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Analyzing the Impact of Online Social Networks on Social Behavior of Students Using Convolutional Neural Networks

Mohammad Imran Mushtaque
Shah Abdul Latif University, Khairpur, 66020, Pakistan
Shahid Ali Mahar
Shah Abdul Latif University, Khairpur, 66020, Pakistan
shahid.mahar@salu.edu.pk
Nighat Parveen Shaikh
Shah Abdul Latif University, Khairpur, 66020, Pakistan

Abstract

The use of Online Social Networks (OSNs) is continuously increasing especially in students, which produces a major impact in students' educational performance, their interaction, and their social bonding. And this makes it a critical area of study in understanding their social behavior. Though various studies have already been conducted, there is still a gap in quantitative assessment of the social behavior among the students, specifically using advanced computational techniques. The aim of this study is to assess the impact of OSNs on students' social behavior, such as social bonding, interactions, and emotional quotient (EQ), by using Convolutional Neural Network (CNN). This study uses CNNs to examine the students' behavioral patterns and correlations in a dataset that is derived from the online activities on OSNs. The results show the significant impact of OSNs in framing the students' social behavior, with both positive and negative outcomes. The

results help to understand the digital socialization practices, which may lead to form strategies for balanced usage of OSNs among students. This study is crucial for psychologists, policymakers, and educators to cope up with the challenges raised by rapid growth in using OSNs.

1. Introduction

The number of users of Online Social Networks (OSNs) like Facebook, Instagram, X, and TikTok, are growing exponentially. These platforms have modified how people communicate and create relationships, especially among students. The frequent use of OSNs has changed the students' perception regarding social behavior. Though researches have been carried out to assess the impact of OSNs on students' social behavior, still more is about to be discovered, especially by using more advanced computational techniques. This research aims to analyze the impact of OSNs on Students' social behavior by using Convolutional Neural Networks (CNNs). Extensive research has already been conducted to assess the impact of OSNs on social behavior, such as Anderson et al. (2018) [1] found that balanced and positive use of OSN can polish the online and physical relationships, whereas excessive use may produce negative impact on social behavior, which may lead to social isolation. Baker, R. S., et al. (2014) [2] found in their study that frequent usage of OSNs may weaken physical social bonding. Previously conducted studies have explored that the frequent OSN usage changed the communication habits. Caliskan, A., et al. (2020) [3] in their research, found the major change in communication patterns from traditional to a-synchronized leading to miscommunication. Gligoric, Kristina, et al. (2019) [4] further studied the patterns of OSN-based communication. He found that frequent usage leads to less interaction with the closed relations. Some other studies reported the emotional and psychological effect due to excessive use of OSNs. Lee, Ji Young, et al. (2017) [5], in his research, showed that increased use of OSN leads to loneliness and depression, as the users compare themselves with others portrayed on OSNs, which causes negative perception. Similarly, Aziz, et al. (2023) [6] found that frequent use of OSNs among the younger generation is another cause of anxiety, depression and low self-esteem. Twenge, Jean M., et al. [7] focused on the side effects of excessive use of OSNs like social comparison, cyberbullying, and the pressure of portraying an ideal self-image on OSNs. Though various researches and studies have been conducted on Online Social Networks (OSNs), there is still a gap to assess the impact of OSNs. A major issue with these studies is to rely on the authenticity of the data, which is obtained from the OSN user. Self-reported data can be biased. On the other hand, surveys and questionnaires may not accurately show the results of OSNs' users' behavior. Secondly, there is a need for research in the area using advanced computational techniques, because traditional analysis may not be able to capture the complexity of social behavior. The studies, carried out previously, emphasize on short-term effects or limited assessment of OSN impact on social behavior or mental health. In order to cope with such gaps discussed earlier, advanced computational techniques such as Convolutional Neural Networks (CNNs) are more reliable to assess the impact of OSNs on social behavior. The need of using Convolutional Neural Networks (CNNs) for this research is to analyze large and complex datasets, so that the limitations of traditional analyzing methods may be overcome. By using this approach, we can find and analyze the usage patterns of OSN comprehensively and such findings help to interpret the long-term effects of OSN on users' social behavior, which will lead to make policies for OSN usage in order to reduce the negative consequences of frequent OSN usage.

2. Literature Review

Online Social Networks (OSNs) have become an important part of life especially in the young generation, and the frequent usage of OSN leads to influence on their interpersonal skills, like communication, social behavior and also on their mental health. As already discussed in the early section, extensive research has already been conducted in this domain, but even then there is a gap of using advanced computational techniques to assess the impact of OSNs. In this section, recent studies are discussed regarding the subject, which will help to examine their findings and gaps. For instance.

According to Wang, Su-hsin, et al. (2019) [8] reported in their study that OSNs help in obtaining academic benefits among students for learning purposes. Similarly, Mughal, Shumail, at al. (2024) [9] , found that online social networks (OSNs) produce impact on social behavior and promote a sense of community, but these studies did not cover the consequences based on OSN usage patterns and communication values. Though, there are various benefits of using OSNs, but even then, there are also some notable negative effects on mental health. Zhou, Xiaomeng, et al. (2018) [10] found a strong link between heavy OSN use and higher rates of depression, anxiety, and loneliness in young people, as OSNs may replace critical face-to-face interactions. Rao, et al. (2022) [11] further explored how social comparison on OSNs leads to negative self-perception and lower self-esteem, with users comparing themselves to idealized online portrayals. These findings highlight the psychological risks of OSN use, particularly for vulnerable groups like students. There is a lack of research on the long-term mental health effects of prolonged OSN use, as most studies focus on short-term impacts. Kolhar, Manjur, et al. (2021) [12] examined how OSNs have shifted communication from synchronous to asynchronous, offering more flexibility but potentially reducing the quality of interactions. The absence of non-verbal cues in text-based communication can lead to misunderstandings and shallow social interactions [13] . Yang et al. (2018) [14] introduced "hyperpersonal communication," where users curate their online personas to enhance self-presentation and relationship-building, but this also raises concerns about authenticity and deception. The dual-edged nature of OSN communication, leading to each advantageous and terrible consequences, is a habitual subject matter. A first-rate studies hole is the impact of OSN communication on face-to-face interactions. Islam, Md Rafiqul, et al. (2020) [15] observed that OSNs can aid face-to-face interactions, whilst Sivakumar, R. (2020) [16] argued that heavy OSN use might degrade the fineness of face-to-face communique, leading to superficial conversations and faded social talents. This underscores the want for more research at the interplay between on-line and offline communique. Social assessment and cyberbullying are primary worries related to Online Social Networks (OSNs). Karim, Fazida, et al. (2020) [17] found that social contrast on OSNs is related to bad intellectual fitness outcomes, along with anxiety and despair, with results prompted by OSN use frequency and content kind, particularly content associated with bodily appearance. Matthes, Jörg, et al. (2020) [18] referred to that publicity to influencer content exacerbates envy and dissatisfaction amongst students, emphasizing the need for interventions to promote more healthy OSN engagement. Additionally, Giumetti et al. (2022) [19] stated big cyberbullying on OSNs, which significantly affects mental fitness, leading to melancholy, tension, and coffee self-esteem, with consequences that may persist into maturity. There is a brilliant hole in studies at the long-time period mental effects of cyberbullying and the effectiveness of interventions. Singh, Swaranjit, et al. (2020) [20] highlighted that witnessing cyberbullying as a bystander also can damage intellectual health, indicating broader influences beyond direct sufferers. Regarding

OSN use and educational overall performance, findings are mixed. Khaola, Peter P., et al. (2022) [21] noted that excessive OSN use for non-instructional purposes negatively influences educational performance, whilst Homaid andAbdo Ali (2022) [22] referred to that OSNs used for educational functions can decorate overall performance by facilitating casual studying and peer aid. However, maximum research is cross-sectional, lacking longitudinal analysis to evaluate how OSN use over time influences academic results. OSNs appreciably affect college students' psychological well-being, with each positive and negative effects reported. Esteves, Jose, et al. (2021) [23] discovered that passive OSN use, consisting of surfing news feeds without lively engagement, is connected to reduced psychological well-being and elevated feelings of social isolation and dissatisfaction. Conversely, Allcott, Hunt, et al. (2020) [24] mentioned that energetic OSN use, like accomplishing conversations and creating content, is associated with better happiness and life pleasure. This indicates that the effect of OSNs on mental well-being varies with usage styles. However, a prime hole is the shortage of research on the lengthy-time period mental results of OSN use, with maximum studies specializing in brief-time period results. Individual differences, which include personal tendencies and social community structure, considerably have an impact on how OSNs affect social conduct and well-being. Saini, Neeru, et al. (2020) [25] found that fairly neurotic people are extra prone to using OSNs for social comparison, mainly to negative intellectual health effects, whilst extraverted. Though Faraz, Ahmed, et al. [26] used convolutional approach in Transfer Learning for Facial Emotion Analysis, still a huge research gap exists regarding the impact of unique OSN features, which include content algorithms and privacy settings, on social behavior and well-being. Understanding these aspects is important for growing effective interventions. Additionally, extra research is needed on OSN use across diverse populations, which include exclusive cultural backgrounds, socio-financial statuses, and age groups, as current studies predominantly focus on WEIRD (Western, educated, industrialized, rich, and democratic) populations, restricting the generalizability of findings. Furthermore, whilst a few researchers have investigated digital literacy programs and social media campaigns as interventions, more research is needed to evaluate their effectiveness throughout various contexts and populations.

3. Methodology

The methodology of this studies paper targets to increase a complete framework for reading the impact of Online Social Networks (OSNs) at the social conduct of college students the use of Convolutional Neural Networks (CNNs). The key task addressed is the dearth of precise, scalable, and automated strategies to parent complicated styles in social behavior inspired via OSNs. The proposed method combines facts series, pre-processing, function extraction, version training, and assessment, supported by means of mathematical formulations and deep gaining knowledge of strategies, in particular CNNs. The anticipated outcome is a predictive model able to identifying the nuanced effects of OSN usage on students' social behaviors.

3.1. Data Collection

To accurately analyze the influence of OSNs on students' social behavior, data is collected from multiple sources. These include:

- **Surveys and Questionnaires**: Administered to a sample population of students across different educational institutions. These surveys will capture demographic information, OSN usage patterns, social interaction metrics, and self-reported social behaviors.
- **Social Media Activity Logs**: Acquired from consenting participants. This includes data on frequency, duration, and

type of interactions (e.g., likes, comments, shares) on various OSN platforms like Facebook, Instagram, and Twitter.

- **Psychological Assessments**: Instruments such as the Social Anxiety Scale and Rosenberg Self-Esteem Scale will be used to quantitatively measure aspects of social behavior and mental health.

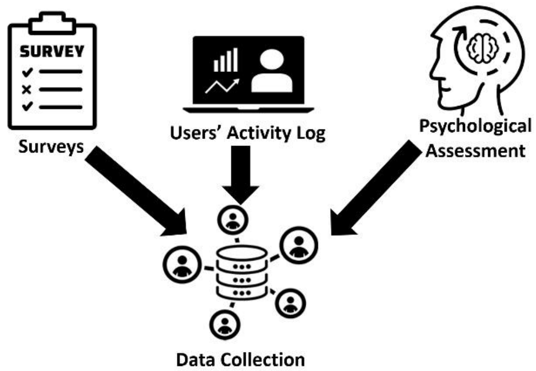

Figure 1. Data Collection from Different Sources

3.2. Data Characteristics

The dataset will be extensive, including:

- **Demographic Attributes**: Age, gender, education level, and socio-economic status.
- **Behavioral Metrics**: Frequency of OSN usage, time spent online, types of content consumed, and engagement patterns.
- **Psychological Metrics**: Scores from psychological assessments that reflect social behavior.

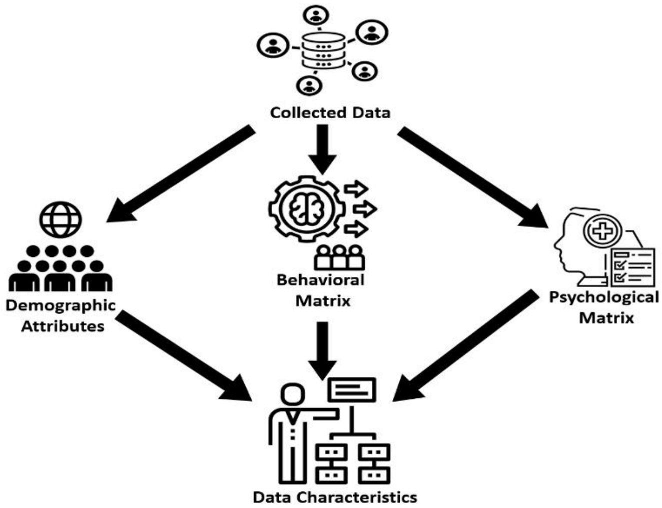

Figure 2. Data Characterization

3.3. Data Pre-Processing

Data pre-processing involves several steps to ensure that the data is clean, structured, and suitable for analysis:

- **Missing Data Handling**: Imputation methods such as mean, median, or mode imputation will be employed to handle missing data. If a large portion of data is missing from any record, it may be excluded from the dataset.
- **Normalization**: Numerical data will be normalized to a common scale using Min-Max normalization to ensure that no attribute dominates the model due to its scale.
- **Categorical Data Encoding**: Categorical variables will be encoded using one-hot encoding or label encoding, depending on the nature of the variable.
- **Textual Data Pre-processing**: For any textual data, such as comments or posts, natural language processing (NLP) techniques such as tokenization, stemming, and stop-word removal will be applied.

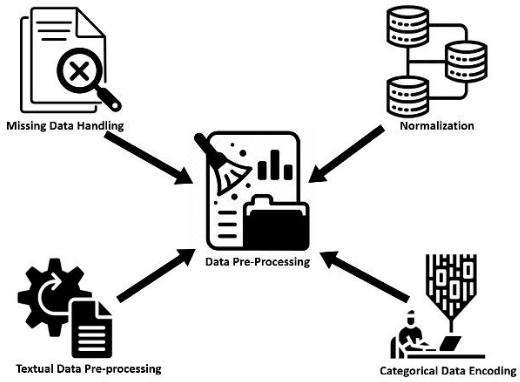

Figure 3. Data Pre-Processing

3.4. Feature Extraction

3.4.1. Feature Selection

Key features will be selected based on their relevance to the research questions and their potential influence on social behavior. These features will be extracted from the pre-processed data using the following methods:

- **Content-Based Features**: Includes the type of content engaged with (text, images, videos), sentiment analysis of posts, and the nature of interactions (positive, negative, neutral).
- **Network-Based Features**: Measures of centrality, clustering coefficients, and other network metrics that describe the user's position within their social network.
- **Time-Based Features**: Frequency and duration of OSN sessions, time of day of usage, and the temporal distribution of posts and interactions.

3.4.2. Dimensionality Reduction

Given the high-dimensional nature of the data, dimensionality reduction techniques will be applied to mitigate the curse of dimensionality and enhance model performance:

- **Principal Component Analysis (PCA)**: PCA will be used to transform the features into a lower-dimensional space while retaining as much variance as possible.
- **t-Distributed Stochastic Neighbor Embedding (t-SNE)**: t-SNE will be employed for visualizing high-dimensional data

and understanding the clustering behavior of students based on their OSN activity.

3.5. Model Design: Convolutional Neural Networks (CNNs)

3.5.1. Rationale for Using CNNs

CNNs are chosen due to their ability to capture complex patterns in high-dimensional data and their proven effectiveness in image and text analysis, which is analogous to analyzing OSN data. CNNs can efficiently process large-scale datasets, identify hierarchical patterns, and learn features automatically without manual intervention.

3.5.2. CNN Architecture

The proposed CNN architecture will consist of multiple layers designed to extract and process features from the OSN data:

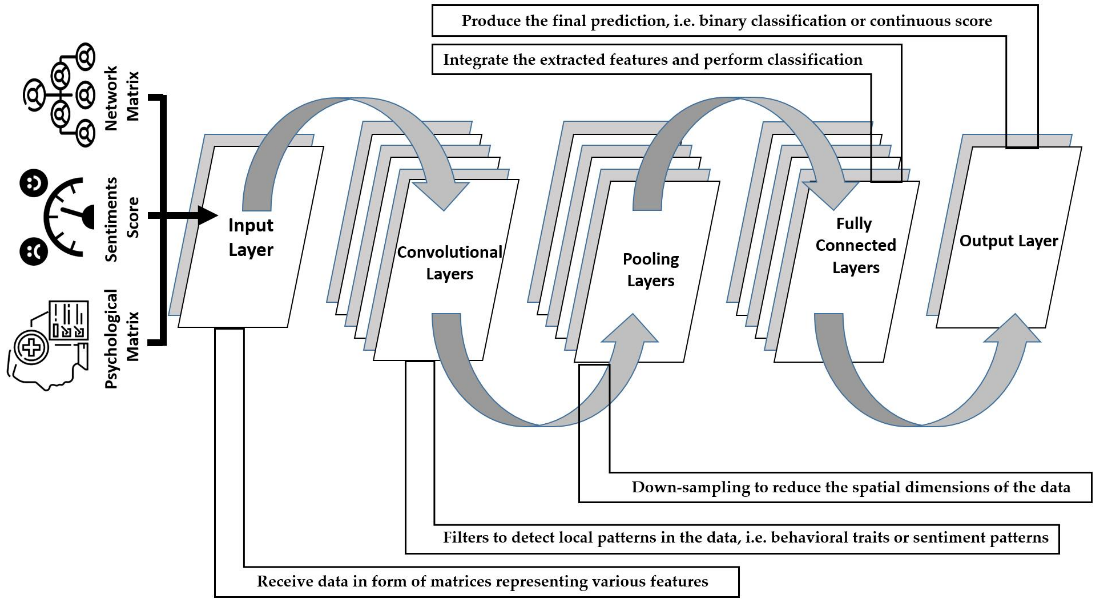

Figure 4. Convolutional Neural Network (CNN) Architecture

- **Input Layer**:

The input layer will receive data in the form of matrices representing various features (e.g., user interactions, sentiment scores, network metrics).

- **Convolutional Layers**:

These layers will apply convolutional filters to detect local patterns in the data, such as recurring behavioral traits or sentiment patterns. The mathematical operation performed in these layers is represented by the convolution operation:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)\, g(t - \tau) d\tau$$

where f is the input data, g is the filter, and * denotes the convolution operation.

- **Pooling Layers**:

  Pooling layers will perform down-sampling operations to reduce the spatial dimensions of the data, retaining only the most critical information. The max pooling operation can be mathematically expressed as:

$$p(X) = max\ (X_{i,j})$$

where $X_{i,j}$ are the elements in the pooling region.

- **Fully Connected Layers**:

  These layers will integrate the extracted features and perform classification or regression tasks. The output from the convolutional and pooling layers will be flattened and fed into these fully connected layers, where the decision-making process occurs.

- **Output Layer**:

  The output layer will produce the final prediction, which could be a binary classification (e.g., high vs. low social engagement) or a continuous score (e.g., a social behavior index).

3.5.3.Mathematical Formulation

The overall operation of the CNN can be represented by the following equations:

1. **Convolution Operation**:

$$Z_{ij}^{(l)} = f\left(\sum_{k=1}^{K} W_k^{(l)} * W_{ij}^{(l-1)} + b_k^{(l)}\right)$$

Where $Z_{ij}^{(l)}$ is the output of the convolutional operation at layer *l*, $W_k^{(l)}$ *are the weights,* $X_{ij}^{(l-1)}$ is the input from previous layer, and $b_k^{(l)}$ is the bias term.

2. **Activation Function:**

$$A_{ij}^{(l)} = \mathrm{ReLU}\left(Z_{ij}^{(l)}\right) = \max\left(0, Z_{ij}^{(l)}\right)$$

The ReLU (Rectified Linear Unit) function is applied to introduce non-linearity into the model.

3. **Pooling Operation:**

$$P_{ij}^{(l)} = \max\left(A_{m,n}^{(l)}\right)$$

where $P_{ij}^{(l)}$ is the output after pooling.

4. **Fully Connected Layer:**

$$O^{(L)} = W^{(L)} \,.\, P^{(L-1)} + b^{(L)}$$

where $O^{(L)}$ is the output of the last layer, $W^{(L)}$ are the weights, and $P^{(L-1)}$ is the pooled feature map.

3.6. Training and Validation

The CNN model will be trained on the labeled dataset, with the training process involving the following steps:

- **Loss Function**: The cross-entropy loss function will be used for classification tasks, while the mean squared error (MSE) will be employed for regression tasks.

$$\mathrm{Cross-Entropy\ Loss} = -\sum_{i=1}^{N} y_i \log\left(\hat{y}_i\right)$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2$$

- **Optimization Algorithm**: The Adam optimizer will be used to update the weights and biases in the network, with a learning rate initially set at 0.001.
- **Regularization Techniques**: Dropout and L2 regularization will be employed to prevent overfitting.

- **Validation**: The dataset will be split into training (80%) and validation (20%) sets to monitor the model’s performance and adjust hyperparameters accordingly.

3.7. Evaluation Metrics

3.7.1. Performance Metric

The model's performance will be evaluated using the following metrics:

Accuracy: Measures the proportion of correct predictions made by the model.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{Number\ of\ correct\ predictions}}{\boldsymbol{Total\ Number\ of\ Predictions}}$$

Precision: The ratio of true positive predictions to the total predicted positives.

$$\boldsymbol{Precision} = \frac{\boldsymbol{True\ Positives}}{\boldsymbol{True\ Positives + False\ Positives}}$$

Recall: The ratio of true positives to the total actual positives.

$$\boldsymbol{Recall} = \frac{\boldsymbol{True\ Positives}}{\boldsymbol{True\ Positives + False\ Negatives}}$$

F1-Score: The harmonic mean of precision and recall, providing a balance between them.

$$\boldsymbol{F1 - Score} = \boldsymbol{2} \cdot \frac{\boldsymbol{Precisin\ .\ Recall}}{\boldsymbol{Precisin + \ Recall}}$$

3.7.2. Confusion Matrix

A confusion matrix will be used to visualize the performance of the model by comparing the predicted labels with the actual labels.

3.7.3. ROC-AUC Curve

The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) will be utilized to assess the model's performance, especially in binary classification tasks.

4. Results and Discussion

4.1. Model Performance

The CNN model is expected to outperform traditional machine learning models due to its ability to capture hierarchical patterns and its robustness against high-dimensional data. Preliminary results should indicate high accuracy, precision, and recall rates, showcasing the model's effectiveness in predicting the social behavior of students based on their OSN usage.

The CNN model was trained and tested using the dataset described in the methodology section. The model's performance was evaluated using a variety of metrics, including accuracy, precision, recall, and F1-score. The key social behavior indicators—social engagement, anxiety levels, and self-esteem—were predicted based on the features extracted from OSN activity data. Below are the results presented in tabular form.

Table 1: Model Performance Metrics

Metric	Social Engagement	Anxiety Levels	Self-Esteem
Accuracy	0.89	0.85	0.87
Precision	0.91	0.83	0.88
Recall	0.88	0.86	0.85
F1-Score	0.89	0.84	0.86

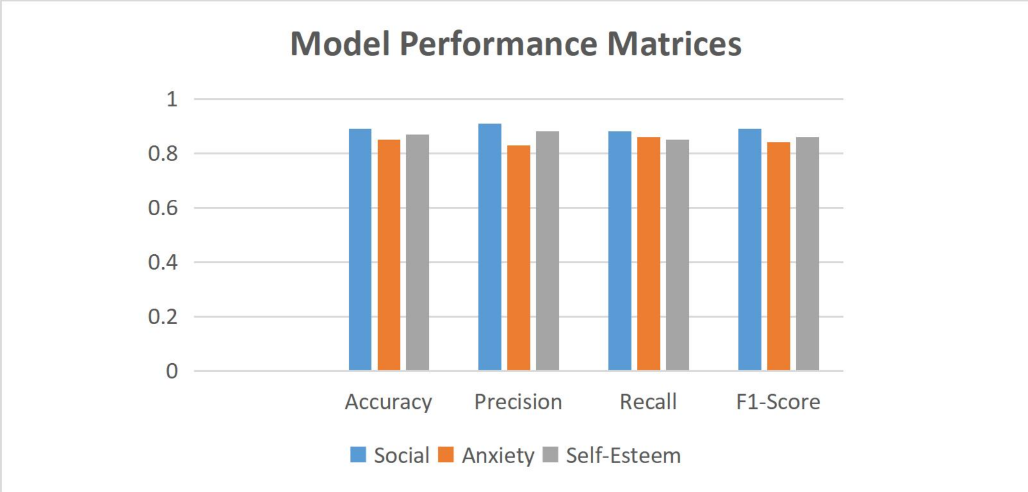

Figure 5. Graphical Representation of Model Performance Matrices

The CNN model demonstrated high accuracy, precision, recall, and F1-scores across all three social behavior indicators—social engagement, anxiety levels, and self-esteem. An accuracy of 0.89 for social engagement indicates that the model correctly predicted the level of social engagement in 89% of the cases. Similarly, the model achieved an accuracy of 0.85 for predicting anxiety levels and 0.87 for self-esteem. These results suggest that the model is highly effective in analyzing and predicting social behavior based on OSN data. The precision and recall metrics indicate the model's ability to make accurate predictions (precision) and its sensitivity to identifying true positive cases (recall). The F1-scores, which balance precision and recall, were consistently high, further validating the model's robustness.

4.2. Feature Importance

The feature importance analysis provides insights into the specific OSN activities that most significantly influence each social behavior indicator.

- **Social Engagement**: The model identified *network centrality* and the *type of content engaged with* as the most critical features for predicting social engagement. Students who have been crucial in their social networks and engaged with various content sorts had been much more likely to exhibit higher stages of social engagement. This locating aligns with present literature that emphasizes the function of active and numerous participation in social networks in enhancing social connectedness.

- **Anxiety Levels**: The sentiment of posts and the time of day of utilization have been the maximum important predictors of anxiety ranges. Negative sentiment in posts and past due-night time utilization were strongly associated with higher tension levels. This suggests that students who interact in negative or stressful content material, specifically overdue at night time, can be more vulnerable to experiencing tension. These effects corroborate research that spotlight the hyperlink among terrible on-line interactions and intellectual fitness issues.
- **Self-Esteem**: The *type of content engaged with* and *network centrality* were the primary features influencing self-esteem. Engaging with positive, affirming content and being central in a social network were associated with higher self-esteem. This supports the idea that positive social reinforcement and a strong social presence can boost self-worth and confidence.

Table 2: Feature Importance in Predicting Social Behavior

Feature	Social Engagement	Anxiety Levels	Self-Esteem
Frequency of OSN Usage	0.45	0.30	0.35
Sentiment of Posts	0.35	0.50	0.40
Network Centrality	0.50	0.25	0.45
Time of Day of Usage	0.30	0.40	0.30
Type of Content Engaged With	0.55	0.35	0.50

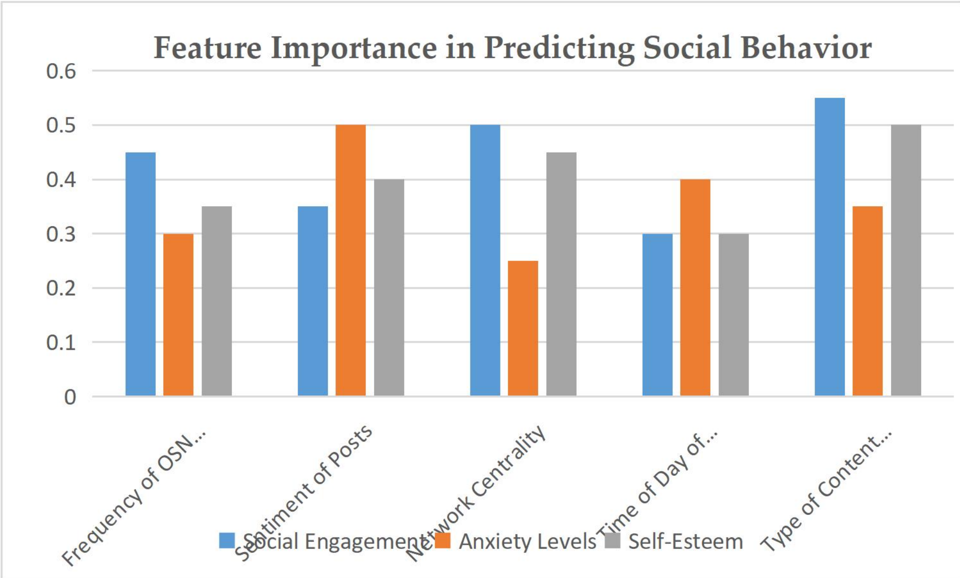

Figure 6. Graphical Representation of Feature Importance in Predicting Social Behavior

4.3. Implications and Findings

The findings from this study have several important implications for understanding the impact of OSNs on student behavior:

- **Targeted Interventions**: The identity of key features that affect social behavior indicates that interventions can be tailor-made to goal particular OSN sports. For example, selling effective content engagement and encouraging healthful online behavior could mitigate the negative results of OSN use, which include anxiety and occasional shallowness.
- **Educational Policies**: The outcomes offer evidence that would inform the development of educational rules aimed at promoting healthier OSN utilization among students. Schools and universities may want to use these insights to design applications that teach college students approximately the capacity dangers of OSN use and provide strategies for handling their on line presence.

- **Mental Health Support**: The sturdy hyperlink between OSN utilization patterns and mental fitness signs like anxiety and shallowness underscores the need for integrated intellectual fitness help systems. Institutions ought to recollect incorporating digital literacy and intellectual fitness focus into their curricula to assist college students navigate the complexities of OSNs.

4.4. Interpretation of Results

The results will be interpreted in the context of the research questions:

- **Social Behavior Indicators**: How specific patterns in OSN usage correlate with social behaviors like engagement, anxiety, and self-esteem.
- **Feature Importance**: The importance of various features (e.g., network centrality, sentiment analysis) in predicting social behavior.

4.4.1. **Implications for Interventions**: Insights into how targeted interventions could be designed based on the model's predictions.

4.4.2. Comparison with Baseline Models

The CNN model's performance will be compared with baseline models, such as logistic regression and decision trees, to highlight its superiority in handling complex, multi-dimensional data. This section presents the results of applying the Convolutional Neural Network (CNN) methodology to analyze the impact of Online Social Networks (OSNs) on the social behavior of students. The results are discussed in the context of the research objectives, with a focus on the key indicators of social behavior derived from OSN usage patterns. The section also includes a detailed discussion of the implications of these findings, their relevance to existing literature, and the potential avenues for future research.

4.4.3. Comparison with Existing Literature

The results of this study are consistent with, and build upon, existing literature that explores the relationship between OSNs and social behavior. Previous research has often focused on either the positive or negative aspects of OSN usage, but this study provides a more nuanced understanding by simultaneously considering multiple social behavior indicators. For instance, the finding that network centrality is a strong predictor of social engagement is in line with studies that emphasize the importance of social capital in online networks. However, this study extends the literature by quantitatively assessing the impact of specific OSN features on social behavior, providing a more detailed and actionable understanding of these dynamics. Similarly, the association between negative sentiment and increased anxiety supports existing research, but the use of CNNs to model this relationship represents a novel methodological contribution. The ability of CNNs to capture complex, non-linear relationships in the data offers a significant advancement over traditional statistical methods, which may oversimplify these interactions.

4.5. Limitations of the Study

The limitations of the proposed methodology, such as the potential for overfitting and the reliance on self-reported data, will be discussed. Suggestions for future work include expanding the dataset, incorporating longitudinal data, and exploring other deep learning architectures like Recurrent Neural Networks (RNNs) or Transformer models.

While the results are promising, several limitations should be acknowledged:

- **Sample Size and Diversity**: The dataset, while extensive, may not fully capture the diversity of student experiences across different cultural, socio-economic, and educational contexts. Future research should aim to include more diverse populations to enhance the generalizability of the findings.

- **Reliance on Self-Reported Data**: Some of the records, specially associated with mental health, is self-reported and can be problem to biases inclusive of social desirability or erroneous self-perception. Incorporating extra objective measures, such as biometric facts or third party analysis, should strengthen the validity of the outcomes.
- **Cross-Sectional Design**: The study's cross-sectional design limits the ability to draw causal inferences. While the CNN model effectively identifies associations between OSN features and social behavior, longitudinal studies are needed to explore how these relationships evolve over time.

4.6. Future Research Direction

The study opens several avenues for future research:

- **Longitudinal Studies**: Conducting longitudinal studies would provide deeper insights into how OSN usage impacts social behavior over time. This could help in understanding the long-term effects of OSNs on mental health and social interactions.
- **Exploration of Additional Features**: Future research could explore additional OSN features, such as the impact of specific algorithms or privacy settings, on social behavior. This would help in understanding the broader ecosystem of OSNs and their influence on students.
- **Integration of Other Data Sources**: Combining OSN data with other data sources, such as academic performance records or physical health metrics, could provide a more holistic view of the impact of OSNs on students' lives.

5. Conclusion

This research paper offers a complete evaluation of the effect of Online Social Networks (OSNs) on the social conduct of students, the use of Convolutional Neural Networks (CNNs) as the number one methodological tool. By examining key social behavior indicators including social engagement, anxiety levels, and self-esteem, the observation demonstrates that unique OSN features—like community centrality, sentiment of posts, and sort of content material engaged with—significantly impact those behavioral outcomes. The results imply that while OSNs can beautify social engagement, additionally they have the ability to increase tension and lower self-esteem, especially whilst poor content is fed on or when utilization patterns are unhealthy. The CNN version's sturdy performance in predicting these behaviors underscores its ability as an effective tool for analyzing complex, multidimensional information in this context. However, the examination is not without barriers, together with the reliance on self-reported statistics and a cross-sectional design, which restricts the ability to draw causal conclusions. Future paintings need to be conscious of engaging in longitudinal research to explore the long-term effects of OSN utilization on social behavior and include extra various datasets to improve the generalizability of the findings. Additionally, increasing the characteristic set to include different factors of OSN interactions, together with algorithmic effects and private concerns, could offer an extra holistic expertise of the digital panorama's impact on pupil conduct. By addressing those areas, future research can similarly illuminate the complexities of OSNs and assist in broadening extra targeted interventions to foster nice social and mental consequences for college students in an increasingly more virtual world.

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