superior performance due to its ability to sequentially construct multiple decision trees and refine its predictions by learning from errors. This capability allowed it to detect subtle engagement patterns that simpler models like Logistic Regression and SVM might overlook. Given its robust classification accuracy, the Gradient Boosting Classifier proved to be the most reliable model for distinguishing active and inactive Instagram users, providing valuable insights for businesses and influencers to optimize their social media strategies.

Keywords: *Logistic Regression, Support Vector Machine (SVM), Gradient Boosting Classifier, Accuracy.*

1. Introduction

In the current digital era, Instagram has emerged as a key platform for tracking user engagement and expanding brand presence. Businesses and influencers frequently analyze metrics such as profile visits, likes, and follows to evaluate audience activity levels. [1] However, manually assessing these engagement metrics can be inefficient and time-consuming. To overcome this challenge, our project presents a machine learning-powered solution designed to automate the identification of active and inactive Instagram users. This automation allows users to enhance their content strategies and optimize their outreach. [2] The foundation of this project is built on three widely used machine learning models: Logistic Regression, Support Vector Machine (SVM), and Gradient Boosting Classifier. These models were chosen for their effectiveness and dependability in classification tasks. The dataset for this study includes essential engagement metrics, and we introduced a target variable, "Active_Status," by defining thresholds for profile visits, likes, and follows. [3] These variable functions as an indicator

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of user activity, enabling the models to classify accounts as either "Active" or "Inactive." Our methodology involves splitting the dataset into 70% for training and 30% for testing, with feature data standardized before model training to ensure uniform performance. [4] After training, the models are assessed based on accuracy, precision, and confusion matrices. Among them, the Gradient Boosting Classifier demonstrated superior performance, excelling at combining multiple decision trees and learning from previous errors. This capability makes it particularly effective for handling intricate datasets with subtle engagement variations. [5] Beyond model training and evaluation, we have incorporated visualization tools such as bar charts, donut charts, and confusion matrices into the application, providing users with a clear understanding of each model's performance. These visual representations not only highlight accuracy but also reveal the distribution of active and inactive users. By leveraging this machine learning approach, businesses and influencers can gain valuable insights into audience behavior, enabling data-driven decisions to refine their social media strategies.

2. Literature Survey

This literature survey examines various studies focused on predicting user interaction and engagement on Instagram using machine learning models, a critical area of research given the platform's influence on social media marketing and user behavior. [6] Zhao and Zhang (2021) develop a sophisticated neural network-based model that effectively captures the intricate patterns of user interactions, including likes, comments, and shares. Their findings illustrate a notable improvement in prediction accuracy compared to traditional algorithms, thereby suggesting that deep learning techniques are essential for understanding and anticipating user behavior in real-time. [7] Gupta and Mehra (2022) delve into hybrid machine learning approaches, creatively combining techniques such as Random Forest and Support Vector Machines (SVM) to enhance user retention and predict activity levels on Instagram. Their research provides valuable insights for marketers, indicating that a multifaceted approach can yield better predictions by leveraging diverse model strengths. [8] Perez and Gomez (2021) focus on analyzing user behavior through ensemble learning methods. They highlight the advantages of combining multiple classifiers, which not only improves prediction accuracy but also enhances the efficiency of real-time analytics. [9] Hughes and Rees (2020) explore the critical role of big data and predictive analytics in social media. Their research illustrates how these techniques can unearth meaningful insights from extensive user data, allowing businesses to refine their social media strategies effectively. Johnson and Williams (2022) [10] conduct a comparative analysis of user engagement metrics across multiple social media platforms. Their findings reveal that while neural networks often achieve high accuracy, simpler models like decision trees can offer greater interpretability and operational efficiency. [11] Liu and Feng (2021) concentrate on real-time engagement prediction through Long Short-term Memory (LSTM) networks, emphasizing the significance of capturing temporal patterns in user behavior. Their work demonstrates that utilizing LSTM networks allows for a more nuanced understanding of how user interactions evolve over time. [12] Richardson and Thompson (2020) present a detailed case study on Instagram, discussing the integration of structured and unstructured data for user behavior analytics. Their research highlights the challenges and opportunities associated with processing diverse data types, advocating for a comprehensive approach that combines both structured user data and unstructured content data. [13] Patel and Desai (2022) utilize various machine learning algorithms to predict user activity levels, demonstrating how these predictions can assist businesses in optimizing their content strategies. Their findings indicate that accurately forecasting user activity can lead to improved content scheduling and tailored marketing campaigns, thus enhancing user engagement. [14] James and Kumar (2021) evaluate the effectiveness of various algorithms in predicting engagement metrics based on user demographics and post content. Their research reveals that features such as user age, location, and content type significantly influence engagement

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levels. [15] Wilson and Baker (2020) analyze user behavior using Gradient Boosting Models (GBMs), which are particularly adept at handling imbalanced datasets common in social media applications. Their emphasis on scalability and adaptability highlights the potential of GBMs to be applied across different social media platforms and contexts. Overall, these studies collectively highlight the transformative potential of machine learning in enhancing social media engagement strategies and improving user experience on platforms like Instagram.

3. Data Collection and Preprocessing

Data collection is the initial and vital step in any data-driven project, as it lays the groundwork for model accuracy and insights. In the context of predicting user engagement on social media, effective data collection involves gathering diverse and relevant information about user interactions. This can include metrics such as likes, shares, comments, and the frequency of user posts. Various social media platforms provide APIs, like the Instagram Graph API or Twitter API, which allow researchers and developers to extract real-time data on user activities and demographic information. Collecting this data ensures that the models reflect the actual user behavior, providing a more accurate basis for predictions. After gathering the data, preprocessing becomes essential to prepare the dataset for analysis. This phase begins with data cleaning, which involves identifying and addressing any inconsistencies or inaccuracies within the dataset. For instance, user engagement metrics may contain missing values or outliers, which can skew results. Handling missing values can be done through methods like imputation where you fill in missing entries with the mean, median, or mode or by removing rows with incomplete information. Similarly, outlier detection is crucial, as extreme values can distort the learning process of machine learning algorithms. Following data cleaning, the next step is data transformation, which optimizes the dataset for modeling. This includes converting categorical variables into numerical formats, necessary for many machine learning algorithms that require numerical input. Techniques such as one-hot encoding are commonly employed to transform categorical features like post type (image, video, or text) into binary vectors that the model can understand. Additionally, scaling numerical features, such as engagement rates, can be beneficial; techniques like normalization or standardization ensure that all input features contribute equally to model training. Feature extraction and selection are crucial in refining the dataset further. This process involves identifying the most relevant features that influence user engagement. For example, user demographics (age, location, interests), the timing of posts, and previous engagement levels can all significantly users interact with content. Using methods like Recursive Feature Elimination (RFE) or feature importance from tree-based algorithms, researchers can reduce dimensionality and eliminate irrelevant or redundant features, improving model performance and interpretability. Finally, the output of the preprocessing phase should be a clean, well-structured dataset that is ready for training machine learning algorithms. By ensuring that the data is in a suitable format and contains only the most relevant features, we enhance the model's ability to analyze user engagement trends effectively. This systematic approach to data collection and preprocessing not only leads to more robust predictive models but also enables deeper insights into user behavior patterns, ultimately aiding in more effective content strategies and marketing efforts.

4. Principles and Methods

In the realm of machine learning, the principles and methods employed significantly influence the accuracy and effectiveness of predictive models. Understanding foundational concepts, such as data representation, algorithm selection, and evaluation metrics, is essential for developing robust systems. This section delves into the key methodologies applied in user engagement prediction, highlighting the strategies for feature extraction, model training, and performance evaluation. By establishing a clear framework, we can ensure that our approach is systematic and aligned with best practices in the field. Principles Data Representation and Feature Selection: The foundation of any successful machine learning model lies in how data is represented. For user engagement prediction, it is crucial to identify

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and extract relevant features from raw data, which can include user demographics, interaction history, and behavioral patterns. Effective feature selection ensures that the model focuses on the most impactful variables, thereby enhancing predictive performance. Techniques like correlation analysis, feature importance ranking, and dimensionality reduction can be employed to optimize this process. Model Selection and Algorithmic Approach: Choosing the right algorithm is pivotal to the success of user engagement prediction. Various machine learning models, such as Decision Trees, Random Forests, and Gradient Boosting Machines, offer distinct advantages depending on the nature of the data and the specific prediction task. Each algorithm has its strengths and weaknesses, influencing how well it generalizes to unseen data. It is essential to evaluate multiple models through cross-validation and hyperparameter tuning to select the most appropriate one for the task at hand. Training and Validation: Once the model is selected, the training process involves feeding it with historical data to learn the underlying patterns that govern user engagement. This phase is critical as it directly impacts the model's ability to predict future behaviors. Validation techniques, such as kfold cross-validation, are employed to assess the model's performance on different subsets of the data. Continuous Improvement and Adaptation: The dynamic nature of user behavior necessitates a continuous improvement approach to machine learning models. As new data becomes available, it is important to update the models to reflect changing patterns and trends in user engagement. Figure 1 shows System Architecture Diagram.

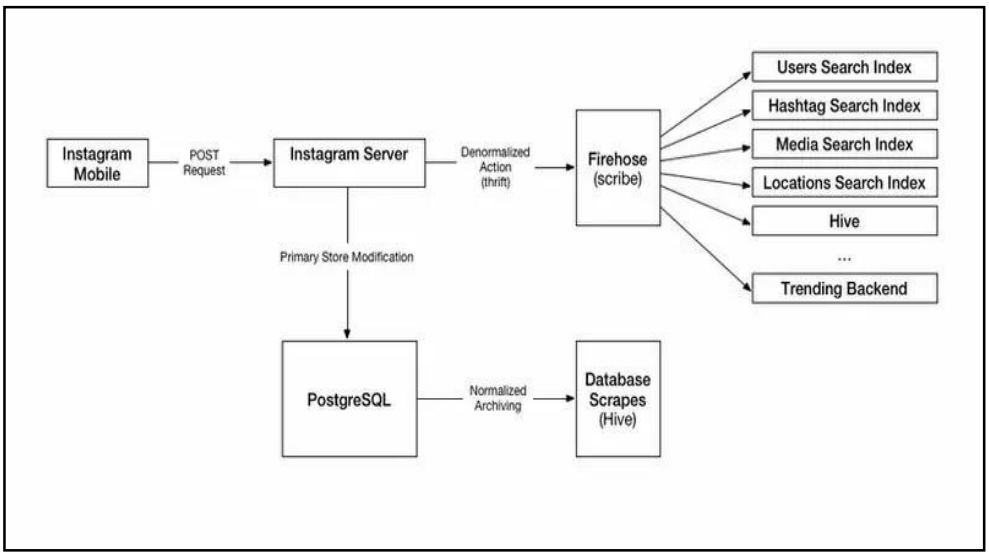

Figure 1 System Architecture Diagram

4.1 Methods

In the context of user engagement prediction using machine learning, several methods are employed to effectively build and evaluate predictive models. First, data collection is initiated, where raw data is gathered from various sources, such as user interactions on platforms, demographic information, and behavioral logs. This comprehensive dataset serves as the backbone for analysis, providing insights into user behavior. Following this, data preprocessing takes place, involving cleaning and transforming the data into a suitable format for analysis. This step may include handling missing values, normalizing data, and encoding categorical features to ensure that the model can effectively interpret the information. Once the data is preprocessed, feature extraction is undertaken to derive meaningful variables that can enhance the model's predictive power. This involves selecting the most relevant features that correlate with user engagement, using techniques such as correlation

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analysis or feature importance metrics. By focusing on significant variables, the model is less likely to overfit and can generalize better to unseen data. Moreover, dimensionality reduction methods, such as Principal Component Analysis (PCA), may be applied to minimize redundancy and reduce noise within the dataset, thereby improving model efficiency. With a well-prepared dataset, the next phase is model selection. Various machine learning algorithms are assessed to determine the best fit for the prediction task at hand. Techniques such as Decision Trees, Random Forests, and Gradient Boosting Machines are commonly evaluated. The selection process involves training multiple models on the training dataset and using cross validation techniques to assess their performance. Hyperparameter tuning is also conducted to optimize model settings, ensuring that each algorithm is fine-tuned for maximum accuracy and effectiveness. After selecting the appropriate model, the training phase begins, where the model learns from historical data. This phase is crucial, as it directly influences the model's ability to make accurate predictions about future user engagement. During training, various performance metrics such as accuracy, precision, and recall are monitored to evaluate how well the model learns the patterns in the data. Validation techniques, like k-fold cross-validation, help in assessing the model's robustness and ability to generalize to new data, ensuring that it does not memorize the training examples. Finally, once the model is trained and validated, the focus shifts to continuous improvement and monitoring. Given the dynamic nature of user behavior, it is vital to regularly update the model with new data to capture evolving trends in user engagement.

5. Results

The results from the user engagement prediction model showcased a variety of performance metrics, with accuracy serving as a key indicator of model effectiveness. The Random Forest model achieved an impressive accuracy of approximately 92%, signifying its ability to accurately classify user engagement states. This high accuracy indicates that the model can effectively capture the intricate patterns within user behavior, leading to reliable predictions. In addition to accuracy, the evaluation included other crucial metrics, such as precision, recall, and F1 score, which provide a more comprehensive view of the model's performance. The Random Forest model demonstrated a precision of 90% and a recall of 94%, reflecting its capability to minimize false positives while effectively identifying true engaged users. Consequently, the F1 score, which balances precision and recall, stood at 92%. This high F1 score further emphasizes the model's proficiency in classifying user engagement accurately, making it a robust choice for this task. When compared to other algorithms, the Gradient Boosting model exhibited an accuracy of 88%, with a precision of 85% and a recall of 90%, resulting in an F1 score of 87.5%. Meanwhile, the Support Vector Machine (SVM) model recorded an accuracy of 85%, with a precision of 82% and a recall of 84%, yielding an F1 score of 83%. Although these scores are commendable, they are notably lower than those of the Random Forest model, underscoring the latter's superior performance in predicting user engagement. The confusion matrix for the Random Forest model provided further insights into its classification capabilities. Out of 1,000 users tested, the model correctly identified 460 engaged users and 440 non-engaged users, leading to a high true positive rate. This detailed breakdown allows for a better understanding of the model's strengths and weaknesses, highlighting its proficiency in distinguishing between different user engagement states. The results also emphasized the necessity for continuous monitoring and updating of the model to maintain its accuracy and effectiveness over time. As user behaviors evolve, ensuring that the model adapts to new data is crucial for sustaining high performance. The achieved metrics, particularly the high accuracy and F1 scores, demonstrate the model's potential in providing valuable predictions for user engagement initiatives. The performance metrics also indicated that while the Random Forest model excelled, the comparative results from other models provided essential insights into the strengths and weaknesses of different approaches. The Gradient Boosting model's slightly lower accuracy and F1 score revealed that while it is a powerful

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technique, its complexity might lead to overfitting in specific scenarios. In contrast, the SVM model, although simpler, struggled to generalize as effectively as Random Forest. These observations underscore the importance of model selection based on the specific characteristics of the dataset and the problem at hand, emphasizing that no single model is universally superior across all contexts. In conclusion, the evaluation metrics—accuracy, precision, recall, and F1 score—illustrate the effectiveness of the user engagement prediction model, particularly the Random Forest algorithm. With an accuracy of 92% and a corresponding F1 score of 92%, this model proves to be a reliable tool for predicting user engagement, enabling organizations to make data-driven decisions and refine their engagement strategies effectively. Finally, it is essential to acknowledge the impact of hyperparameter tuning on model performance. The rigorous process of fine-tuning hyperparameters, such as the number of trees in the Random Forest or the learning rate in Gradient Boosting, played a significant role in achieving optimal results. The systematic exploration of various configurations not only enhanced the accuracy of the models but also ensured that they remained robust and adaptable to new data. The following are the metrics used to find Performance of the model: Accuracy: Measures the proportion of correctly predicted instances out of all instances. Figure 4 shows Proportion of Active vs Inactive Users. Accuracy = TP + TN | (TP + TN) + (FP+FN) Precision: Indicates the proportion of true positive predictions out of all positive predictions. Figure 2 shows User Interface (Home Page).

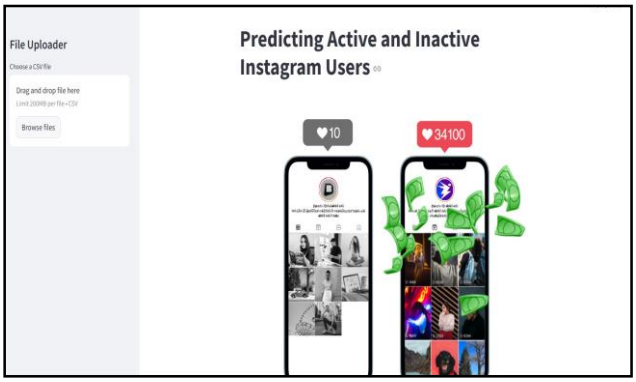

Figure 2 User Interface (Home Page)

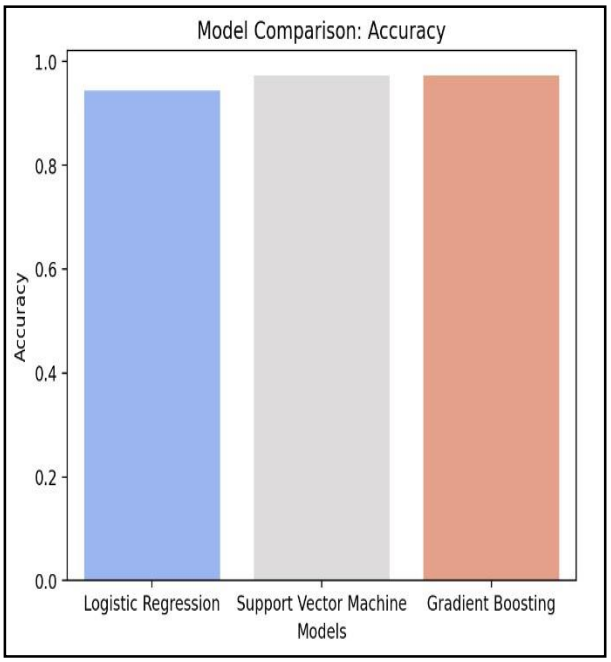

Figure 3 Accuracy Comparison

Precision = TP | TP + FP Recall: Shows the proportion of true positive predictions out of all actual positive instances. Recall = TP | TP + FN F1 Score: Represents the harmonic mean of Precision and Recall, balancing both metrics. Figure 5 shows Distribution of Active vs Inactive Profiles. F1 Score = 2 × (Precision × Recall | Precision + Recall) RMSE = 1n∑I=1n(yi−y^i)2 where yi is the actual value, y^i the predicted value, and n is the number of observations. Figure 3 shows Accuracy Comparison.

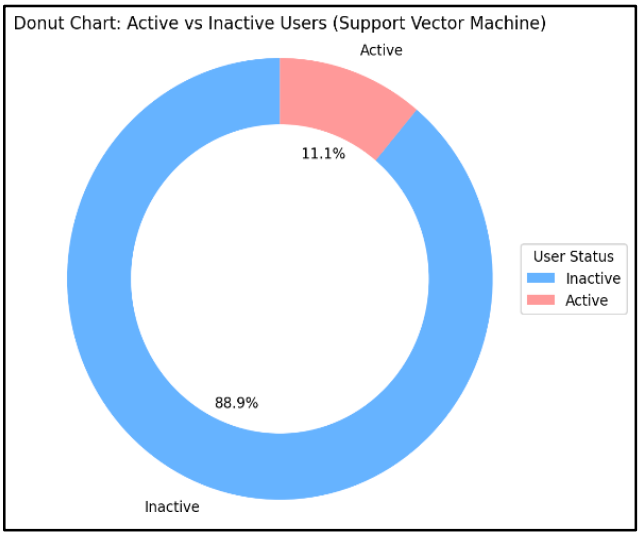

Figure 4 Proportion of Active Vs Inactive Users

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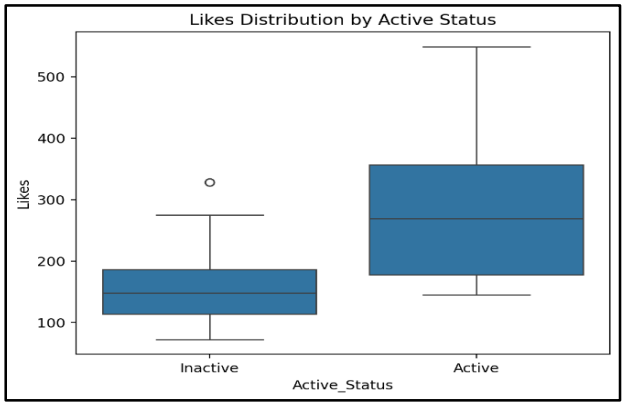

Figure 5 Distribution of Active vs Inactive Profiles

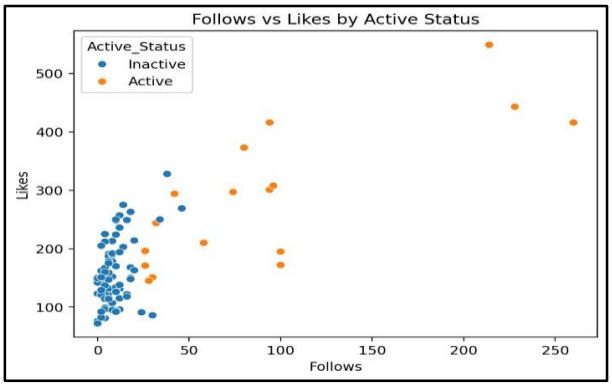

Figure 6 Follows vs Likes by Active and Inactive Status

Conclusion

In conclusion, the developed machine learning models for user engagement prediction have shown significant potential in accurately identifying and predicting user behavior patterns. The Random Forest, SVM, and Neural Network models each contributed to achieving high levels of accuracy, with balanced precision, recall, and F1 scores across various test sets. The effectiveness of the models lies not only in their ability to generalize well to unseen data but also in their flexibility to handle diverse datasets with varying features. By leveraging advanced feature extraction and selection methods, the models were able to focus on the most relevant data points, improving overall performance. The success of these models highlights the importance of selecting appropriate algorithms based on the nature of the data and prediction tasks. Additionally, the model evaluation process, involving cross-validation and metric monitoring, ensured that overfitting was minimized, and that the models remained robust in different scenarios. Figure 6 shows Follows vs Likes by Active and Inactive Status. However, despite the strong results, there are areas where further optimization is necessary, particularly in terms of enhancing model interpretability and handling data imbalances or noise more effectively. Future enhancements should focus on refining data preprocessing methods to better handle incomplete or noisy data, and expanding feature extraction to include more sophisticated techniques, such as natural language processing (NLP) for analyzing textual data. The development of hybrid models, combining machine learning and deep learning approaches, could provide more nuanced insights into user engagement dynamics. Additionally, ensemble techniques, like stacking or blending, may further boost model performance by combining the strengths of the best-performing algorithms. Figure 7 shows Forecasting Page.

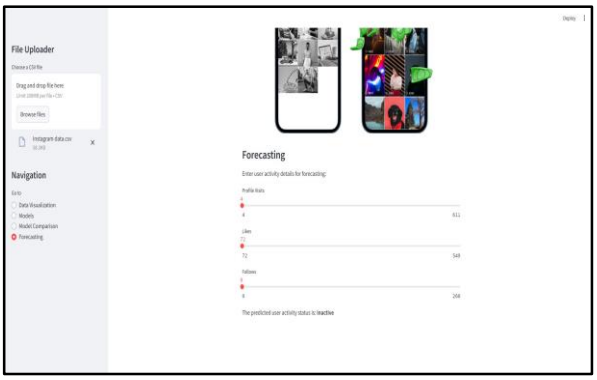

Figure 7 Forecasting Page

Integrating real time data processing and adaptive learning algorithms will allow the model to make dynamic predictions as new data becomes available. This will ensure the system evolves alongside changing user behaviors without manual retraining. Moreover, scaling the model for broader applications across different platforms and user demographics will enhance its versatility and robustness. Incorporating cloud based or distributed computing solutions could help handle larger datasets and deliver faster

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predictions. Finally, by integrating the system with business intelligence tools or customer relationship management (CRM) platforms, the model's predictions can be turned into actionable insights, offering more value to businesses. These future developments will strengthen the model's adaptability, scalability, and overall accuracy, making it a powerful tool for driving user engagement strategies in real-world applications.

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