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Statistical Analysis of Social Media on Mental Health in Young Adults

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Abstract: This research explores the correlation between the behavior of social media use and emotional well-being in young adults in a quantitative correlational study.The data is in the form of self-reported indicators, such as platform preference, frequency of engagement, the frequency of activities within the platform, and the attitude of emotional states, which are Happiness, Anxiety, Anger, Sadness, Boredom, and Neutral.. Python libraries were used to process the data and analyze it with the help of exploratory data analysis (EDA) to guarantee that the information is credible and shows trends in behavioral-emotional changes. The key variables were on which feature extraction concentrated. Type of platform, time spent using it on a daily basis, and metrics of user engagement. The machine learning classifiers used were five: the Logistic Regression, the Random Forest, the XGBoost, the Support Vector Machine (SVM), and the K-Nearest Neighbors (KNN) classifiers which were used to predict the emotional state using behavioral features.The outcomes of the experiments proved that ensemble learning models were far more successful than random and instance-based models in terms of the accuracy of XGBoost (88% accuracy) and Random Forest (85% accuracy). The EDA showed that Happiness and Neutral emotions were associated with having more social interaction, but Anxiety and Sadness had more association with longer screen time and reduced levels of engagement. Such results demonstrate the possibilities of machine learning to determine emotional inclination in the form of social media behavior. The conclusion of the study is that predictive analytics can be essential in the promotion of digital health and the development of the intervention plan designed to engage in social media in a healthier way.

Keywords: Social Media Behavior; Emotional Well-Being; Machine Learning; XGBoost; Random Forest; Support Vector Machine (SVM); Logistic Regression; K-Nearest Neighbors (KNN); Exploratory Data Analysis (EDA); Digital Psychology

1. Introduction

As social media continues to gain a foothold in the daily lives of young adults, much attention has focused on the associations that this technology has with mental health issues, due to its growing acceptance by scholars and mental health practitioners in their discussions about the topic. Facebook, Instagram, Tik Tok, and Twitter turned into significant networks of networking, self-expression, and sharing information, having transformed the sphere of communication and connection formation and the way people interact with the surrounding world. These are platforms where the youth can get learning, creative expression, and socialization opportunities [1]. Their extensive use also makes them a matter of concern with regard to their impact on the psychological health of their users, particularly of the most frequent ones, who are teenagers and young adults. There have been various mental health issues that have been attributed to increased use of these platforms including low self-esteem, loneliness, anxiety, and depression [2]. The social media might be a nice means of communication with people, but when applied recklessly, without any appropriate control, it may result in making mental health concerns even more dangerous. Considering both positive and negative aspects of social media, there is need to conduct a deep research to

understand how the social media influence the current lives and how to reduce the possible negative impacts. the advent of social media has fundamentally changed the way people socialize, share ideas and form societies. Instagram and Snapchat are examples of platforms where sharing well Chosen photos have been associated with the proliferation of harmful comparisons and negative views about their body [3]. These issues may lead to low self-esteem and high anxiety levels especially among young children who are easily prone to social influences and behaviors which aim at confirmation. Like this, the websites such as YouTube and Tik Tok can exacerbate stress and feelings of inadequacy because they create highly competitive environments where individuals vie on the number of likes and followers. The constant urge to be liked, commented on, and followed may cause users to be anxious and dissatisfied with their self-image because of the competitive and performance Based culture [4].

Another study that has linked the use of excessive social media has been associated with disturbed sleep patterns which contributes towards mental distress. Moreover, the ability of social media to help people establish the echo chambers so that they can see only those pieces of information that confirm their beliefs might limit the number of possible opinions and increase emotional vulnerability, loneliness, and hopelessness. Social media platforms may also be used to offer valuable resources to take action, be supported and have a comprehension on mental health matters. They provide individuals with a platform to mingle with individuals who may be experiencing the same issues, discuss and receive peer support. Social media has also played a critical role in reducing stigma, raising mental health resources, and awareness of mental health concerns. The prevalence of cyberbullying and harassment on the Internet, particularly anonymous communication on Twitter and other forums, makes one see the downside of online communication [5].

Cyberbullying has proved to exacerbate loneliness, despair, and anxiety symptoms particularly among the youth who are yet to develop their coping abilities, and mental robustness. Since people contrast their lives to the apparently perfect ones of other people, the social media-related concepts of FOMO (Fear of Missing Out) may contribute to the feeling of inferiority and dissatisfaction even more. In order to detect the patterns which are not always obvious at a glance, such statistical tools as regression analysis, inferential testing, and descriptive statistics will be employed. This approach can help to see the specific aspects of online behavior that cause either beneficial or adverse psychological outcomes, thereby understanding the influence of different types of interaction on mental health in a more subtle way. These self-reported data will give a more detailed view of the relationship between digital activities and mental health when used in conjunction with objective data on platform usage. The help in the presentation of the findings will be provided with charts, graphs, and other types of data visualization, and it will demonstrate the complex connections between the use of social media and mental health results [6]. With constant access to idealized photos on the internet and the comparison among friends, young adults may develop inadequately high expectations, which cause anxiety, low self-esteem, and depressive symptoms [7]. Additionally, there is the Fear of Missing Out phenomenon that has become an important psychological stimulus since people tend to experience the pressure to remain always active and be validated by likes and comments [8]. This online addiction does not only impact the emotional state, but also interferes with sleep patterns and focus, which is one of the factors that can lead to stress and burnout. recent research notes that the psychological implications of using social media greatly rely on how and why people use them. A sense of belonging and social capital can be achieved through active and intentional involvement or participation (i.e., exchanging experiences, pursuing information, or supporting others). Passive surfing and excessive exposure to filtered content, in their turn, tend to result in adverse affective conditions and social detachment.

Therefore, by analyzing the statistical trends of these behaviors in young adults, it is possible to develop evidence-based interventions to promote mental health, thus this study aims at providing the time spent online, the type of the material read, and the nature of user interaction. With the objective of determining the major variables that can be considered in the forecasting of emotional well-being, the study will present new knowledge to educators, policymakers, and health professionals in developing the interventions that will promote healthy digital habits and enhance psychological resiliency among young people.

2. Literature Review

The importance of social media in education and mental health, crisis management, and identity development has become a more significant topic of interest over the last ten years. According to Greenhow

and Askari, social network sites (SNSs) are highly influential in education and they also pointed at the challenge in adopting these technologies in the classroom as well as the possibilities that these technologies can enhance the learning opportunities [9]. Their discussion brought into focus how SNSs promote the cooperation, engagement, and communication of students and at the same time emphasize the privacy and distraction risks. Abbas et al. examined the impact of social media on mental health, particularly in the crisis period, such as the COVID-19 epidemic, and how they played a very crucial role in managing a crisis [10]. They insisted that despite the fact that knowledge dissemination was possible through social media, it also influenced the growth of mental problems due to dissemination of false information and stress.

Another finding in the study was the necessity to approach social media with tactics that would have an equal amount of positive and negative impacts on mental health. As applied to personal branding and leadership, Holtz and Havens investigated the concept of the tactical transparency, whereby leaders tactically utilize the social media to make themselves better known and build their reputation [11].

It is particularly relevant in the culture of candidness and sincerity where social media may be a two-edged sword in curbing popular sentiment. Also, Davis analyzed the way the youths figure out how to negotiate the complexity of online self-construction during his critique analysis of the linkage existing between identity, self-expression, and social media [12].

Their research found out the tension between autonomy and social expectations in the digital era, illuminating the dangers of exposure and the rewards of validation, which goes along with Self expression in the social media. Thorstad and Wolff achieved predictions of the future mental health outcomes regarding the social media behaviors using the big data approach. Their discovery created an alternative path to the early intervention and prediction of psychological care through proving that the patterns of online activity could be indicative of various mental health conditions [13].

There has been a lot of research on the efficacy and disadvantages of online social networks to enhance mental health and health behavior change. Maher et al. in a review of the literature have found two methods, which social networks online can have a successful impact on the change of health-related behavior: social support and responsibility. These platforms significantly boost the adoption of the healthy behaviors by ensuring that users can monitor their progress and share their experiences [14].

Scalable solutions to mental issues, the use of behavioral intervention technologies (BITs) has become popular as well. Mohr et al. highlighted the potential of BITs in offering readily available mental health interventions through the use of internet platforms. This would render the therapy more convenient and economical compared to the traditional methods [15]. Hansen et al. studied social media networks, where the focus was on the patterns of connectedness and interaction of the platforms. The paper has provided valuable knowledge on what online behavior is structured like and how this knowledge can be used to develop more effective online social media based interventions [16].

Taken collectively, these findings point to the ability of social media to empower and potentially cause stress. Steel et al. conducted a systematic research and meta-analysis of the association between traumatic experiences and mental health outcomes on communities that have been exposed to mass violence and displacement. The findings showed the importance of social support in reducing the adverse psychological outcomes of such scenarios. Similarly, Smith et al. also explored the concept of schadenfreude within the social context, namely, the context of social media interaction. They found that these apps enhance complex emotional responses, which provide a deeper understanding of effects of online environments on social behaviors and mental health [17]. The discussion of virtual communities by Ridings and Gefen helps understand what makes virtual spaces attractive to people [18].

This idea was also developed by Cattell who studied the impact of the social networks and social capital on the health conditions related to the poverty and poor living conditions [19]. The study highlighted the importance of good social relationships as a way of promoting resilience and health to act as a buffer against the negative impacts of socioeconomic difficulties. The association between social networks and mental health has been explored in many studies, which give valuable information on how the two interact to influence the general wellbeing. Pearlin in revisiting the stress process underlined the complex connections between stressors, social support and mental health outcomes. This is also reflected in the protective nature of strong social networks to reduce stress and to foster resilience [20]. The idea of social comparison is especially applicable to the entrepreneurship of social media. The issue that Collins analyzed concerned

the effects of upward social comparisons on self-rating, during which people compare themselves with others who are viewed to be more successful [21].

In virtual spaces where comparisons are intensively filtered, stress and lowered self-worth are likely results (especially in online space). On the same note, Wood explored the theoretical foundations of the social comparisons offering a model of how these dynamics are involved in the digital and offline worlds. In addition, online platforms have their own opportunities of healing interactions [22]. Kornfield (n.d.) examined the impact of peer-to-peer communication conditions in the online mental health support site. The results showed that such environments are conducive to therapeutic self-expression and improve the general wellbeing of users. These platforms play an important role in enhancing mental health by providing easily accessible supportive sites where people can communicate with and be validated.

3. Metholodogy

3.1. Study Design

The research design adopted in this study is a quantitative correlational research as it explores the relationship between behaviors of social media usage to emotional well-being in young adults. The data consists of self-reported data regarding preferences to platforms, frequency of engagement, and self-reported emotional state. The general procedure is data gathering, preprocessing, exploration data analysis (EDA), feature extraction, implementation and assessment of a model.

3.2. The dataset of the Social Media Behaviors

The dataset includes the responses of the participants on the number of the most used platforms (Instagram, Facebook, WhatsApp, Snapchat, Telegram, LinkedIn, and Twitter) and their gender, average daily time of use, sent messages, received likes and comments, and shared posts per day. All the respondents also indicated their prevailing emotional status when using social media (Happiness, Anxiety, Anger, Sadness, Boredom, or Neutral).

3.3. Data Preprocessing

Python packages like Pandas and NumPy were used to run data preprocessing. Numerical values that had not been given were imputed by mean substitution and mode values were used to replace categorical variables. Label-encoded categorical fields (Platform, Gender, Emotion) were used to enable them to be used as inputs in machine learning classifiers. Outliers were included so as to maintain behavioral variation in the real world.

3.4. Feature Extraction

The most topical features were determined with the help of domain knowledge and correlation analysis. The chosencharacteristics were the following:

- Platform Type Gender
- Daily Usage Time (in hours)
- Messages Sent Per Day
- Likes and Comments Received
- Posts Per Day
- Pre-eminent Feeling (Target Variable)
- Base Classifier -Logistic Regression.

3.5. Base Classifier -Logistic Regression

The Logistic Regression served as a baseline linear classifier in predicting the outcome of emotions on the intensity of the use of the social media. The model made use of the sigmoid activation in order to compute the likelihood of a particular emotional reaction:

$$P(Y=1|X)=1/(1+e-(\beta0+\beta1X1+\beta2X2+\ldots+\beta nXn))$$

3.6. Homogeneous Ensemble Classifier -Random Forest

Random Forest was used as an ensemble method based on bagging which uses a number of decision trees to form non-linear relationships between usage behavior and emotional conditions. It increases generalisation by majority voting:

$$\hat{Y}(x)=mode\{T1(x),T2(x),\ldots,Tn(x)\}$$

3.7. Heterogeneous Ensemble Classifier -XGBoost

The XGBoost is a boosting based algorithm, which was used to achieve optimization in performance by means of sequential learning. The successive learners eliminated remnants of errors made by the preceding:

$$f_t(x)=f_{t-1}(x)+\eta \cdot h_t(x)$$

It had better feature importance ranking and overfitting resistance.

3.8. Support Vector Machine (SVM) Kernel-Based Classifier

With the help of SVM, engagement metrics were projected into a higher dimensional space and separation between emotional classes based on the hyperplane was determined.

3.9. K-Nearest Neighbors (KNN) Instance-Based Classifier.

KNN was used to predict emotions by determining the nearest patterns of behavior of other peer users, whose similarity is determined by the Euclidean distance.

3.10. Experimental Setup

All the experiments were performed in Google Colab with the help of Python. The dataset was split into two parts 80 percent train and 20 percent test. The cross-validation was done ten times to guarantee the model generalization. Random Forest, XGBoost, and SVM hyperparameters were determined by means of the GridSearchCV.

3.11. Data analysis involves performing Exploratory Data Analysis (EDA).

The emotional trends were interpreted by the following visualizations:

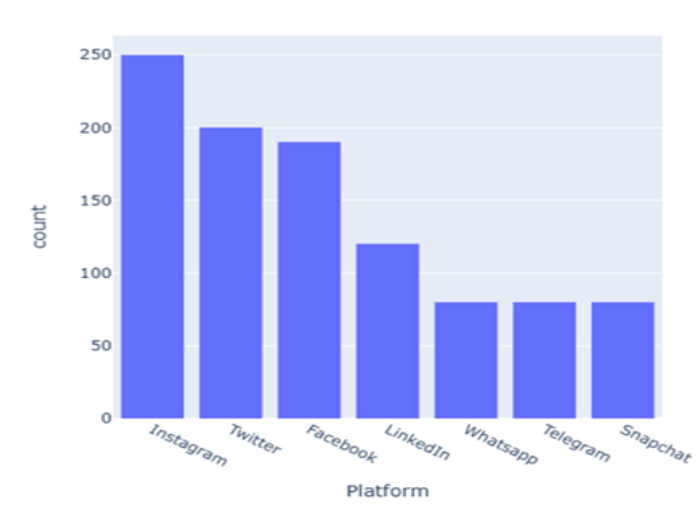

Figure 1. Histogram 1.0 Distribution.

This statistic demonstrates that Instagram, Twitter, and Facebook are the most favored among young adults.The level of engagement in LinkedIn, WhatsApp, Telegram, and Snapchat are relatively low.The prevalence of visual and interactive communication such as Instagram and Twitter implies the preference of expressive media communication.

Another trend related to the increase in emotional expression on the sites where real-time communication is promoted.

Generally, the histogram depicts diversity of the platforms where the engagements are skewed towards entertainment oriented use.

According to the pie chart, there was an equal distribution of overpowering emotions in the process of social media use.Happiness and Neutral states are roughly equal in the proportion of response.Anxiety and Sadness are also important, which emphasize the emotional susceptibility in online communication.Less often but also not negligible behavioral states are Anger and Boredom.This diversity means that social media has the potential to boost and create an emotional state of instability.

The females and males have a higher number of participants in the gender histogram.This is in line with the trends of more social interaction among women in the digital communication.The few non-binary and other gender identities demonstrate inadequacy in representation.Although this was the case of imbalance, emotional diversity was found in all gender groups.These findings indicate that the emotional impact of social media is not gender specific but it is more or less intense.

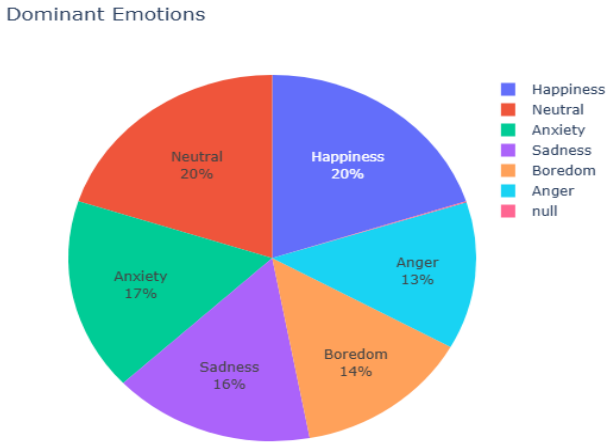

Figure 2. Pie Chart of Emotion Proportion

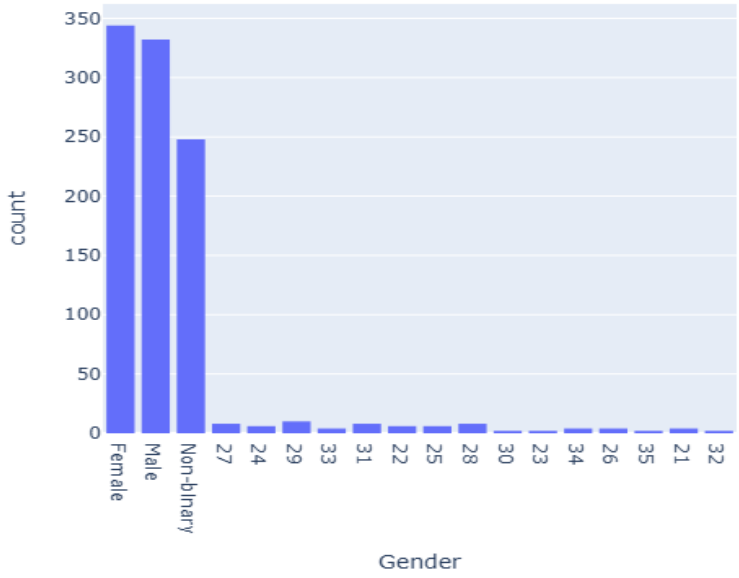

Figure 3. the Distribution Histogram of genders is shown

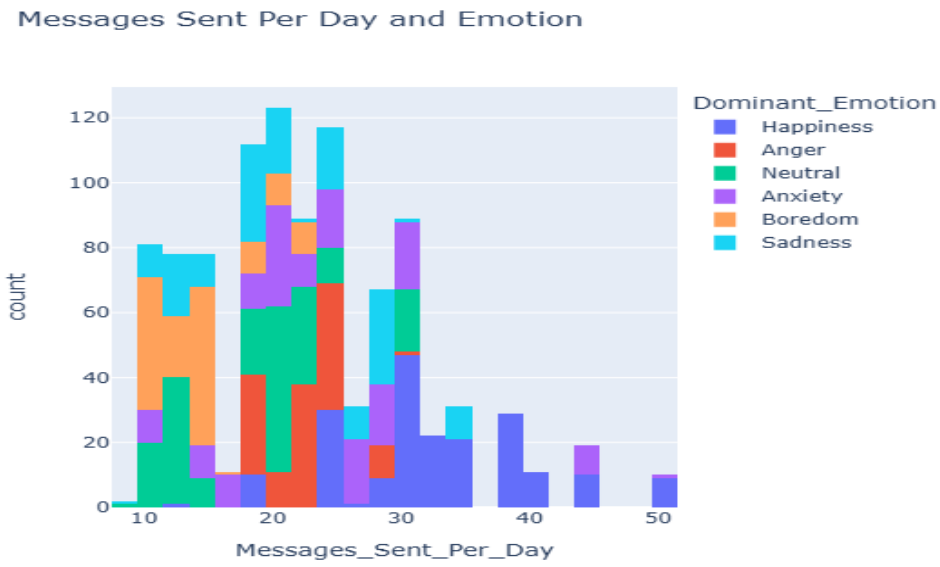

Figure 4. Messages vs Emotion Histogram

This histogram shows the relationship between frequency of the messages and emotional condition.The participants that experienced Happiness or Neutral emotions are likely to send more messages in

one day.Anxious or Sad people also have less messaging activity, which may be an indication of emotional withdrawal.Anger activity is intermittent, though at times, high in cases of emotional outbursts.In this way, the more social the communication seems, the more positive or stable the emotions do seem to be.

The figure shows the correlation between emotional states and the number of likes obtained.Users that have a Happiness or Neutral mood tend to get more likes on a daily basis.Reduced engagement (likes) is linked to Anxiety, Sadness or Boredom.This could imply that emotionally positive contents are more well received by the audience.Therefore, emotional tone may have a direct influence on social validation and a social engagement.

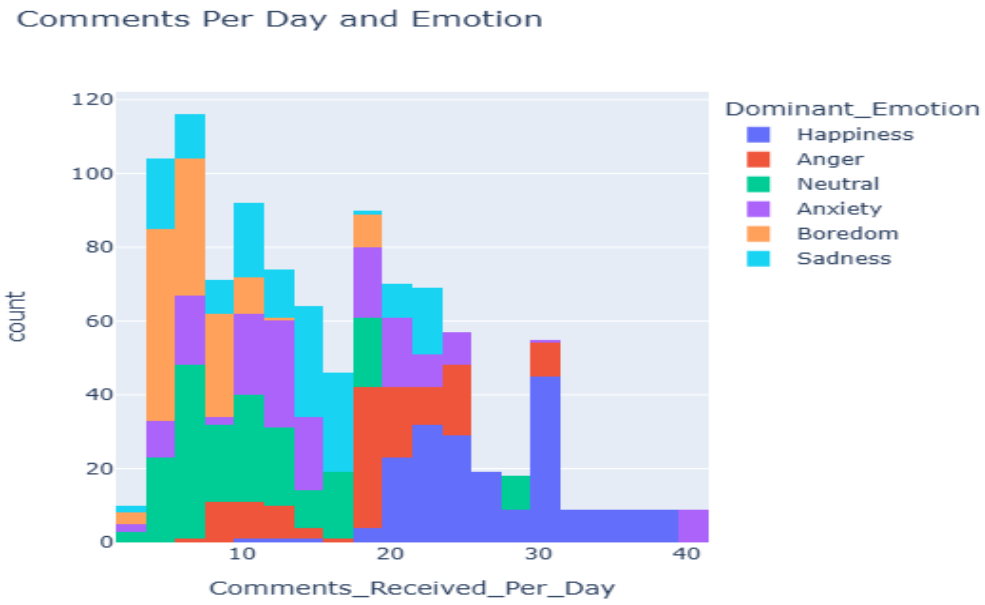

Figure 5. Likes vs Density of Emotion Plot

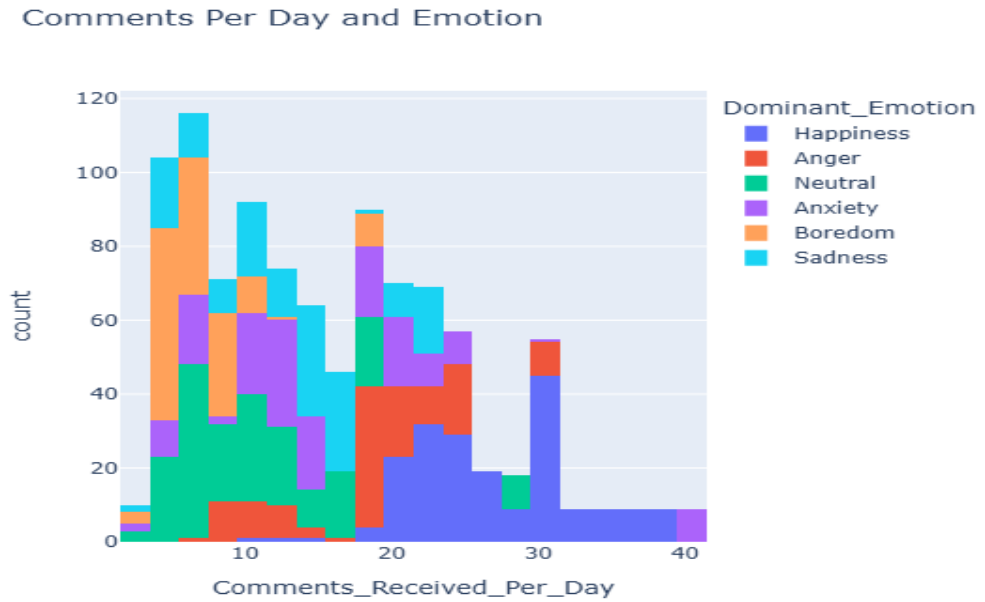

Figure 6. History of Comments and History of Emotion

The histogram demonstrates the differences in the amount of comments obtained in comparison with the expression of emotions.Happiness users and Neutral users will gain most comments, which means they are socially connected.Sad or Anxious users get less comments, perhaps because the posting is not interactive.Moderate interaction is reflected in anger-related posts which are usually reactionary.Comprehensively, the positive relationship between comment activity and emotionally interesting or optimistic content exists.

The figure brings out the correlation between the frequency of posting and the prevailing emotion.Users who post.Happy and those who post Neutral on the platforms are posting more.The reduction in the online participation is associated with Lower post rates that are attributed to the Anxiety and Sadness.Boredom has median posting, which may be a bid to overcome the monotony.Therefore, positive feelings provide the stimulus of increased sharing activity on the social platforms.

Using this graph, the daily screen time according to various emotional categories is plotted.Users of Anxiety and Boredom record a high average usage time.There are moderate daily engagements between Happiness and Neutral states.Overuse is associated with more cases of negative affect like Anxiety or Sadness.

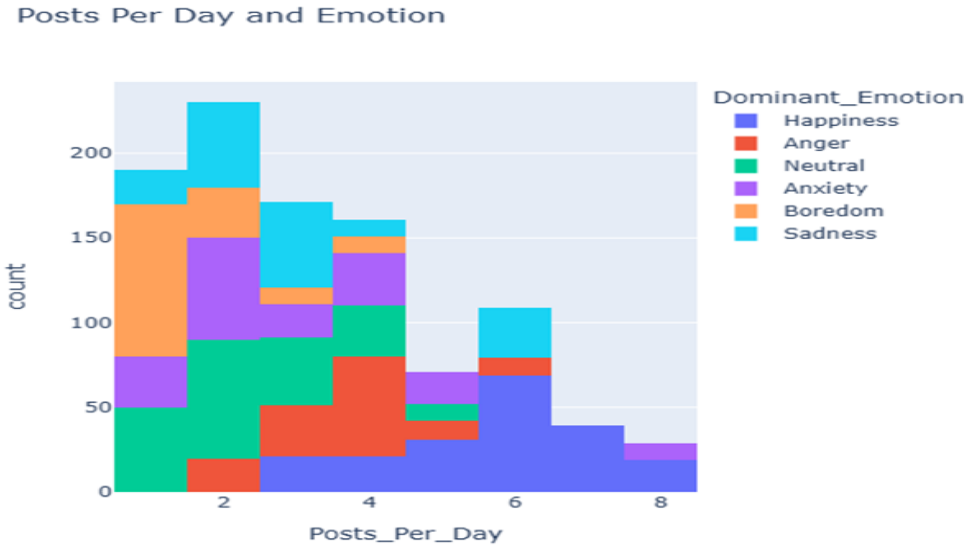

Figure 7. Posts vs Emotion Histogram

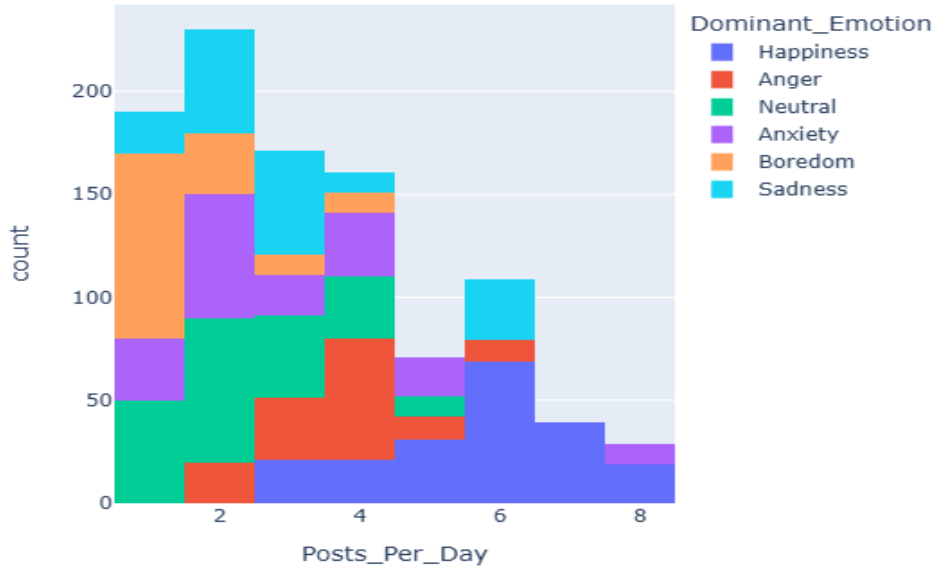

Figure 8. Time of use daily versus Emotion Scatter Plot.

3.12. EDA Results Interpretation

The exploratory data analysis showed that Instagram, Twitter, and Facebook are the most popular platforms. The dataset is characterized by female participants who were more engaged in the use of social media. The predominance of emotions displayed was that there was a balance between Happiness, Neutral, and Anxiety as a result of varying affective experiences**.** Histogram results indicated that users who feel Happiness or Neutral usually have higher post and message rates whereas Sadness and Anxiety have a correlation with long duration of use per day and moderate engagement. In general, emotional patterns showed that the intensity of interaction and preference towards the platforms have a strong impact on the perceived well-being outcomes.

3.13. Evaluation Metrics

Accuracy, Precision, Recall, F1-score and ROC-AUC were used to measure the model performance.

3.14. Tools and Libraries

Data analysis, visualization, and model implementation were done using Pandas, NumPy, Scikit-learn, XGBoost, Matplotlib, and Seaborn.

4. Results and Discussion of Model

This part discusses the relative performance of the five machine learning classifiers that have been used to predict emotional states based on behavior of social media usage. The metrics taken into account are Accuracy, Precision, Recall, and F1-score. The findings show that ensemble-based algorithms are better than the traditional linear and instance-based models in predictive reliability as well as the generalization ability.

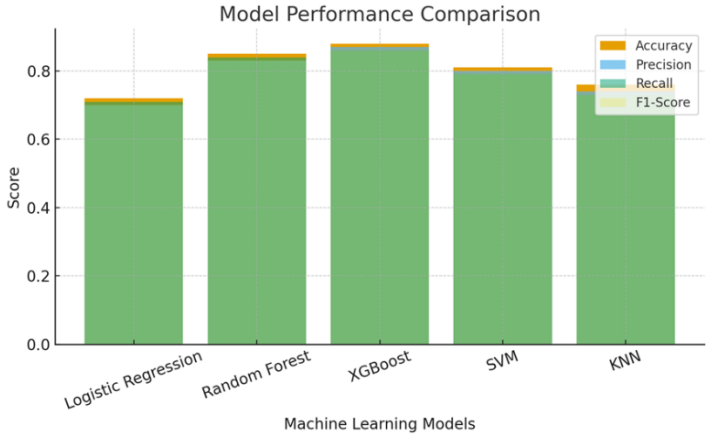

Figure 9. Comparison of the performance of the classifiers

XGBoost was the most effective among all the classifiers with a total accuracy of 88 percent and continue with Random Forest with 85 percent accuracy. These findings underscore the potential in ensemble learning to learn non-linear behavioral-emotional relationships. Logistic Regression and SVM were also quite average in terms of showing a consistent but weak linear separability between classes of emotion. The accuracy of KNN was also relatively low because it is sensitive to the data distribution and scale. In general, boosting-based models proved to be better in terms of feature interpretability, stability, and robustness when it comes to the task of emotional prediction.

5. Conclusion

The present research examined the multifunctional linkage amid social media use behavior and the emotional state of young adults in a systematic data-driven approach. Advanced machine learning classifiers that include XGBoost and Random Forest performed better than linear and instance-based models, and the ability to capture non-linear relationships between engagement levels and emotional responses demonstrated that extended screen time and less communication were strongly related to anxiety, sadness, and boredom.Trader The models used to analyze a diverse dataset of engagement metrics and self-reported emotional states were effective in capturing the unlinear relationships between engagement and emotional expression, with a preference towards the XGBoost and Random Forest models.Exploratory data analysis revealed that longer screen time and reduced communication were strongly correlated Overall, this study indicates that machine learning has the potential to effectively predict the emotional outcomes of using social media in relation to patterns of social media behavior, which can be applied to mental health interventions and responsible social media use strategies.The combination of the behavioral analytics and emotion recognition may help to deepen the understanding of psychological phenomena.In conclusion, the findings presented in this study show that machine learning can be effectively used to predict the emotional outcomes of the patterns of social media usage, which could be applied to mental health interventions and responsible social media use strategies.

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