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Nationwide Self Harm Behavioral Analytics Using Deep Contextual Language Representations

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Abstract: *The rise of online social networks has changed how people communicate, share their experiences and convey emotional distress, and led to increased opportunities to gain insights into self-harm behaviors on a national level. The development of online social networks has altered how people communicate, share experiences and express emotional distress, which has expanded opportunities for understanding self-harm behaviors at a national level. According to recent public health reports, each year hundreds of thousands of people die from self-destruction or suicide-related issues throughout the world, and more than one billion people have mental health disorders. To overcome these drawbacks, in this work, a new national level self-harm trend with Online Social Network (OSN) framework is proposed where the Twitter Dataset is used for large-scale behavioral analysis. First, Natural Language Processing (NLP) was used to clean, normalize and quality-check the textual data. Then, the Extreme Language Network (XLNet) Feature Extraction is employed to extract the contextual semantic representations, long-range dependencies, and subtle emotional expressions from user posts. The extracted features are then fed into an Extreme Ensemble Gradient Boosting–Classification and Regression Tree (EEGB-CART) framework, which consists of two sub-components: one is a Classification and Regression Tree (CART) based classification, which categorizes the Self Harm and Non-Self Harm, and the other is a regression component that provides sentiment intensity associated with the data. The framework proposed can expand across the nation and is data-driven and interpretable, providing for national-level proactive mental health monitoring and evidence-informed intervention planning.*

Key Word: *Classification, Mental Health Analytics, Natural Language Processing, Online Social Networks, Self Harm Detection, XLNet Feature Extraction.*

I. INTRODUCTION

The use of OSNs has greatly influenced the way in which digital communication occurs, allowing people to express their thinking, feelings [1] and personal experiences in real time. Recent international health statistics indicate that over 700,000 people commit suicide each year and millions of people participate in self-destructive behaviors, which frequently are not reported. At the same time, people create billions of posts daily on social media, some that include emotional distress cues, depressive expressions, and self-harm-related cues [2]. With the rising rate of mental health issues among adolescents and young adults, the detection of self-harm tendencies is now a pressing public health problem [3] that requires intelligent monitoring systems that are scalable and can analyse large scale online interactions [4].

Several tech firms and social media networks have realized the significance of mental wellness surveillance by means of AI and data analytics [5]. X Corp. continually monitors users' content for harmful activity and crisis-related discussions, while META uses machine learning methods [6] to identify indicators of suicide and self-harm on a social network. Likewise, Google uses sophisticated NLP techniques to gain insights into how mental health-related research is conducted and offers resources to support these queries [7]. Crisis Intervention Centers, public health agencies, mental wellness platforms and healthcare organizations are increasingly using artificial intelligence (AI) [8] based sentiment analysis and behavioral prediction systems to help with early intervention and large-scale mental health surveillance programs.

Even with these developments, the present manual monitoring strategies require a great deal of human effort, relying mainly on psychologists, healthcare professionals, and human moderators for content moderation on social media platforms [9]. These approaches are not scalable for millions of posts that are generated daily, and are also labor intensive, time consuming, and costly. Often manual assessment does not reflect the hidden meanings of the language, changing language patterns, sarcasm and subtle emotional cues that are associated with self-harm behavior. To address these drawbacks, this study introduces a novel framework based on the use of sophisticated models for the simultaneous classification of self-harm and sentiment regression. The proposed system will allow for the national level trend analysis of self-harm data to be accurate,

scalable and easily understood, allowing for timely intervention, risk assessment and evidence-based decisions for mental health.

II. LITERATURE SURVEY

Jang and Heo [10] used data to create a machine learning framework to predict whether a Korean adolescent with suicidal ideation would attempt suicide. To study four decades of advances in the field of emotional abuse and suicide, Vîşcu et al. [11] undertook an AI-driven bibliometric and empirical study. To create an AI-driven, scalable national debt intervention framework, Devadas [12] integrated predictive analytics and behavioral segmentation approaches. The methodology was developed with focus on financial risk management and cannot be directly applied to the task of self-harm or mental health prediction.

Aftab et al. [13] developed the GBRT++ model that predicts the likelihood of self-harm in postpartum depression patients. Ndikumana et al. [14] developed a machine learning framework for predictive modelling to evaluate mental health status of the youth in Rwanda. Onker et al. [15] developed a machine learning based educational analytics system to analyse learners' performance in Bhopal, India and provide useful suggestions to students. The framework was directed towards predicting educational performance and did not include behavioral analysis for mental health.

Adetunji and Odili [16] developed an ensemble machine learning model for predicting the risk of adolescent opioid exposure in state health systems. In a purpose-driven approach to digital mental health, Househ et al. [17] explored the use of advanced technologies to enhance the delivery of mental healthcare. Eken et al. [18] created an AI-based digital technology system for behavioural addiction management by means of intelligent monitoring and intervention systems.

Kong et al. [19] developed a machine learning prediction model to evaluate the smartphone overdependence of older adults and to find the factors that affect its overdependence. Cruz et al. [20] combined artificial intelligence methods and traditional analytical ones to assess social and psychological factors related to addictive behaviors. The framework focused on the analysis of addictive behaviours and did not include a specific system designed to classify and predict self-harm and sentiments on a large scale from online social networks.

III. PROPOSED METHODOLOGY

The The proposed methodology proposes a novel Hybrid National Self Harm Intelligence (HNSHI) Framework as depicted in Figure 1. First, raw tweets are gathered and sent to a Context-Aware NLP Preprocessing module for noise removal, hashtag decomposition, preserving the sentiment of the emoji, expanding abbreviations and normalizing the tokens by context to retain psychologically relevant expressions. Subsequently, a Semantic-Aware XLNet Feature Extraction mechanism is used to generate bidirectional contextual embeddings to capture long-range linguistic dependencies, implicit emotional cues and self-harm indicative patterns. As opposed to current studies which use XLNet as a means of classification, the proposed framework introduces a novel, EEGB-CART architecture using XLNet embeddings in a mixture of heterogeneous gradient boosting learners and adaptive CART decision structures. The EEGB-CART model is trained using a two tasks approach, where the classification task classifies the posts as Self Harm vs. Non-Self Harm, and the regression task generates sentiment intensity scores that represent the emotional severity levels of the posts.

Additionally, a Dynamic Error Guided Feature Fusion (DEGFF) strategy is introduced to enhance the importance of weighting and enhance the reliability of the decisions made for different types of user expressions. The novelty of the proposed approach for a large-scale national mental health trend analysis using data from the ONS relies on the novel integration of the following as a unified framework: (1) Context-Aware NLP preprocessing, (2) Semantic-Aware XLNet embeddings, (3) DEGFF, and (4) dual-purpose EEGB-CART learning for concurrent self-harm classification and sentiment regression. To the best of the author's knowledge, the above-mentioned paradigm has not yet been reported as an integrated framework in existing survey studies.

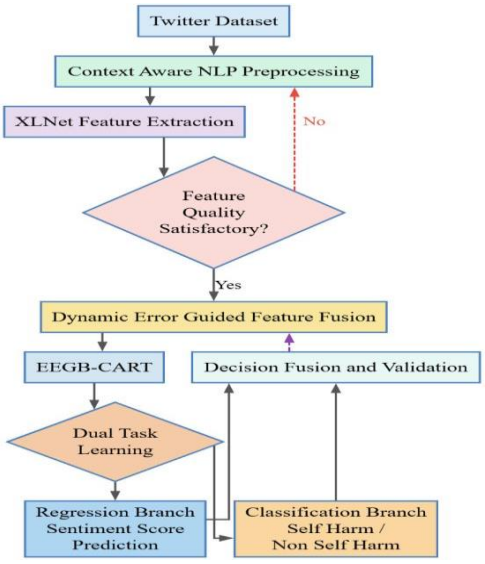


Fig. 1. Proposed HNSHI Architecture.

A. XLNet Feature Extraction with DEGFF

To detect self-harm and sentiment pattern from Twitter data, the proposed XLNet feature extraction with DEGFF framework as shown in Figure 2 aims to capture the contextual semantic information and adaptively improve feature representations. Then, let the preprocessed Twitter sentence be represented as an n-length sequence of tokens $T = \{t_1, t_2, \dots, t_n\}$, with n denoting the number of tokens. These tokens are all mapped to dense embedding vectors using an embedding matrix E. These tokens are converted to dense embedding vectors via an embedding matrix. The token representation is found from the top of the stack. Let x_i represent the embedding vector for the token t_i. The whole sequence of input is shown as

$$x_i = (t_i) \quad (1)$$

$$X = [x_1, x_2, \dots, x_n] \quad (2)$$

where X denotes the embedded input matrix. The XLNet uses permutation language modeling to learn the contextual dependencies of various factorizations. Consider $Z_n$as the set of all possible permutations of that sequence. The objective function to be minimized is:

$$(\theta) = \mathbb{E}_{z\sim Z}\left[\sum_{t=1}^{n} \log P(x_z \mid x_{z<t})\right] \quad (3)$$

where θ is model parameters, z denotes the position of the token under permutation order z, and $x_{z<t}$ is the previous context tokens. To model semantic relationships between words, XLNet calculates query, key, and value matrices as

$$Q = XW, K = XW_K, V = XW_V \quad (4)$$

Here, W, W_K, and W_V were learnable projection matrices. The attention score matrix is calculated by

$$A = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

where d_k denotes key vector dimensionality. The XLNet's hidden representation is represented by

$$H = \{h_1, h_2, \dots, h_n\} \quad (6)$$

Here, h_i is the contextual feature vector associated with a token i. Then, average pooling is used to get a sentence-level representation:

$$f_{XLNet} = \frac{1}{n}\sum_{i=1}^{n} h_i \quad (7)$$

Where f_{XLNet} denotes the Semantic Feature Vector extracted. To determine the contribution of each feature dimension, a prediction error measure is computed as

$$e_j = | y - \hat{y}_j | \quad (8)$$

Where y is the true label, $\hat{y}_j$ is the prediction based on the dimension j of the features and e_j is the error. The lower the error in the prediction of a feature, the higher the weight. An adaptive weight is calculated for each feature as

$$w_j = \frac{1}{e_j + \epsilon} \quad (9)$$

where w_j denotes feature importance weight and ϵ is a small positive term to avoid division by zero. To keep the learning stable, weights are normalized as per

$$\hat{w}_j = \frac{w_j}{\sum_{k=1}^{m} w_k} \quad (10)$$

where m is the total number of extracted feature dimensions and $\hat{w}_j$ is the normalization score of the corresponding feature's importance. The weighted fusion feature vector is created as follows:

$$F_{DEGFF} = \sum_{j=1}^{m} \hat{w}_j f_j \quad (11)$$

where f_j is the jth component of the XLNet feature and F_{DEGFF} is a dynamically fused semantic representation. Feature regularization is used as:

$$F_{reg} = F_{DEGFF} - \lambda \| F_{DEGFF} \|^2 \quad (12)$$

where λ is called the regularization coefficient and F_{reg} denotes the optimized feature vector. Non-linear transformation is used to get final feature vector forwarded to the EEGB-CART model:

$$F_{final} = (W_f F_{reg} + b_f) \quad (13)$$

In the above, Wf denotes the transformation matrix, bf denotes bias parameters, $(\cdot)$ denotes the activation function, and $Ffinal$ denotes the optimized contextual feature representation that is employed to classify self-harm and predict sentiment (regression). The framework effectively captures the contextual, emotional and behavioural patterns and adapts to highlight the most informative features to support large-scale self-harm trend analysis by integrating XLNet semantic learning and DEGFF.

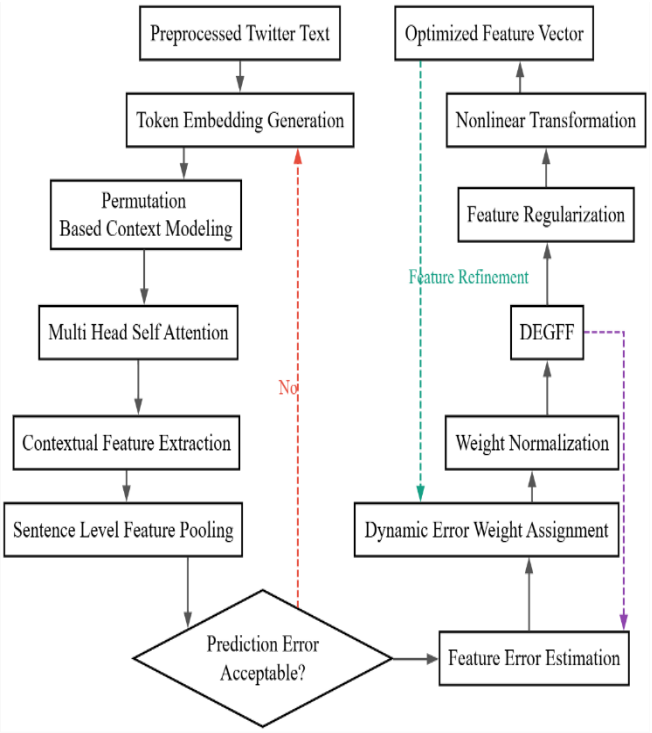


Fig. 2. Proposed XLNet Feature Extraction with DEGFF Architecture.

B. EEGB-CART

The proposed framework of EEGB-CART simultaneously classifies self-harm and regresses the sentiment in the proposed framework as shown in Figure 3.

Step 1: Feature Vector Acquisition: The feature vectors, optimized by the XLNet-DEGFF module, are then gathered and arranged into a training matrix. Each feature vector is composed of semantic, contextual and emotional information related to a Twitter post.

Step 2: Sample Weight Assignment: These weights are used by the learning algorithm to find the instances that are hard to classify. The initialization stage is used to obtain thebalance of learning and avoid making a prior assumption in the model with the dominant patterns of the data.

Step 3: Base CART Learners: The CART is created from the weighted training data. CART recursively splits the feature space into homogeneous regions using optimal split points determined by impurity reduction. The tree classifies instances of self-harm, or it predicts a continuous sentiment score for sentiment analysis instances. The tree generated is a weak learner that represents local decision boundaries in the feature space.

Step 4: Gradient Error Computation: A CART learner is created, and prediction errors are computed by comparing the actual outputs with the predicted outputs. Regions with higher prediction errors show the need for further training of the model.

Step 5: Extreme Ensemble Boosting Process: This process continually enhances the predictive performance of the ensemble by fusing different decision trees produced from error-scrubbed data. The boosting strategy is iterative, which helps increase the robustness of the model, decreases the variance of the model, and boosts the generalization capability for different self-harm expressions and sentiment patterns.

Step 6: Adaptive Ensemble Aggregation: This is a dynamic weighting method that allows the framework to focus more on strong learners and less on weak learners. This means that the predictions made by the ensemble is more stable and accurate compared to the prediction made by each of the CART learners.

Step 7: Dual Task Prediction Module: The output of the aggregated ensemble is sent to two prediction branches at the same time. The initial branch is used for binary classification, which classifies a Twitter post as Self Harm or Non-Self Harm. The second branch is used to do regression analysis to estimate the sentiment intensity of the post. The dual-task architecture enables the framework to collect behavioral risk indicators as well as emotional severity scores from a shared feature representation.

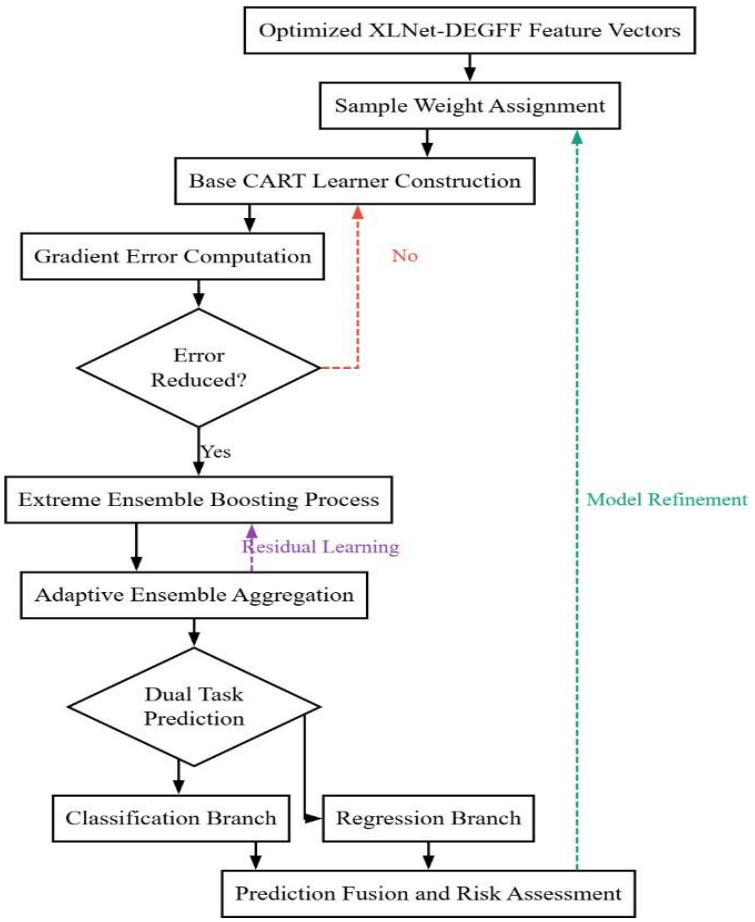


Fig. 3. Proposed EEGB-CART Framework.

IV. RESULTS AND DISCUSSION

This section provides a detailed comparison of various methodologies, which were evaluated on the same data set with the same performance measures, providing a fair comparison of the methodologies.

A. Datasets

The Twitter data used in this research is self-harm related and non-self-harm social media posts publicly available on Twitter used for mental health analysis. Self-harm studies on Twitter previously reported data of ~8000 self-harm related tweets to over 32,000 collected posts from over 11,000 users, yielding rich data from behavioral and emotional aspects. These texts span a range of emotional disclosures, support-seeking messages, recovery dialogues, and other types of conversations, allowing for a thorough examination of self-harm tendencies and sentiment in the texts. These social media datasets can provide meaningful real-world insights for training and testing of intelligent models for national-level self-harm detection, sentiment classification, mental health trend monitoring, and more.

B. Performance Estimation

The adopted hyperparameter configuration for the proposed HNSHI framework is shown in Table I. The learning rate range was considered from 0.001 to 0.100 and 0.010 was deemed to be optimal for stable convergence while training. The number of boosting trees was set from 50 to 500, but 300 trees gave the best trade-off between prediction accuracy and computational speed. The maximum tree depth in the range of 3 to 15 and the tree with eight depth was the best hierarchical decision structure. The minimum samples split, and minimum samples leaf were optimized at 5, and 2 respectively, from the ranges of 2 to 20, and 1 to 10. XLNet feature extraction used an embedding dimension range of 256 to 1024, and selected 768, and a dropout rate of 0.30 and a batch size of 32 ensured efficient training and reduced overfitting. Additionally, the best performance for the DEGFF module was found to be with a feature fusion weight of 0.75 and a regularization coefficient of 0.0010, where feature enhancement and model generalization were well balanced.

Hyper parameter	Minimum Value	Maximum Value	Best Value
Learning Rate	0.001	0.100	0.010
Number of Boosting Trees	50	500	300
Maximum Tree Depth	3	15	8
Minimum Samples Split	2	20	5
Minimum Samples Leaf	1	10	2
XLNet Dimension	256	1024	768
Batch Size	8	128	32
Dropout Rate	0.10	0.60	0.30
Feature Fusion Weight	0.10	1.00	0.75
Regularization Coefficient	0.0001	0.1000	0.0010

Table I. Hyper parameter Settings of the Proposed Framework.

Table II shows the comparison of the proposed HNSHI classification with some of the existing approaches. The Random Forest model achieved an accuracy of 89.52%, precision of 88.93%, recall of 89.01%, and F1-score of 88.97%. The MiniLM-XGBoost model achieved 91.84% accuracy and 91.16% F1 score, while the BERT-CNN model achieved even higher accuracy of 94.63% and an F1 score of 94.14%. XLNet-GBRT showed good performance with an accuracy of 96.15%, a precision of 95.88%, a recall of 95.71% and an F1-score of 95.79%. The proposed HNSHI framework exhibited a superior performance capacity to all the other techniques by achieving 99.74% accuracy, 99.51% precision, 99.62% recall, as well as 99.56% F1-score to identify the self-harm related content in social media data with great accuracy.

Table III shows the performance of sentiment regression methods in terms of the conventional regression measures. Random Forest resulted in a Mean Absolute Error (MAE) of 0.214, Mean Squared Error (MSE) of 0.118, Root Mean Squared Error (RMSE) of 0.343 and R^2 score of 0.842. MiniLM-XGBoost achieved a better prediction quality (MAE=0.183, R^2=0.886), and BERT-CNN further lowered the MAE to 0.151 and raised the R^2 score to 0.921. The performance of XLNet-GBRT was found to be better in terms of regression with an MAE of 0.127, RMSE of 0.241 and R^2 score of 0.948. The proposed HNSHI framework achieved the best overall sentiment prediction performance and obtained the lowest MAE (0.084), MSE (0.031), and RMSE (0.176), and obtained the highest R^2 score (0.982) which shows the highest accuracy in sentiment intensity estimation.

Methodology	A (%)	P (%)	R (%)	F1 (%)
Random Forest [11]	89.52	88.93	89.01	88.97
MiniLM-XGBoost [13]	91.84	91.27	91.06	91.16
BERT-CNN [14]	94.63	94.01	94.27	94.14
XLNet-GBRT [17]	96.15	95.88	95.71	95.79
Proposed HNSHI	99.74	99.51	99.62	99.56

Table II. Classification Performance Comparison of Various Methods.

Methodology	MAE	MSE	RMSE	R^2 Score
Random Forest [11]	0.214	0.118	0.343	0.842
MiniLM-XGBoost [13]	0.183	0.094	0.307	0.886
BERT-CNN [14]	0.151	0.073	0.270	0.921
XLNet-GBRT [17]	0.127	0.058	0.241	0.948
Proposed HNSHI	0.084	0.031	0.176	0.982

Table III. Regression Performance Comparison (Sentiment Prediction) of Various Methods.

Compared with the other models, the evaluated models were found to be efficient in terms of training time, testing time and memory consumption as shown in Table IV. MiniLM-XGBoost took 198 seconds to train, 45 seconds to test and used 792 MB memory, but suffered from lower accuracy. Training time for BERT-CNN was 465 seconds, testing time was 28 seconds, and memory usage was 1538 MB. XLNet-GBRT used the most computing resources, taking 521 seconds to train, 31 seconds to test and 1684 MB of memory. The proposed HNSHI framework, on the other hand, showed good accuracy and efficiency, with a training time of 448 seconds, a testing time of 24 seconds, and a memory consumption of 1496 MB. The results show that the proposed framework not only achieves better predictive accuracy but also consumes fewer computational resources than XLNet-GBRT.

An ablation study is used to test the contribution of individual components in the proposed HNSHI framework to test it in a systematic manner, as shown in Table V. The standalone EEGB-CART model attained 88.46% accuracy, 88.11%

precision, 87.95% recall and R2 value of 88.03%, which shows moderate performance. The results showed that the accuracy of adaptive feature weighting was enhanced by 91.87% and the R^2 score by 91.45% with the help of the DEGFF module. The best performance was attained by the XLNet with Bagging model with an accuracy of 94.32%, a precision of 94.07%, a recall of 93.95% and an R^2 of 94.01%. The evaluation of the HNSHI framework without the DEGFF component resulted in high accuracy and R^2 score of 97.15% and 96.85% respectively, reinforcing the significance of XLNet and ensemble learning. Finally, the complete HNSHI system achieved the best performance with 99.74% accuracy, 99.51% precision, 99.62% recall, and R^2 score of 98.20%, which confirmed the overall effectiveness of the XLNet feature extraction, the DEGFF and the EEGB-CART learning.

Methodology	Training Time (s)	Testing Time (s)	Memory Usage (MB)
MiniLM-XGBoost [13]	198	45	792
BERT-CNN [14]	465	28	1538
XLNet-GBRT [17]	521	31	1684
Proposed HNSHI	448	24	1496

Table IV. Computational Complexity Analysis of Various Methods.

Model Configuration	A (%)	P (%)	R (%)	R2-Score
EEGB CART Only	88.46	88.11	87.95	88.03
EEGB + DEGFF	91.87	91.54	91.36	91.45
XLNet with Bagging	94.32	94.07	93.95	94.01
HNSHI without DEGFF	97.15	96.93	96.78	96.85
Full HNSHI	99.74	99.51	99.62	98.20

Table V. Ablation Study of the Proposed HNSHI Framework.

V. CONCLUSION

The experimental results clearly show the effectiveness of the HNSHI framework on large-scale online social network data to detect self-harm and sentiment. The framework achieved excellent classification accuracy of 99.74%, precision of 99.51%, recall of 99.62%, and F1 score of 99.56%, which was much better than the previous models. For sentiment prediction, the proposed model achieved the lowest error values, which are MAE = 0.084, MSE = 0.031, and RMSE = 0.176, and best R^2 score of 0.982, which is highly reliable for predicting sentiment. Moreover, its training time was 448 seconds, testing time was 24 seconds, and its memory usage was 1496 MB, which was more efficient than XLNet-GBRT in both efficiency and predictive ability. The results demonstrate the effectiveness of the proposed architecture in monitoring trends of self-harm, assessing behavioral risk and sentiment analysis of social media platform information at the national level, which is robust, scalable and highly accurate. Further, this work can be extended with cross domain data analysis with large language models.

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