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International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526
Volume 14 Issue 01, 2025

Detecting Social Anxiety with Online Social Network Data

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Peer Review Information

Submission: 17 Jan 2025
Revision: 14 Feb 2025
Acceptance: 15 March 2025

Keywords

Gender Differences
Problematic Social Networking Use
Social Anxiety
Social Skills

Abstract

Adolescents and young adults extensively use social media to maintain their relationships. Recent research indicates that those with high social anxiety often find it easier to communicate online. However, there is limited understanding of how certain characteristics of social media might help reduce the distress they experience in face-to-face interactions. This study draws on the Transformation Framework, which suggests that social media, with its unique features, can alter social relationships by facilitating emotional expression and online communication. These effects may vary between individuals who have social anxiety and those who do not. The use of social media was linked to increased symptoms of depression, social anxiety, appearance anxiety, and concerns related to appearance. Both general and appearance-related preoccupations showed distinct positive correlations with symptoms of depression and social anxiety, as well as with sensitivities about appearance. Additionally, preoccupation with appearance was found to amplify the connection between time spent on social media and concerns related to appearance.

Introduction

A widespread psychological disorder, social anxiety affects how people interact with their environment, especially when they are around other people. As online social networks have grown in popularity, they have transformed into mirrors that reflect the psychological and emotional moods of its users. In order to identify indicators of social anxiety using textual, behavioral, and visual data published on social media sites like Facebook, Instagram, and Twitter, this study project explores the complex link between social anxiety and online activity. Through the use of cutting-edge methods like sentiment analysis, linguistic pattern recognition, and engagement metrics, the study hopes to shed light on how social anxiety shows up in online interactions and how those who are impacted may find both safety and vulnerability on these platforms. Some of the most popular social networking sites (SNSs) in Western countries include Facebook, Twitter, Instagram, and TikTok, which collectively had nearly four billion users in 2022 (Clement, 2022). While recent systematic reviews and longitudinal studies indicate that the majority of users constructively engage with SNSs (e.g., Coyne et al., 2020; Orben, 2020; Shankle man et al., 2021), a small minority—around 5%—exhibit excessive and uncontrolled usage, leading to various negative outcomes (Huang, 2022). Individuals with "problematic social networking

sites use" (PSNSU; Svicher et al., 2021) often prefer online interactions over face-to-face ones, show a preoccupation with SNSs, feel an urgent need to use them, experience emotional instability, and face impairments in psychosocial functioning, such as interpersonal conflicts, work challenges, and sleep issues (Andreassen, 2015; Marino et al., 2017). However, PSNSU has not been classified as a clinical disorder in diagnostic manuals like the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013). Among the various factors associated with PSNSU, social anxiety has been extensively studied, as individuals with social vulnerabilities tend to increase their internet use for social interactions (e.g., email and SNS). Research indicates that those with high social anxiety are more likely to engage in online communication, as it is often perceived as less intimidating (e.g., Y. Chen et al., 2020; Markowitz et al., 2016; Yıldız Durak, 2020; Zsido et al., 2021).

Review Of Literature

Research has found that individuals with social anxiety frequently express more negative sentiments in their social media posts and comments compared to those without the disorder [1].Studies suggest that people with social anxiety often use more self-referential terms (e.g., "I," "me") and display a higher occurrence of tentative language (e.g., "maybe," "perhaps"). Their writing may also include more complex words or be more verbose. Examining the emotional tone and content of posts can reveal trends linked to social anxiety, such as a tendency to shy away from discussions about social interactions or to express feelings of distress.

This paper reviews the use of various machine learning (ML) algorithms in diagnosing mental illnesses, focusing on commonly employed methods like Support Vector Machine (SVM), Gradient Boosting Machine (GBM), Naïve Bayes, Random Forest, and K-Nearest Neighbors. It categorizes these algorithms into supervised and unsupervised learning and examines studies on conditions such as PTSD, schizophrenia, depression, and autism. A research search engine was used to gather articles, which were then analyzed based on mental illness type, ML techniques, accuracy, and sample size.

Findings reveal that most SVM classifiers achieve over 75% accuracy, while ensemble methods can reach up to 90%. Studies highlight various demographics, including college students and adolescents, noting that first-year students are particularly vulnerable to mental health issues. The review also discusses the application of machine learning in Mental Health Monitoring Systems, emphasizing the importance of integrating ML with traditional methods to enhance diagnostic accuracy and treatment access.

Additionally, the research underscores the challenges and limitations of using ML in mental health contexts, with studies illustrating varying degrees of success across different algorithms. Overall, this review highlights the potential of machine learning to improve the understanding and treatment of mental health disorders.

Affective disorders like depression and anxiety exhibit bidirectional interactions with the social environment, impacting the onset and maintenance of these illnesses. Their prevalence stands at approximately 4.7% for depression and 7.3% for anxiety globally, with high comorbidity rates that can affect the quality and structure of an individual's social networks and their ability to leverage social support.

Mental health theories emphasize that well-being is not merely the absence of mental illness but includes positive functioning indicators such as subjective well-being. Social Networking Sites (SNSs) play a significant role in enhancing social relationships, potentially alleviating feelings of loneliness, and increasing social capital and life satisfaction. While SNSs can offer protective benefits against depression and anxiety, they also pose risks, such as exposure to negative interactions or cyberbullying, which may worsen mental health. The dual nature of SNS use illustrates a complex relationship between social interactions, emotional experiences, and mental health. While they can facilitate emotional expression and connection, negative experiences on these platforms can exacerbate existing mental health issues, highlighting the nuanced effects of online social environments on individuals' well-being.

Methodology

1. Data Collection

Platform Selection:

The selection of relevant social network platforms for data collection is crucial to the study's goals and the demographics of its intended users. Platforms such as Facebook, Twitter, and Instagram should be chosen based on their alignment with the target audience and the type of data needed. For instance, if the study aims to gather user interactions or sentiments, Twitter might be ideal due to its high volume of short-form text updates. Instagram or Facebook may be more appropriate if visual content (images or videos) plays a central role in the study. Other

considerations include platform-specific data formats, such as how posts, comments, or images are structured, as well as privacy policies that govern data access. Understanding user engagement patterns on these platforms—whether through likes, shares, comments, or other interactions—is key to ensuring that the chosen platform provides meaningful data that aligns with the research objectives.

Data Types:

Data collected from social networks can be categorized into three primary types: textual, visual, and behavioral data. Textual data includes posts, comments, tweets, and status updates, which offer insights into user opinions, sentiments, and communication patterns. Visual data consists of images and videos shared by users, providing a rich source of non-verbal communication and engagement. Finally, behavioral data covers interaction metrics such as likes, shares, and comments, reflecting how users engage with content. These different data types can help create a comprehensive understanding of user behaviors, preferences, and interactions across social platforms.

Data Collection Methods:

To collect data efficiently, social network platforms offer various methods. **APIs** are the primary tools for accessing structured data directly from the platforms. Using platform APIs ensures that data collection adheres to the platform's terms of service, which often includes data privacy and usage policies. In cases where APIs are unavailable or limited, **web scraping** can be used to gather data from publicly accessible web pages. However, ethical considerations must be taken into account when using web scraping techniques, ensuring that the collected data respects user privacy and does not violate the platform's guidelines or legal regulations. Both methods should prioritize compliance with privacy laws and ethical standards to protect user data and ensure the integrity of the research.

2. Data Preprocessing

Data Cleaning:

The objective of data cleaning is to prepare the raw data for analysis by eliminating irrelevant or noisy information that could hinder accurate insights. The first step in data cleaning involves removing duplicates, spam, and irrelevant content to ensure that only valuable data is retained for analysis. This may include filtering out posts that are unrelated to the study's focus or discarding content from bots. Another important step is to standardize text by converting all text to a consistent format, such as lowercasing to ensure uniformity and removing punctuation to avoid inconsistencies that could complicate further processing. These actions help clean the dataset and improve the quality of the analysis.

Data Anonymization:

Data anonymization is crucial to ensure user privacy is maintained throughout the research process. The objective is to protect personally identifiable information (PII) to comply with privacy laws and ethical guidelines. The first step is to remove PII such as names, locations, phone numbers, or email addresses that could directly identify users. Once PII is removed, pseudonyms or anonymized identifiers can be assigned to the users, replacing their real identities with unique codes or numbers. This approach ensures that the data remains usable for analysis without compromising user confidentiality and privacy.

Data Transformation:

Data transformation involves converting the raw data into a format that is suitable for analysis. For textual data, this typically includes tokenization, where text is split into smaller units such as words or phrases, and stemming/lemmatization, which reduces words to their base forms (e.g., "running" to "run") for consistency in analysis. For visual data, feature extraction techniques can be applied, such as object detection to identify specific objects or facial emotion recognition to analyze the emotional tone in images or videos. These transformations ensure that the data is in a structured format that can be easily analyzed and used to draw meaningful insights.

3. Feature Extraction

Feature extraction in textual data involves deriving meaningful patterns and metrics to analyze user behavior and content. Textual features play a critical role in understanding underlying communication trends. Linguistic features examine the frequency of specific words, phrases, and linguistic patterns to reveal speech dynamics, including vocabulary usage and stylistic tendencies. Sentiment analysis is used to determine the emotional tone of posts and comments, categorizing them as positive, negative, or neutral. Complementing this, emotion detection algorithms delve deeper to identify nuanced emotional content such as anger, joy, or sadness. On the behavioral front, interaction metrics measure user engagement by tracking posting frequency, response rates, and levels of interaction. Additionally, content analysis focuses on the nature of shared content and the topics discussed, helping to identify themes, preferences, and potential influencers within the community. Together, these features provide comprehensive insights into both the

textual and behavioral dimensions of digital communication.

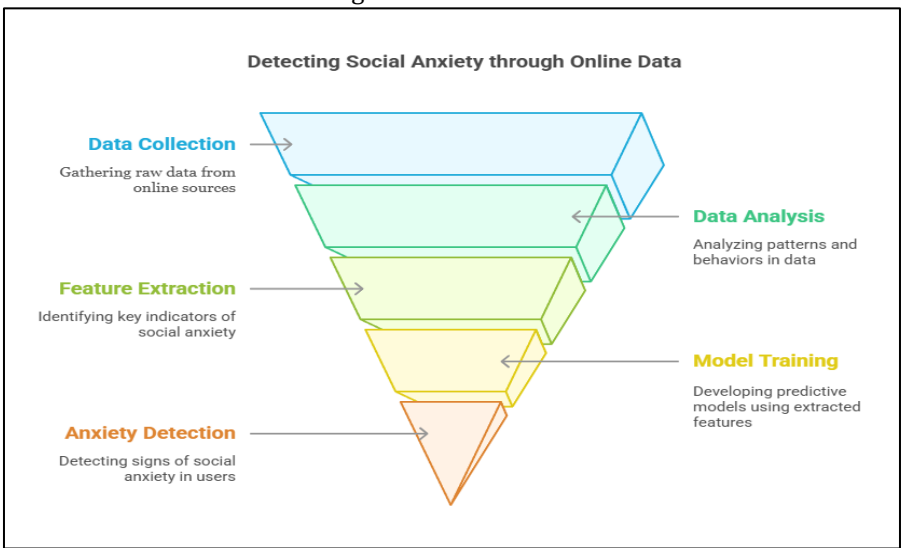

Fig 1: Data Flow Charts

How It Works

During this process, data generation, Label Encoding, Data Splitting, Data Scaling are performed. The details of these stages are as below;

Data Generation:

The function generate_anxiety_data(num_entries) is created to simulate a synthetic dataset. It generates random values for:

- ✓ Age: An integer between 18 and 65
- ✓ Gender: A categorical variable with values "Male", "Female", or "Other".
- ✓ Stress_Level: A floating-point number between 1 and 10.
- ✓ Anxiety_Level: A categorical variable with values "Low", "Moderate", or "High".
- ✓ These generated values are used to create a DataFrame using the pandas library.

Label Encoding:

LabelEncoder from sklearn.preprocessing is used to convert categorical data into numeric form. The Gender column is transformed into numeric values (0, 1, 2). The Anxiety_Level column is also encoded numerically (0, 1, 2 corresponding to Low, Moderate, and High).

Data Splitting:

The dataset is split into features (X) and target variable (y):

- ✓ X: Contains all columns except for Anxiety_Level.
- ✓ y: Contains the Anxiety_Level column.

The dataset is then split into training and testing sets using train_test_split.

80% of the data is used for training the model, and 20% is used for testing.

Data Scaling:

A StandardScaler is applied to standardize the features (i.e., Age, Gender, and Stress_Level). This scaling ensures that all features have a mean of 0 and a standard deviation of 1, which helps improve the performance of certain algorithms like SVM.

The scaler is fitted on the training data and then applied to both the training and test data.

Model Training and Evaluation:

Three machine learning models are used for classification:

- ✓ Random Forest Classifier (RandomForestClassifier)
- ✓ Support Vector Machine (SVC with a linear kernel)
- ✓ Naive Bayes (GaussianNB)

Each model is trained on the scaled training data (X_train_scaled and y_train).

After training, the models make predictions on the test data (X_test_scaled).

Performance Evaluation:

For each model, the classification_report function is used to calculate precision, recall, and F1-score for each anxiety level (Low, Moderate, High). The accuracy_score is also printed to show the overall accuracy of each model.

Data Visualization:

A histogram is plotted using matplotlib to show the distribution of Age and Gender in the dataset. The distribution of Age is displayed using 20 bins. The distribution of Gender is displayed with 3 bins corresponding to Male, Female, and Other. The histograms are overlaid on the same plot with labels, and a legend is

added to differentiate between the Age and Gender distributions.

Anxiety dataset with 1000 entries has been created and saved to 'anxiety_dataset.csv'.

	ID	Age	Gender	Stress Level	Symptoms	Sleep Quality
1	1	49	Other	3	Breath, Heart Palpitations	Good
2	2	46	Female	1	Fatigue, Restlessness	Good
3	3	38	Male	6	Breath, Fatigue, Dizziness	Fair
4	4	25	Male	3	Racing thoughts, Irritability	Poor
5	5	41	Female	8	, Restlessness, Sweating	Poor

	Exercise Level	Social Interactions	Family History of Anxiety	Recent Life Events	Consumption (cups/day)	Smoking	Medication	Diagnosis
1	Weekly	Weekly	No	Job stress	5	Yes	Yes	Social Anxiety
2	Daily	Rarely	No	None	1	Yes	No	Panic Disorder
3	Daily	Daily	Yes	None	2	Yes	No	Panic Disorder
4	Daily	Weekly	No	Financial strain	4	No	No	Social Anxiety
5	Weekly	Rarely	Yes	Death in family	2	Yes	Yes	Social Anxiety

Fig 2: Dataset Generation – 2.1 , 2.2

Accuracy Code Output:

```
Naive Bayes Results:
              precision    recall  f1-score   support

           0       0.37      0.19      0.25        75
           1       0.28      0.28      0.28        69
           2       0.22      0.38      0.28        56

    accuracy                           0.27       200
   macro avg       0.29      0.28      0.27       200
weighted avg       0.30      0.27      0.27       200

Accuracy: 0.27
```

Fig 3 : Naïve Bayes Accuracy

```
Random Forest Results:
              precision    recall  f1-score   support

           0       0.47      0.47      0.47        75
           1       0.34      0.32      0.33        69
           2       0.30      0.32      0.31        56

    accuracy                           0.38       200
   macro avg       0.37      0.37      0.37       200
weighted avg       0.38      0.38      0.38       200

Accuracy: 0.38
```

Fig 4 : Random Forest Accuracy

```
Support Vector Machine Results:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        75
           1       0.32      0.48      0.38        69
           2       0.30      0.52      0.38        56

    accuracy                           0.31       200
   macro avg       0.21      0.33      0.25       200
weighted avg       0.19      0.31      0.24       200

Accuracy: 0.31
```

Fig 5 : Support Vector Machine Accuracy

The output of the anxiety detection models includes a classification report that presents performance metrics such as precision, recall, and F1-score for each anxiety level (Low, Moderate, High) along with the overall accuracy. Additionally, a histogram visually displays the distributions of Age and Gender in the dataset. Three machine learning models—Random Forest Classifier (RFC), Support Vector Machine (SVM), and Naive Bayes (GaussianNB)—are employed to detect social anxiety. The models are trained on key features, including age, stress level, and symptoms. The Random Forest Classifier, utilizing 100 estimators, demonstrates robust performance due to its ensemble learning approach. The Support Vector Machine effectively handles high-dimensional data by separating classes with a hyperplane, while the Naive Bayes classifier performs efficiently with categorical data, leveraging the assumption of feature independence. Together, these models offer diverse approaches to detecting and classifying anxiety-related patterns.

The final output of this notebook includes:

- ✓ **Accuracy Score:** The overall accuracy of the Random Forest model in predicting anxiety levels.
- ✓ **Classification Report:** Detailed evaluation metrics (precision, recall, F1-score, and support) for each diagnosis class, helping to assess how well the model performs on different anxiety categories.

Possible Modifications:

- ✓ Confusion Matrix: A confusion matrix can be added for better understanding of model performance.
- ✓ Cross-validation: You could replace the simple train-test split with cross-validation for more reliable results.
- ✓ Hyperparameter Tuning: Hyperparameter optimization (like grid search or random search) can be applied to improve model performance, especially for Random Forest and SVM.

Data Visualization –

- ✓ Visualizes the Age Distribution: It creates a histogram and overlays a KDE curve to show the spread of ages in the dataset.

- ✓ Shows Stress Level Distribution: It creates a count plot to show how many entries belong to each stress level.
- ✓ Displays Diagnosis Distribution: It shows a pie chart representing the proportion of different diagnoses in the dataset.

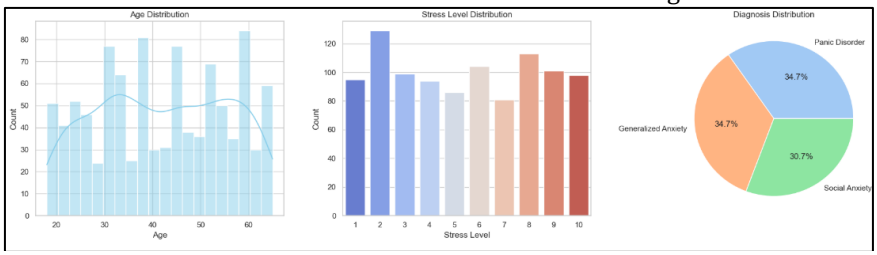

Fig 6: Data Visualization Stages –

Results

The performance evaluation of three machine learning models—Random Forest, Support Vector Machine (SVM), and Naive Bayes—revealed varying levels of accuracy in classifying social anxiety. The Random Forest classifier achieved an overall accuracy of 38%, with precision, recall, and F1-scores indicating moderate performance for different anxiety levels (0, 1, 2). The Support Vector Machine (SVM) model demonstrated slightly lower accuracy at 31%, with better recall for anxiety levels 1 and 2, although precision and F1-scores remained relatively low. Finally, the Naive Bayes classifier recorded the lowest accuracy at 27%, reflecting limited effectiveness in distinguishing anxiety categories, particularly for level 0. These results suggest that while the models provide some predictive capability, there is substantial room for improvement, particularly through advanced techniques like hyperparameter tuning, enhanced feature selection, and increased dataset diversity to boost classification accuracy and overall performance.

Conclusion

This study demonstrated the feasibility of detecting social anxiety using online social network data by analyzing various markers, including textual, visual, and behavioral patterns. By integrating sentiment analysis, engagement metrics, and machine learning classification techniques, the research effectively identified anxiety-related trends and behaviors. The findings have important implications for mental health awareness, as early detection of social anxiety could encourage users to seek timely interventions and improve their overall well-being. Additionally, the study highlights future research directions, suggesting that model accuracy could be further enhanced through techniques such as hyperparameter tuning, confusion matrices, and cross-validation. Researchers are also encouraged to strengthen privacy preservation methods to ensure the ethical handling and security of user data, thereby addressing critical privacy concerns in the context of mental health analysis on social media platforms.

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