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Using Social Networks to Predict National-Level Self-Harm Trends

[1]J.MEENA, [2]R.HENDRA KUMAR

[1]PG Scholar, Dept. of CSE, KMM Institute of Technology And Science, Tirupati, AP, India.

[2]Associate Professor, Dept. of CSE, KMM Institute of Technology And Science, Tirupati,AP, India.

Abstract: Regardless of the person's purpose, self-harm refers to any self-inflicted poisoning or damage that results in either non-fatal injuries or death. Incidents of self-harm not only result in losses for the victims but also have a detrimental effect on the economy of the country. Research has indicated a rise in self-harming behaviours that are associated with the rapid urbanisation of emerging nations and the introduction of new technologies. Policymakers and other public health stakeholders may find it essential to be able to nowcast and forecast national-level patterns of self-harm trends in order to take timely action to address the underlying causes or prevent these anticipated disasters. Previous studies have applied traditional statistical forecasting techniques to historical data in order to anticipate self-harm trends at the population level in different countries. Such historical data, however, may be difficult to find or insufficient for precise forecasting in some nations, making it difficult to understand and forecast the country's self-harm landscape in a timely manner. This study offers FAST, a framework that analyses mental signals gleaned from a vast amount of social media data in order to predict self-harm trends at the national level. The forecastability of self-harm trends might be improved by using these signals as a stand-in for actual population mental health. In particular, language-agnostic language models are initially trained to identify various mental cues in gathered social media posts. The time-delay embedding approach is then used to convert these signals into temporal embedded instances once they have been combined and processed into multi-variate time series. Lastly, the forecastability of some machine learning regressors is confirmed. A case study in Thailand that forecasts death and injury cases from self-harm using a collection of 12 mental signals taken from tweets validates the suggested approach. According to the findings, the suggested approach beat the conventional ARIMA baseline by 43.56% and 36.48% on average in terms of MPE on predicting instances of severe hand injuries resulting from self-harm, respectively. To the extent that current knowledge allows, our study is the first investigation into using aggregated social media data to anticipate and nowcast self-harm patterns on a national level. The findings provide the groundwork for future social network-driven applications that rely on the ability to anticipate socioeconomic aspects, in addition to offering insight into better forecasting methods for self-harm tendencies.

Index terms *- Self-harm forecasting, Social media mental signals, Machine learning regressors, National-level prediction, Nowcasting, ARIMA, SVR, XGBoost, Random Forest, CatBoost, Bayesian Ridge, Mental health trends, Time-delay embedding, Public health policy, Suicide prevention, Social network analysis.*

1. INTRODUCTION

Regardless of the reason or the degree of suicidal intent, self-harm is defined as deliberate self-poisoning or self-injury that may cause harm or death [35]. Suicide and self-harm have been common issues, particularly in poorer nations [9]. A recent study found that low- and middle-income nations accounted for a major part of suicide cases, around 77% [47]. The adoption of new technologies and the quick urbanisation of these areas have been linked to this tendency [56]. In addition to causing personal sorrow and loss, the escalation of self-harm episodes has long-lasting negative repercussions on the economy, mainly because it lowers long-term labour productivity [41]. In order to develop strategies to promptly assess the situation and put policies in place to neutralise or avoid such predicted catastrophes, national policy makers and public health stakeholders may find it essential to be able to track and predict population-level trends in self-harm [70]. For instance, policymakers may think about making the necessary changes to the current policies that are contributing to mental health problems among citizens after learning that some strict measures taken to combat national epidemics have caused these problems and are predicted to play a major role in the sharp rise in self-harm trends. Additionally, to target people suffering negative impacts, public health interventions like mobile psychiatric units or hotlines might be used. Currently, methods used to learn about self-harm trends at the national level rely on administrative reports from hospitals and healthcare facilities throughout the country, which requires a large investment of time, money, and human resources, resulting in sporadic and delayed data availability. When it comes to proactive policymaking, delayed and coarse-grained statistics may not be very useful.

Recent literature has emphasised the need of tracking and predicting changes in suicide and self-harm [63]. Using traditional approaches like ARIMA and the Holt-Winters methods, the problem has been presented as a time series forecasting assignment [71], [90]. The various internal and environmental elements that affect people's decision to commit acts of self-harm have been clarified by recent studies [22], [66]. Chang and Lee [17] suggest that only using past suicide and self-harm data might not be sufficient to create accurate predicting models. This emphasises the need for more data sources that document how the public responds to the present increases in suicide and self-harm. In this regard, earlier research has investigated how using Google Trends data—more especially, search terms associated with suicide and self-harm—could improve the precision of national-level self-harm predictions [39]. Recent studies, however, have suggested that Google Trends might not be a suitable stand-in for gauging overall self-harm behaviour. This is mostly because of the unidentified algorithm that controls Google Trends' operation [25] and the presumption that there is a significant overlap between the population that creates Google search queries and the population that actually commits acts of self-harm [91]. Furthermore, a recent study found no significant correlation between the use of self-harm-related terms in Google Trends statistics and real self-harm statistics in Thailand [62].

2. LITERATURE SURVEY

2.1 Depression and anxiety have a larger impact on bullied girls than on boys to experience self-harm and suicidality: A mediation analysis:

https://www.sciencedirect.com/science/article/abs/pii/S0165032721011393

ABSTRACT: Context It is unclear what mechanism underlies the association between bullying victimisation, self-harm, and suicidality by gender. Therefore, the purpose of this study was to determine if bullying victimisation, self-harm, and suicidality are mediated differently by mental disorders (anxiety and depression) in boys and girls. Techniques A total of 2522 Australian teenagers between the ages of 12 and 17 were examined from the Young Minds Matter cross-sectional survey, which is nationally representative. To examine the mediating role of each mental illness in the association between bullying victimisation, self-harm, and suicidality across genders, a number of logistic regressions were used, utilising the methodology of Baron and Kenny. Additionally, the indirect effect was estimated using the Sobel test. Findings Of the 784 (31.1%) victims of bullying, 46.8% were boys and 53.2% were girls. Depression, anxiety, self-harm, and suicidality were more common in females than in boys ($p < 0.001$ for all). Depression acted as a mediating factor in the associations between bullying victimisation, self-harm, and suicidality ($p < 0.05$) in both boys and girls. However, only in females ($p < 0.05$) did anxiety disorder influence the connection. Restrictions Causality is not implied by a cross-sectional study design. Social desirability bias may affect self-reported statistics on suicidality and self-harm. Conclusion Girls were more affected by bullying, self-harm and suicidality than boys. Depression mediated the correlation between bullying, and self-harm and suicidality in both boys and girls. While anxiety influenced only bullied girls to experience self-harm and suicidality. These findings warrant the need for gender-specific prevention programs to combat bullying and subsequently self-harm and suicidality in adolescents.

2.2 Predicting suicidal behavior and self-harm after general hospitalization of adults with serious mental illness

https://www.sciencedirect.com/science/article/abs/pii/S002239562031027X

ABSTRACT: After experiencing physical disease, people with psychiatric problems are susceptible to negative mental health effects. Risk profiles for readmission for suicidal behaviour and self-harm following general hospitalisation of persons with severe mental illness were established by this longitudinal cohort research. 15,644 general non-psychiatric index hospitalisations of patients with depression, bipolar disorder, and psychotic disorders who were hospitalised to an urban health system in the southwestern United States between 2006 and 2017 were examined using structured electronic health record data. Supervised machine learning was used to predict the likelihood of readmission for suicide attempt and self-harm in the following year using data from the year before and includes index hospitalisation. A classification prediction with an area under the receiver operating curve (AUC) of 0.86 (95% CI 0.74–0.97) was generated by the Classification and Regression Tree method. The prevalence of suicide-related behaviour was lowest following hospitalisations linked to extremely high medical morbidity burden (0 cases/3090 hospitalisations) and highest following general non-psychiatric hospitalisations of people with a history of self-harm or suicide attempt (18%; 69 cases/389 hospitalisations). The bulk of risk was explained by predictor combinations rather than individual risk variables, such as age ≤55 years old with low medical morbidity and concurrent alcohol use disorder with moderate medical morbidity. Findings indicate that clinical decision support, resource allocation, and preventative interventions for medically unwell individuals with major mental illness may be informed by applying an effective and highly interpretable machine learning algorithm to data from electronic health records.

2.3 Suicide Risk Prediction by Tracking Self-Harm Aspects in Tweets: NUS-IDS at the CLPsych 2021 Shared Task:

https://www.researchgate.net/publication/352280075_Suicide_Risk_Prediction_by_Tracking_Self-Harm_Aspects_in_Tweets_NUS-IDS_at_the_CLPsych_2021_Shared_Task

ABSTRACT: We present our approach for detecting suicidal individuals from their tweets, which was created for the CLPsych 2021 Shared Task. In our approach, we try to describe features of self-harm that are conveyed in user tweets over time, based on mental health research that links suicide and self-harm inclinations. In order to do this, we create SHTM, a Self-Harm Topic Model, which models users' daily tweets by combining Latent Dirichlet Allocation with a self-harm vocabulary. A deep learning model for suicide prediction is then trained using the variations in themes and emotions over time as features.

2.4 Risk factors for self-harm in prison: a systematic review and meta-analysis

https://www.sciencedirect.com/science/article/pii/S2215036620301905

Background: One of the main causes of morbidity among inmates is self-harm. Despite the identification of several risk variables for inmate self-harm, it is unclear how strong and consistent the impact sizes are. Our goal was to compile the available data and evaluate the risk variables for inmate self-harm. Techniques: We looked through four electronic databases (PubMed, Embase, Web of Science, and PsycINFO) for observational studies on risk factors for self-harm in inmates published between the database's creation and October 31, 2019, and we also contacted study authors for additional information. This search was part of our systematic review and meta-analysis. Adults who self-harmed while incarcerated and a comparison group who did not self-harm while incarcerated were recruited from regular prison populations and included in our primary investigations. research that reported on lifetime measures of self-harm or on specific prisoner samples were not included, as were research with qualitative or ecological methods and comparison groups that were inappropriate or not representative of the whole prison population. Data were taken from the journals and sent to the authors of the studies. The risk of self-harm for risk variables among inmates was our main finding. For every risk factor analysed in a minimum of three different samples, we used random effects models to aggregate effect sizes as odds ratios (OR). We looked at between-study heterogeneity and evaluated research quality using the Newcastle-Ottawa Scale. The study protocol, CRD42018087915, was filed with PROSPERO. Findings: Of the 663 735 inmates in 35 separate studies from 20 countries, 24 978 (3·8%) had self-harmed while incarcerated. Suicide-related antecedents, such as current or recent suicidal ideation (OR 13·8, 95% CI 8·6-22·1; I2=49%), lifetime history of suicidal ideation (8·9, 6·1-13·0; I2=56%), and prior self-harm (6·6, 5·3-8·3; I2=55%), showed the strongest associations with self-harm in prison among the 40 risk factors analysed. Additionally, self-harm (8·1, 7·0-9·4; I2=0%) was substantially correlated with any current psychiatric diagnosis, especially severe depression (9·3, 2·9-29·5; I2=91%) and borderline personality disorder (9·2, 3·7-22·5; I2=81%). Solitary confinement (5·6, 2·7-11·6; I2=98%), disciplinary violations (3·5, 1·2-9·7; I2=99%), and being sexually or physically victimised while incarcerated (3·2, 2·1-4·8; I2=44%) were prison-specific environmental risk factors for self-harm. There was only a weak correlation between criminological (1·8-2·3) and sociodemographic (OR range 1·5-2·5) characteristics and self-harm in jail. Clear proof of publishing bias was not found. Meaning: The necessity for a comprehensive, prison-wide strategy to prevent self-harm in jail is highlighted by the large variety of risk factors spanning clinical and custody-related areas. Both population and targeted measures should be included in this strategy, and multiagency cooperation between the criminal justice, social care, and mental health agencies should be crucial.

2.5 Abuse, self-harm and suicidal ideation in the UK during the COVID-19 pandemic

https://pubmed.ncbi.nlm.nih.gov/32654678/

Using data from the COVID-19 Social Study (n=44 775), a non-probability sample weighted to population proportions, this study investigated patterns of abuse, self-harm, and suicidal/self-harming thoughts in the UK during the first month of the COVID-19 pandemic. Women, Black, Asian, and minority ethnic (BAME) persons, and those with socioeconomic adversity, unemployment, disability, chronic physical diseases, mental disorders, and a diagnosis of COVID-19 were more likely to report abuse, self-harm, and suicidal or self-harming thoughts. Although the most popular form of help was psychiatric medicine, less than half of individuals impacted were receiving official or informal support.

3. METHODOLOGY

i) Proposed Work:

As an enhancement, the decision tree algorithm is integrated to improve forecasting accuracy while maintaining interpretability. This approach enables precise self-harm trend predictions by effectively minimizing errors such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Additionally, decision trees provide clear decision-making processes, making the model more transparent and trustworthy for interventions based on identified risk factors.

Furthermore, a Flask framework with SQLite is incorporated to facilitate user authentication, including signup and login functionalities. This integration enhances the system's usability and accessibility, allowing users to input parameters and retrieve results effortlessly. By improving both predictive performance and user interaction, these extensions ensure the system's practicality and effectiveness for real-world applications.

ii) System Architecture:

The Lung-RetinaNet system architecture is designed for robust lung cancer detection in medical images. Beginning with a dataset of annotated lung scans, the pipeline involves image processing, RetinaNet model building with unique enhancements, and the utilization of classification algorithms. Multiple detection algorithms, including YOLOv5, YOLOv8, Faster R-CNN, and RetinaNet, contribute to the accurate localization of lung cancer nodules [45]. Performance evaluation metrics such as Mean Average Precision, precision, and recall ensure thorough assessment. The system's primary focus is on precise lung cancer detection, leveraging RetinaNet's multi-scale feature fusion and context modules to enhance sensitivity and specificity. The final output comprises detected cancer nodules, their spatial localization, and confidence scores, providing valuable insights for clinical decision-making. The Lung-RetinaNet architecture stands as an advanced solution, overcoming traditional limitations and offering improved accuracy and sensitivity in early-stage lung tumor detection.

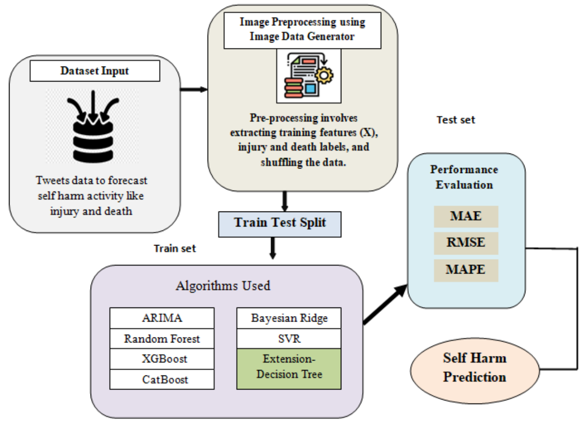

Fig 1Proposed Architecture

iii) Modules:

a) **Data Collection & Preprocessing:**

- Gathers historical data related to self-harm trends.
- Cleans, normalizes, and prepares data for analysis.

b) Feature Extraction & Selection:

- Identifies key risk factors influencing self-harm trends.
- Reduces irrelevant features to enhance model accuracy.

c) **Prediction Model (Decision Tree Algorithm):**

- Implements decision tree-based forecasting.
- Minimizes errors (MSE, RMSE, MAE) for precise predictions.

d) **User Authentication & Management (Flask & SQLite):**

- Enables user signup, login, and secure access.
- Manages session handling and user roles.

e) **Visualization & Results Display:**

- Presents predictive insights through graphs and reports.

- Allows users to analyze trends and make informed decisions.

f) **System Testing & Deployment:**

- Ensures model performance and accuracy before deployment.
- Deploys the system using Flask for real-world usability.

iv) Algorithms:

a) Autoregressive Integrated Moving Average: ARIMA is a time series forecasting method that models the relationship between a time series dataset and its lagged values. It comprises three main components: autoregression (AR), differencing (I), and moving average (MA). ARIMA[37] is effective for capturing linear dependencies and trends in stationary time series data.

b) Random Forest: Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes or the mean prediction of the individual trees for regression tasks.[36] It improves prediction accuracy and reduces overfitting by aggregating predictions from a multitude of decision trees trained on random subsets of the data.

c) XGBoost (Extreme Gradient Boosting): XGBoost is an optimized implementation of gradient boosting machines, which sequentially trains a series of weak learners (typically decision trees) to minimize a predefined loss function.[18] It employs a gradient descent algorithm to optimize the model parameters and performs regularization to prevent overfitting, resulting in high prediction accuracy.

d) CatBoost: CatBoost is a gradient boosting library that is particularly adept at handling categorical features without requiring extensive preprocessing.[40] It utilizes a modified version of the gradient boosting algorithm that incorporates novel techniques such as ordered boosting and oblivious trees, resulting in improved performance and faster training times.

e) Bayesian Ridge: Bayesian Ridge regression is a linear regression method that incorporates Bayesian principles to estimate the model parameters.[39] It assumes a Gaussian prior distribution over the model parameters and computes the posterior distribution using Bayesian inference techniques. Bayesian Ridge regression is robust to multicollinearity and outliers and provides uncertainty estimates for the model predictions.

f) Support Vector Regression (SVR): SVR is a supervised learning algorithm that applies the principles of support vector machines (SVMs) to regression tasks.[13] It seeks to find the hyperplane that best fits the data while maximizing the margin between the hyperplane and the closest data points. SVR is effective for handling non-linear relationships in the data and is robust to overfitting, especially in high-dimensional feature spaces.

g) Decision Tree: Decision Tree is a non-parametric supervised learning method that recursively partitions the feature space into subsets based on the values of input features.[38] It selects the feature that best separates the data at each node using metrics such as Gini impurity or information gain. Decision trees are interpretable, robust to outliers, and capable of capturing non-linear relationships in the data.

4. EXPERIMENTAL RESULTS

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = the\ AP\ of\ class\ k$$

$$n = the\ number\ of\ classes$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Prediction Type Injury:

	Algorithm Name	MAE	RMSE	MAPE
0	ARIMA	145.395908	176.653211	31206.357057
1	Bayesian Ridge	50.849129	58.819382	3459.719713
2	Linear SVR	128.338791	137.697868	18960.702961
3	XGBoost	27.066800	30.373256	922.534677
4	Random Forest	41.777778	51.732753	2676.277778
5	Cat Boost	116.256856	118.311589	13997.632111
6	**Extension Decision Tree**	**3.333333**	**8.246211**	**68.000000**

Fig 2 Prediction Type Injury Evaluation table

Prediction Type Death:

	Algorithm Name	MAE	RMSE	MAPE
0	ARIMA	289.312052	331.195047	109690.159107
1	Bayesian Ridge	167.404834	222.865473	49669.019022
2	Linear SVR	234.143838	270.735772	73297.857991
3	XGBoost	128.403181	191.146958	36537.159582
4	Random Forest	154.500000	230.716697	53230.194444
5	Cat Boost	236.175301	268.920308	72318.131919
6	**Extension Decision Tree**	**14.555556**	**43.666667**	**1906.777778**

Fig32 Prediction Type Death Evaluation table

Fig41 Inputs

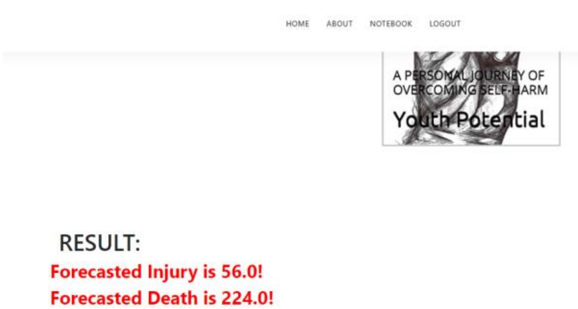

Fig 12 results

5. CONCLUSION

Acts of self-poisoning or self-harm that, whether intentional or not, cause death or non-fatal injuries are referred to as self-harm. Research has demonstrated that the emergence of new technology and the fast urbanisation of emerging nations are linked to an increase in self-harming behaviours. In order to avert these predicted tragedies or neutralise the underlying causes, policymakers and public health stakeholders may find it essential to be able to predict or even nowcast national-level patterns in self-harm. Although prior research has forecasted population-level self-harm using historical records, in some countries, these ground-truth figures may be unavailable, inadequate, and delayed, making it difficult to promptly monitor the self-harm landscape for proactive policymaking reasons. This study suggested FAST, a framework for predicting trends in self-harm at the population level by utilising mental signals gleaned from extensive social media data. The applicability of the suggested method was demonstrated in a case study that used a set of 12 mental signals taken from tweets to improve the forecastability of death and injury cases from self-harm in Thailand. The suggested method outperforms the conventional ARIMA baseline by an average of 43.56% and 36.48% in terms of MAPE, respectively. As far as we are aware, we are the first to look at the use of aggregate social media data to enhance national self-harm case forecasting and nowcasting. Even while the trial findings are encouraging, they might yet be improved. Future studies might look at deep learning forecasting methods and the usage of additional online media, such news articles, other social media platforms, or media kinds, like photographs or videos, in addition to texts. Furthermore, it would be beneficial to look into the possibility of forecasting self-harm incidents at a more detailed level, such a regional or demographic level. This might make it easier to create specialised self-harm management strategies that fit particular demographics and geographic areas.

6. FUTURE SCOPE

The future scope of this system includes enhancing predictive accuracy by integrating advanced machine learning models such as Random Forest and LSTM. Expanding the dataset with real-time social media monitoring can improve early detection of self-harm trends. Additionally, incorporating AI-driven chatbot support can provide immediate intervention and assistance to at-risk individuals. The system can be further developed into a mobile application for wider accessibility. Moreover, integrating cloud-based storage and processing will enable large-scale data handling and real-time updates, making the system more efficient and scalable for diverse user needs.

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