Predicting Emotional Well-Being from Social Media Usage: An Optimum Machine Learning Approach

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***Abstract*—The rapid expansion of social media has significantly influenced emotional well-being, impacting users both positively and negatively. This paper aims to investigate the relationship between social media usage patterns (Posts, Likes, Comments, etc.) and emotional well-being using various machine learning models. The study leverages the "Social Media Usage and Emotional Well-Being" dataset and applies multiple Machine Learning algorithms, including Decision Tree, Random Forest, K-Nearest Neighbors, to predict emotional states based on user activity. The results demonstrate that machine learning models like Decision Tree, Extra Trees, K-Nearest Neighbors, Stacking Regressor achieved testing accuracy of 96.12%, 94.17% and 89.32%, respectively. The findings highlight how advanced machine learning techniques are crucial to determine complex relationship between social media behaviors and its impact on emotional health. This research contributes valuable insights into the data-driven approaches to enhance emotional well-being through targeted interventions and improved user experiences.**

***Index Terms*—Social media, Machine Learning models, Decision Tree.**

I. Introduction

In our day-to-day life, emotional well-being plays a crucial role. Emotional well-being refers to the state of experiencing positive emotions, managing stress effectively, and maintaining a sense of balance and resilience in life. In our daily lives, we also rely on social media to stay updated. As of October 2024, there were 5.52 billion internet users worldwide, accounting for 67.5% of the global population [1]. Of this total, 5.22 billion people, or 63.8% of the world's population, were social media users [1].

In the digital age, social media has become a ubiquitous part of daily life, significantly influencing users' emotional well-being. Research indicates that engagement with social media platforms correlates with various emotional states, raising concerns about mental health implications. According to a study by Primack et al. (2017), increased social media usage is associated with higher levels of perceived social isolation, which can adversely affect emotional health [2]. Furthermore, the World Health Organization (2021) highlights the growing prevalence of mental health issues linked to excessive social media engagement, underscoring the need for effective assessment and intervention strategies [3].

Several previous studies have employed various models to analyze the relationship between social media usage and emotional well-being. For instance, traditional statistical methods such as regression analysis have been utilized to explore these dynamics; however, they often fall short in capturing the complexities of user interactions and emotional responses [4]. Machine learning approaches have emerged as a promising alternative, yet many existing models face limitations regarding their predictive accuracy and generalizability across diverse populations. Research by Liu et al. (2022) demonstrated that while machine learning algorithms can enhance prediction capabilities, they often lack the robustness required for real-world applications due to insufficient training data and inadequate feature selection [5].

The primary objective of this study is to develop an optimum machine learning approach for predicting emotional well-being based on social media usage patterns. By leveraging advanced techniques such as ensemble models, this research aims to create robust predictive models that can effectively classify users' emotional states from their online interactions.

This study contributes to the existing body of literature by providing insights into how machine learning can be utilized to better understand the relationship between social media behaviors and emotional health. The findings are expected to inform both individuals and healthcare professionals about the potential impacts of social media on mental health, ultimately aiding in the development of targeted interventions that promote healthier online habits.

II. Literature Review

Social media has become an inseparable part of the life of this generation. The intensive use of social media often impacts the very way of living. Posts and blogs from platforms such as Facebook, Instagram, Twitter, and Reddit significantly influence users' emotions and behaviors.

A systematic review of studies applying machine learning approaches to text data from social media has been conducted to detect depressive symptoms and predict emotions. Various machine learning models have been employed in these studies. Notable results include Bayesian Classifier (Mean Absolute Error = 0.186), Random Forest (Post Classification Accuracy = 0.898), and Support Vector Machine (Post Classification Accuracy = 0.8), all of which showed promising results [6].

An overview of sentiment analysis methods and machine learning approaches for emotion detection using social media data compared techniques and discussed their limitations. Datasets such as ISEAR, SemEval, and AWS were used, focusing on classification problems. While traditional machine learning models like Naïve Bayes and K-Nearest Neighbors

TABLE I
SUMMARY OF VARIOUS MACHINE LEARNING AND DEEP LEARNING APPLICATIONS IN EMOTION DETECTION AND HEALTHCARE

Reference	Findings/Objectives	Models	Results
[6]	Using text from social media to detect symptoms of depression. It summarizes findings from previous research and suggests directions for future work, focusing on the challenges of sampling, prediction optimization, generalizability, privacy, and ethical issues.	Bayesian Classifier, Lasso, Random Forest, SVM, CNN, LSTM	Bayesian Classifier (Mean absolute error = 0.186), Random Forest (Post classification accuracy = 0.898), SVM (Post classification accuracy = 0.8) models showed promising results.
[7]	The paper provides an overview of various sentiment analysis methodologies and machine learning approaches for emotion detection from social media data. The aim is to compare techniques and discuss limitations and future research directions.	CNN, Bi-LSTM, Naive Bayes, K-Nearest Neighbors, SVM	CNN outperformed others with an accuracy of 92.09% in the movie domain and 91.19% in the agriculture domain.
[8]	ML techniques for recognizing emotions from human speech. The focus is on extracting acoustic features, reducing dimensionality, and using machine learning classifiers to identify emotions conveyed in speech.	Hybrid classification methods, K-NN, Neural Network, SVM	K-Nearest Neighbors (K-NN) achieved the highest accuracy of 79.5%, and Neural Networks (NN) performed the worst with an accuracy of 50%.
[9]	Develop a Chatbot that can recognize and analyze human emotions through textual conversations. The system is aimed at enhancing human–machine interactions by detecting emotions like joy, sorrow, irritation, and anger, and responding accordingly. This application has potential uses in social networking, business applications, and healthcare.	NLTK, TextBlob, Flair, Naive Bayes, Deepmoji	Naive Bayes classifier achieved an emotion detection accuracy of 76%, making it the best-performing model.
[10]	Create a rule-based algorithm to collect and annotate data from Twitter posts, focusing on identifying specific emotions using Plutchik's eight core emotions.	Decision Tree, Random Forest, Neural Networks	Best performing models are Random Forest (accuracy: 75%-85%) and Neural Networks (accuracy: 82%-90%).
[11]	Review of machine learning algorithms analyzing sentiment from text.	Several traditional, deep learning, and hybrid models	Naïve Bayes, Decision Tree, and SVM (Accuracy = 81.16%), Hybrid (Accuracy = 96.75%).

(KNN) showed decent results, deep learning models such as Convolutional Neural Networks (CNN) and BiLSTM performed better with large and complex datasets. CNN achieved 92.09% accuracy, outperforming other machine learning and deep learning models [7].

Machine learning models have also been used for emotion recognition from speech data. For instance, the Linguistic Data Consortium (LDC) Emotional Prosody Speech Corpus, containing approximately 2,300 utterances from seven actors (three males and four females) expressing 14 emotional states and a neutral state, was utilized. Support Vector Machine (SVM), KNN, and hybrid models were applied, with KNN achieving the best accuracy at 79.5% [8].

In another study, a chatbot was developed to recognize and analyze human emotions through textual conversations using data from various messaging platforms. The goal was to classify emotions using machine learning models such as the Naïve Bayes Classifier and tools including NLTK Vader, TextBlob, Flair, and DeepMoji. The Naïve Bayes Classifier achieved an emotion detection accuracy of 76% [9].

Research was also conducted to create a rule-based algorithm for collecting and annotating data from Twitter posts, focusing on the classification of specific emotions based on Plutchik's eight core emotions. Decision Tree, Random Forest, and Neural Networks were employed, with Neural Networks achieving the highest performance, ranging from 82% to 90% accuracy [10].

A review of text-based data analysis for sentiment detection and emotion classification was conducted, using datasets collected from social media platforms, blogs, and e-commerce websites. Datasets such as Stanford Sentiment Treebank (SST) and SemEval Task were utilized for training and testing machine learning and deep learning models. These included Support Vector Machines (SVM), Random Forest (RF), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), K-Nearest Neighbors (KNN), Logistic Regression, Naïve Bayes, and hybrid models combining SVM and RF. The models effectively detected and classified emotions such as joy, sadness, and fear [11].

III. Methodology

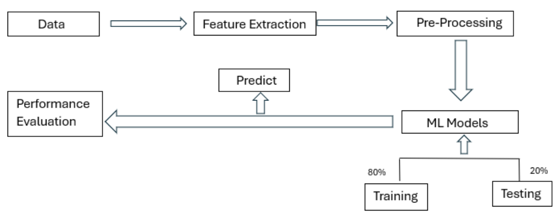

Fig. 1. Flowchart representing the adopted direction of flow in the project.

The direction of flow adopted in this project is shown in Fig. 1. The dataset was obtained from Kaggle, and necessary features were extracted from it. The data was then divided into training and testing sets. The performance of various machine learning models will be evaluated using four performance metrics: Accuracy, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared score.

A. Dataset Overview

The dataset used in this research is the "Social Media Usage" dataset, obtained from Kaggle. This dataset captures essential information regarding users' social media activities and their dominant emotional states based on interactions. It provides demographic details such as User_ID, Age, and Gender, along with platform usage information. Key variables include:

- **Daily Usage Time**: Time spent on social media (in minutes).
- **Posts Per Day**: Number of posts made daily.
- **Likes Received Per Day**: Number of likes received daily.
- **Comments Received Per Day**: Number of comments received daily.
- **Messages Sent Per Day**: Number of messages sent daily.
- **Dominant Emotion**: Categorizes emotional states such as Happiness, Sadness, Anger, Anxiety, Boredom, and Neutral.

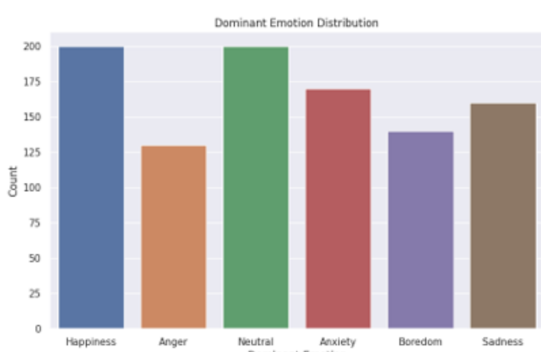

Fig. 2. Dominant emotion distribution

The dataset provides a comprehensive basis to explore the relationship between social media usage patterns and emotional well-being.

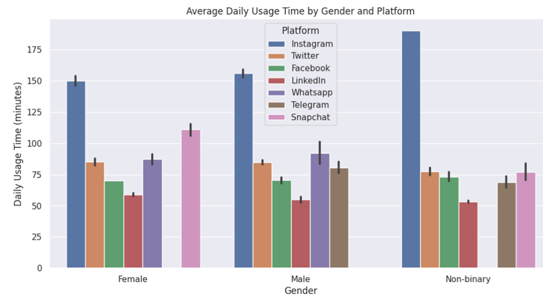

Fig. 3. Average daily usage time by gender and platform

The data visualization in Fig. 3. depicts the average daily usage time across various social media and messaging platforms, segmented by gender identity. The key findings indicate that female users tend to spend more time on platforms like Instagram, Facebook, WhatsApp, and Snapchat, while male users exhibit higher engagement on Twitter and LinkedIn. Non-binary individuals demonstrate the highest average daily usage times overall. Instagram emerges as the platform with the greatest average daily usage, particularly among female and non-binary respondents, while Telegram and Snapchat have the lowest average daily usage times across all gender categories.

B. Data Preprocessing

Prior to analysis, the dataset underwent rigorous preprocessing to ensure data quality and relevance. The preprocessing steps included:

1) **Data Cleaning**: Missing values were handled by imputing with mean or median values, or by removing records with excessive missing data.
2) **Normalization**: Continuous variables (e.g., Daily Usage Time, interaction counts) were normalized to a standard scale to improve model performance.
3) **Encoding Categorical Variables**: Emotional states were converted into numerical format using one-hot encoding.
4) **Outlier Detection**: Outliers were identified using statistical methods (e.g., Z-score) and removed or adjusted accordingly.

C. Feature Extraction

Feature extraction was conducted using Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE):

- **PCA**: Reduces dimensionality by transforming the original features into principal components that account for most of the variance in the dataset.
- **RFE**: Eliminates less important features to ensure only relevant attributes are selected for classification.

D. Machine Learning Models

A variety of machine learning models were employed to predict emotional well-being based on social media usage patterns. These models included:

- **Linear Models**:
  - **Linear Regression**: A foundational approach to assess the relationship between independent variables and the target variable.
  - **Ridge Regression**: A type of regularization that adds a penalty term to regression coefficients to prevent overfitting.
  - **Lasso Regression**: Incorporates an L1 regularization term to enhance model performance and interpretability.
- **Tree-Based Models**:
  - **Decision Tree Regressor**: A non-parametric algorithm that predicts continuous values based on recursive partitioning.
  - **Random Forest Regressor**: An ensemble method that predicts by averaging the predictions of multiple trees to reduce overfitting.
  - **Extra Trees Regressor**: Similar to Random Forest but with a random selection of split points for each tree.
- **Ensemble Learning Techniques**:
  - **Gradient Boosting Regressor**: Builds a predictive model in a stage-wise manner by sequentially combining weak learners to minimize loss.
  - **AdaBoost Regressor**: Focuses on misclassified instances from previous models to improve prediction accuracy.
  - **Voting Regressor**: Combines predictions from different base models to produce a final prediction.
  - **Stacking Regressor**: Uses a meta-model to combine predictions from multiple base models.
- **Support Vector Regression (SVR)**: Finds a function that predicts continuous values while balancing model complexity and prediction accuracy.
- **K-Nearest Neighbors (KNN)**: A non-parametric algorithm that predicts values based on the average of the target values of the nearest neighbors.

The performance of these models was evaluated using Accuracy, MSE, RMSE, and R-squared scores.

E. Evaluation

The evaluation of model performance was conducted using the following metrics:

- **Mean Squared Error (MSE)**: Quantifies the average squared difference between predicted and actual values:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

  where:
  - n = Number of data points.
  - y_i = Actual value of the target variable for the i-th data point.
  - $\hat{y}_i$ = Predicted value for the i-th data point.
- **Root Mean Squared Error (RMSE)**: Provides a measure of prediction error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

  where:
  - n = Number of data points.
  - y_i = Actual value of the target variable for the i-th data point.
  - $\hat{y}_i$ = Predicted value for the i-th data point.
- **R-Squared Score**: Measures the proportion of the variance in the dependent variable that is predictable from the independent variables:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

  where:
  - y_i = Actual value of the target variable for the i-th data point.
  - $\hat{y}_i$ = Predicted value for the i-th data point.
  - $\bar{y}$ = Mean of the actual values.
- **Pseudo-Accuracy for Regression**: A tolerance level was set at 10

$$Pseudo\_Accuracy = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i| \leq 0.1 \times \bar{y}}{n}$$

  where:
  - n = Number of data points.
  - y_i = Actual value of the target variable for the i-th data point.
  - $\hat{y}_i$ = Predicted value for the i-th data point.
  - $\bar{y}$ = Mean of the actual values.

IV. Result

The table presented in Table III provides a detailed classification report for a Decision Tree model, showcasing its performance across various emotion classes. The model demonstrates high precision, recall, and F1-scores for the majority of the classes, indicating its ability to accurately classify instances into the respective emotional categories. The overall accuracy of the model is 96%, further corroborating its strong predictive capabilities. The table also includes macro-averaged and weighted-averaged metrics, which offer a comprehensive evaluation of the model's performance. This comprehensive classification report can be valuable for researchers and practitioners working on emotion recognition tasks, as it highlights the strengths and potential areas for improvement in the Decision Tree classifier.

In this research, we utilized ensemble learning methods to achieve better outcomes. For training and testing the machine learning models, 80% of the data was used for training, while the remaining 20% was allocated for testing.

TABLE II
PERFORMANCE METRICS OF VARIOUS MACHINE LEARNING MODELS

Model	Training Accuracy	Testing Accuracy	Testing RMSE	Testing R^2 Score
Random Forest	94.70%	87.38%	0.5560	0.8774
K-Nearest Neighbors	94.81%	89.32%	0.6894	0.8115
Extra Trees	100.00%	94.17%	0.5369	0.8857
AdaBoost	18.40%	14.56%	1.4628	0.3036
Decision Tree	100.00%	96.12%	0.4725	0.9114
Linear Regression	9.42%	7.77%	1.5329	0.0679
Ridge Regression	9.42%	7.77%	1.5328	0.0680
Gradient Boosting	52.38%	46.60%	0.8178	0.7347
Support Vector Regression	28.03%	31.07%	1.4730	0.1393
Voting Regressor	28.90%	25.24%	0.8437	0.7177
Stacking Regressor	94.48%	86.41%	0.5518	0.8792

TABLE III
DECISION TREE CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score	Support
Anger	1.00	1.00	1.00	9
Anxiety	1.00	0.95	0.98	22
Boredom	1.00	0.94	0.97	16
Happiness	0.93	1.00	0.97	14
Neutral	0.93	1.00	0.97	28
Sadness	0.92	0.86	0.89	14
Accuracy			**0.96**	**103**
Macro Avg	0.96	0.96	0.96	103
Weighted Avg	0.96	0.96	0.96	103

Using the stacking regressor, we achieved a training accuracy of 95.20% and a testing accuracy of 88.35%. The testing mean squared error (MSE) was 0.3045, and the root mean squared error (RMSE) was 0.5518. The training and testing R^2 scores were 0.9839 and 0.8792, respectively.

The decision tree model provided 100.00% training accuracy and 96.12% testing accuracy. The testing MSE was 0.2233, and the RMSE was 0.4725. The training and testing R^2 scores were 1.0000 and 0.9114, respectively. The confusion matrix for the decision tree is shown in Figure 4.

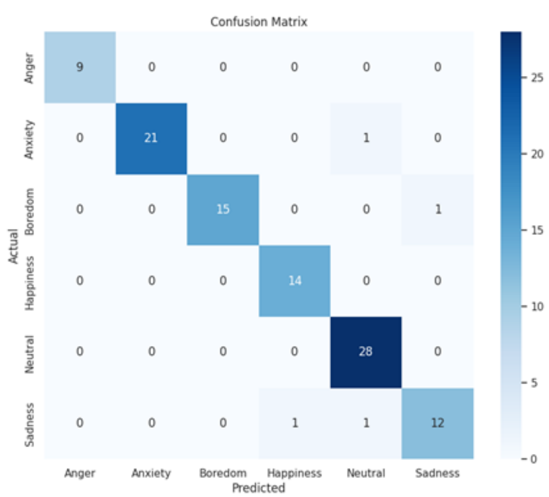

Fig. 4. Confusion Matrix for Decision Tree

Using the random forest model, we obtained a training accuracy of 94.70% and a testing accuracy of 87.38%. The testing MSE was 0.3091, and the RMSE was 0.5560. The training and testing R^2 scores were 0.9866 and 0.8774, respectively.

The K-Nearest Neighbors (KNN) model achieved a training accuracy of 94.81% and a testing accuracy of 89.32%. The testing MSE was 0.4753, and the RMSE was 0.6894. The training and testing R^2 scores were 0.9391 and 0.8115, respectively.

For the extra tree regressor, the training accuracy was 100.00% and the testing accuracy was 94.17%. The testing MSE was 0.2882, and the RMSE was 0.5369. The training and testing R^2 scores were 1.0000 and 0.8857, respectively.

From the model comparison, we observed that the decision tree model yielded the highest testing accuracy of 96.12%. Although other models like stacking regressor, random forest, and extra tree regressor also performed well, none surpassed the decision tree in terms of accuracy. Other models such as AdaBoost, gradient boosting, and support vector regression provided lower accuracy, as summarized in Figure 5.

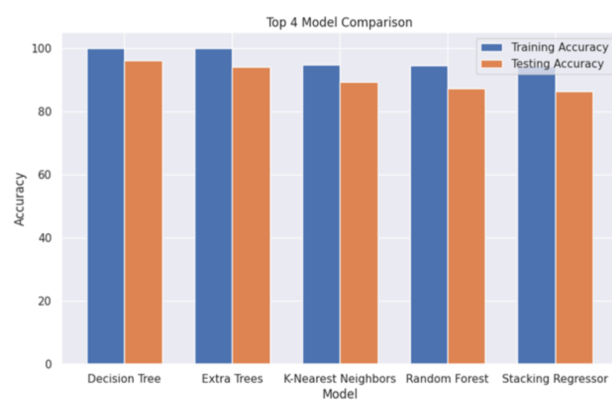

Fig. 5. Top-5 performing models comparison

V. DISCUSSION

In this research, we assessed various machine learning models to identify the most accurate predictor for outcomes. The Decision Tree model excelled with an accuracy of 96.12% on our test dataset, significantly outperforming Random Forest at

87.38% and more complex methods like Stacking at 86.41%. The Decision Tree correctly predicted outcomes 96 times out of 100 on new data, indicating its superior performance. However, its perfect classification of training examples raised concerns about potential overfitting, suggesting the model may have memorized the training data instead of learning underlying patterns. To address this, we plan to simplify the tree and conduct further tests to ensure its effectiveness on truly unseen data.

While Random Forest showed reasonable performance, it did not match the Decision Tree's accuracy, possibly indicating that our dataset is not well-suited for more complex models or that we could have optimized them better. Even a model that combines multiple techniques failed to surpass the Decision Tree's results. Our evaluation metrics consistently highlighted the Decision Tree's superior performance, suggesting it could be a valuable tool for predicting emotional well-being based on social media usage. However, resolving the potential memorization issue is crucial before fully relying on this model. Future work may involve exploring additional algorithms, refining existing models, expanding our dataset, or analyzing the features emphasized by the Decision Tree during predictions.

VI. Conclusion

This study highlights the efficiency of machine learning ensemble models, particularly tree-based models like Decision Tree, in predicting emotional well-being from social media usage patterns. These models excel at handling the correlated and non-linear relationships inherent in social media data, significantly outperforming other models. The high performance of these models suggests that they could play a crucial role in identifying potential emotional distress in users by analyzing social media interactions.

Despite the success, the study is limited by the lack of temporal data and deeper sentiment analysis from user-generated content. Future work could explore deep learning models and incorporate sentiment analysis of textual data to improve predictive accuracy. Additionally, including more diverse datasets and real-time analysis would offer deeper insights into how specific social media behaviors impact psychological outcomes, ultimately paving the way for proactive mental health interventions and better-designed social media platforms that promote emotional well-being.

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