Prediction of Self-Harm Trends Using Machine Learning

C.Siva Kumar[1], P Lakshmi Sagar[2] , Patnam Venkataiah[3], Setti Partha Saradhi[4*], Annam Mohan Kumar [5], Velagaleti Bhavan[6]

[1]Dept of CSE(DS), Mohan Babu university (Erstwhile Sree Vidyanikethan Engineering College), Tirupati, India,
[2]Assistant Professor,Dept of CSE,SV College of Engineering, Karakambadi, Tirupati,India,
[3,4,5,6]Dept. of CSSE, Sree Vidyanikethan Engineering College, Tirupati, India

[1]Sivakumar.c@vidyanikethan.edu,[2]lakshmisagar.p@svec.edu.in, [3]joeljyo1438@gmail.com,[4*] settyparthu@gmail.com, [5]iammohankumar2659@gmail.com,[6] bhavanvelagaleti@gmail.com

Abstract. People hurt themselves by poisoning or hurting themselves in ways that cause injuries or death, even if they don't mean to. This is called self-harm. Self-harm not only hurts the people who do it, but it also hurts the income of the whole country. Self-harm is becoming more common, and studies have found a link between this and rapid growth of cities in developing countries and new technologies. It may be crucial for policymakers and public health professionals to forecast and anticipate national self-harm trends. But in some countries, it might be hard to get these kinds of past data or there might not be enough of it to make accurate predictions. This makes it harder to understand and predict the national self-harm landscape quickly. This essay suggests FAST, a system that will look at mental signs from a lot of social media data to predict trends of self-harm on a national level. These signs can be used as a stand-in for the mental health of the whole community and could be used to make it easier to predict trends in self-harm. These signals are combined into multivariate time series. Then, the time-delay embedding approach embeds these occurrences in time. Finally, several machine learning regressors are tested for future prediction. A Thailand case study found that 12 mental indications from tweets may predict self-harm-related mortality and injuries. The recommended technique predicted self-harm fatalities and injuries 43.56% and 36.48% better than ARIMA baseline. We believe our research is the first to utilize social media data to forecast and anticipate self-harm trends. Results not only help us figure out better ways to predict trends in selfharm, but they also lay groundwork for new social network-based apps that depend on being able to guess socioeconomic factors. We tried the Decision Tree algorithm and the Voting regressor, which are the best machine learning algorithms. These algorithms gave us lower MAE errors than other algorithms.

Keywords: Self-harm, cross-lingual text classification, forecasting, nowcasting, and online social networks.

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1 Introduction

Self-harm is when someone poisons or hurts themselves on purpose, no matter what their reason is or how desperate they are thinking. It can hurt or kill them. A lot of people, especially in poor countries, hurt themselves or kill themselves. A recent study found that a large number of suicides (about 77%) happened in countries with low and medium or high incomes. People think this trend has something to do with how quickly people in these areas are moving to cities and using new technologies. Self-harm is becoming more common, which not only causes sadness and loss for individuals but also has long-lasting negative effects on the economy, mostly because it lowers long-term work output. Being able to track and predict trends in self-harm across a community could help national lawmakers. Self-harm trends is via hospital and healthcare facility administrative records. This method requires a lot of money, people, and time, so data is only available sometimes and late at times.

Statistics that are too general or come too late may not be very useful for making effective policy decisions. This article presents FAST, a way to predict trends of self-harm across the country by using brain cues taken from social media data. Language-agnostic models look at messages and turn them into multivariate time series that have been changed by time-delay embedding. Decision Tree and Voting are two machine learning regressors that are better at predicting death and damage from self-harm than standard methods. This gives lawmakers useful information.

2 Literature Survey

This research looks into the complicated link between being bullied, hurting yourself, and thinking about suicide. It looks at how sadness and anxiety affect the relationship between these things differently for men and women. Based on Baron and Kenny's method, the study looks at data from 2522 Australian teens ages 12 to 17 to find out how the effects are different for boys and girls. 53.2% of the bullied people were girls and 46.8% were boys. This means that girls are more likely to be depressed, anxious, hurt themselves, or think about suicide. Logistic regressions and the Sobel test show that sadness plays a big role in the link between being bullied and self-harm and suicidality in both men and women. But worry disorders only play a role as a deciding factor in girls. These results show that bullying has a big effect on girls, which is why we need safety programs that are tailored to each gender. The study's cross-sectional methodology and reliance on self-reported data could be problems, so it's best not to draw conclusions about cause and effect. Overall, the results show how important it is to quickly create specialized programs to help deal with the different ways that bullying affects the mental health of boys and girls, with a focus on how sadness and anxiety play a part in these complicated connections.

This long-term cohort research examines 15,644 general non-psychiatric hospitalizations of persons with major mental diseases such depression, bipolar disorder, and psychosis. The aim is to determine the risk of suicide and self-harm after general hospital admission. A classification and regression tree approach were used to predict suicide attempts and self-harm in the following year using structured electronic health records from a metropolitan health system in the southwestern United States from 2006 to 2017. The previous year's data and hospitalization index were used. The program's categorization estimate was excellent since its AUC was 0.86, indicating great prediction abilities. Different types of suicide-related behavior were found in different groups of people. The highest rates were found in people who had been hospitalized after trying to kill themselves or hurt themselves in some other way. Most of the risks could be explained by mixtures of predictors, especially having an alcohol use problem along with a middling medical morbidity and being younger than 55 years old with a low medical morbidity. These results show how useful and easy-to understand machine learning algorithms could be for helping doctors make decisions, allocating resources, and planning preventative measures for adults with major mental illnesses who are in general hospitals.

3 Methodology

A. Proposed Work:
This essay suggests FAST, a system that will look at mental signs from a lot of social media data to predict trends of self-harm on a national level. These signs can be used as a stand-in for the mental health of the whole community and could be used to make it easier to predict trends in self-harm. In particular, language-agnostic models are taught to first pull out different mental signs from social media messages that have been collected. After that, various signals are combined to create multivariate time series. These are then made into instances that are embedded in time using the time-delay embedding technique. Lastly, different machine learning regressors are checked to see if they can accurately predict the future. We tested the Decision Tree algorithm and the Voting regressor, which is one of the best machine learning algorithms. It makes a smaller MAE mistake than other methods.

B. System Architecture

A method for predicting trends in self-harm at the national level using social networks is made up of several important parts. The first step is to look through the "Self-harm_and_mental_signals" collection and focus on traits that are important. After that, methods for data processing are used to clean the information and get it ready for analysis.To make it easier to test the model, the information is then split into training and testing sets. ARIMA, Bayesian Ridge, Support Vector Regression (SVR), XGBoost, Random Forest, CatBoost, Decision Tree, and a Voting Regressor ensemble are some of the predicting models.

The different methods are used to train and build each model, with hyperparameter tuning being used as needed. Performance rating measures, like accuracy, precision, memory, and F1 score, are used to see how well each model can predict trends in self-harm.

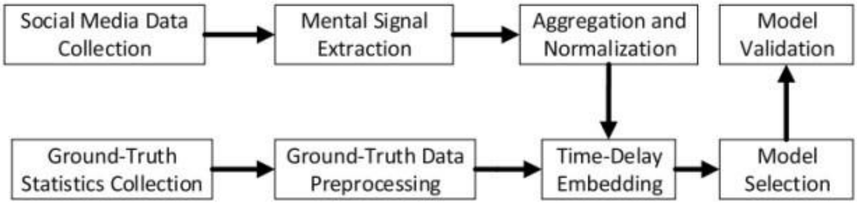

Fig.1. System Architecture

C. Dataset Collection:

The data set used in this study is an important part of looking into the connection between mental signs taken from social media data and predicting the number of self-harm cases across the country. The study is mostly about Thailand and uses a case study method that combines data from social media with real-life information about people who hurt themselves. In this study, two separate sets of data are used. The first set of data is made up of about 4.9 million tweets that were randomly gathered from October 2017 to January 2021 using the Twitter API. To make sure that the results are the same across all social media sites, only the timestamp and text from each tweet are kept. The suggested forecasting method can be used with multivariate time series data because it doesn't depend on language when pulling mental signs. This makes it easier to use in different linguistic and location settings. Thai self-harm fatalities and injuries from previous months are the second set of statistics. The Department of Mental Health of Thailand's Ministry of Public Health provided this data. It provides dependable model validation data. The dataset displays monthly tweets (bar chart on right Y-axis) and self-harm-related fatalities and injuries (line chart on left Y-axis). Specifically, death and injury cases increased from September to October 2019. Case reporting may have changed with Thailand's fiscal year changeover from October to September.

	date	MS-Pos	MS-Neg	MS-Amb	MS-Neu	ME-Ang	ME-Dis	ME-Fea	ME-Joy	ME-Sad	ME-Sur	ME-Neu	M-NST	M-ST	GH-Death	GH-Injure
0	2017-10-31	0.124349	0.217099	0.002639	0.655914	0.060558	0.001121	0.010423	0.180025	0.042351	0.098291	0.607230	0.734283	0.265717	56.0	224.0
1	2017-11-30	0.122213	0.199027	0.002266	0.676494	0.041806	0.001326	0.016026	0.182476	0.033406	0.104943	0.620016	0.753447	0.246553	45.0	239.0
2	2017-12-31	0.103728	0.244845	0.002444	0.648983	0.057183	0.001756	0.011395	0.179296	0.040314	0.113988	0.596068	0.743003	0.256997	60.0	255.0
3	2018-01-31	0.096537	0.269589	0.002332	0.631543	0.055182	0.001676	0.012206	0.152939	0.024959	0.116959	0.636079	0.746279	0.253721	88.0	336.0
4	2018-02-28	0.093888	0.288119	0.001998	0.615995	0.063627	0.001289	0.011892	0.163508	0.035321	0.118380	0.605983	0.728080	0.271920	60.0	299.0

Fig. 2. Dataset

D. Pre – processing:

Python tools like pandas and numpy are used to handle and change the datasets effectively during the data processing phase. Initially, the datasets are organized into pandas dataframes, which make it easy and quick to work with the tabular data. Then, Numpy is used for bending tasks, which makes it easier to work with data and do preparation. Dropping unnecessary fields from the datasets makes sure that only the important data is kept for training the models. This step makes the computer work faster and focuses on traits that are important for predicting trends in self-harm based on mental cues from social media. The training data is normalized, which is an important step in the planning process to make sure that all the numbers are the same size. This normalization keeps some features from being more important than others while the model is being trained, which leads to better convergence and performance.

After cleaning, the next step is to take training features and labels out of the dataset. Labels show the goal variable, which in this case is the number of recorded cases of self-harm, while features show the input factors that the model uses to make predictions. This split makes sure that the model learns patterns from the features so that it can make accurate guesses about the goal variable. This makes the forecasting system work better as a whole.

E. Training & Testing:

The information is split into training and testing sets so that the model can be tested on data it hasn't seen before. This is an important step in making sure that the predicting model works in all situations. This section lets the model learn trends from the training data and then try its ability to guess on separate test data that it hasn't seen before.For training the predicting models, the training set, which is usually a bigger part of the information, is used. The algorithms learn from the past patterns and connections in this group of data. This lets them figure out the main patterns and changes in cases of self-harm.On the other hand, the testing set stays separate during the training phase and is only used to test how well and how accurately the model works. The model's ability to make predictions based on this new data is a key indicator of how well it can predict self-harm trends in general. This test makes sure that the model doesn't just remember the training data, but also understands the patterns that can be used on new cases that haven't been seen before.Randomly splitting the data into training and testing sets is often done to make sure that the data is spread out evenly. The results on the testing set show how well the model can predict and how it might work in the real world.

F. Algorithms:

ARIMA(AutoRegressive Integrated Moving Average): This time-series forecasting technique models data temporal connections. It uses autoregression, differencing, and moving averages. This study uses ARIMA to observe self-harm tendencies over time for reliable predictions.

Bayesian Ridge: This probabilistic regression approach uses Bayesian regularization. This study uses it to estimate self-harm incidents, giving a probabilistic framework to address uncertainty and increase model resilience against dataset noise.

Support Vector Regression: SVR uses support vector machines for regression. SVR models the non-linear correlations between mental signals and self-harm in this study. It can foresee complicated dynamics due to its versatility in recording complex patterns.

XGBoost (eXtreme Gradient Boosting): This ensemble learning technique excels in regression. This project uses XGBoost for complicated connections, feature

interactions, and outlier identification. Combining numerous weak models in its boosted tree structure improves prediction accuracy.
Random Forest: This ensemble learning method mixes numerous decision trees' predictions. Due to its non-linear relationship handling, feature significance analysis, and overfitting resistance, Random Forest is used in this study to predict selfharm.
CatBoost: CatBoost supports categorical features with gradient boosting. CatBoost is used in this study because it efficiently handles category social media data, guaranteeing that mental signal information is used to accurately predict self-harm incidents.
Decision Tree: Decision Tree is a basic yet powerful regression technique. This project models self-harm decision-making using Decision Trees. Their interpretability and non-linear pattern capture make them ideal forecasting tools.
Voting Regressor: This ensemble method combines various regression algorithm predictions. This project uses it to combine model strengths to improve forecast accuracy. Diversifying algorithms improves national self-harm trend predictions.

4 Experimental Results

MAE:Without considering direction, Mean Absolute Error (MAE) measures the average magnitude of predictive errors. A regression model's efficacy is assessed by the average absolute difference between predicted and actual values.
The MAE loss function formula:

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

Where:
$\hat{y}_i$ = Predicted value for the i^{th} data point
y_i = Actual value for the i^{th} data point
n = number of observations

RMSE:
RMSD stands for Root Mean Squared Deviation, which is another name for MSE. MSE is the base for RMSE. The Root Mean Squared Error (RMSE) is a common way to find out how wrong a model is at guessing numbers. The square root of the Mean Squared mistake (MSE) tells you how big the mistake is in the same unit as the output value.RMSE is found by taking the square root of the mean of the squared differences between what was expected and what actually happened. Here's how to do it:

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

Where:
$\hat{y}_i$ = Predicted value for the i^{th} data point
y_i = Actual value for the i^{th} data point
n = number of observations

MAPE:
Mean Absolute Percentage Error, or MAPE, is a way to figure out how accurate a predicting model is as a percentage. It shows the average absolute percent difference between what was expected and what happened for all readings.

MAPE is found by taking the average of the exact percentage differences between what was expected and what actually happened. Here's how to figure out MAPE:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y_i} - y_i}{y_i}\right| \times 100$$

Where:
$\hat{y_i}$ = Predicted value for the i^{th} data point
y_i = Actual value for the i^{th} data point
n = number of observations

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

Fig.3. Performance evaluation table for death prediction

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

Fig.4. Performance evaluation table for injury prediction

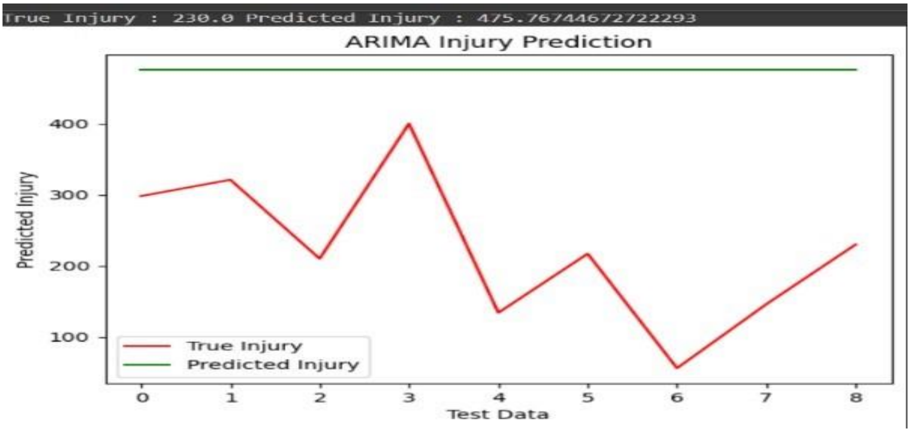

Fig.5. ARIMA injury prediction graph

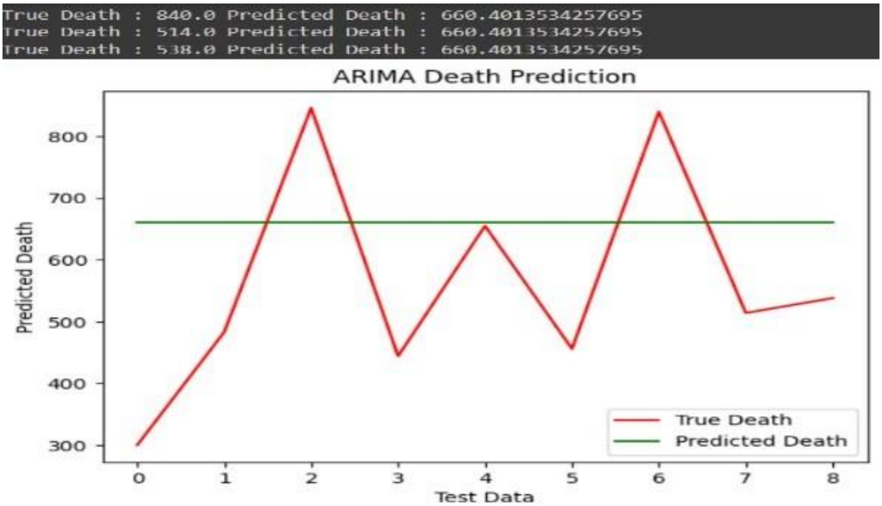

Fig. 6. ARIMA death prediction graph

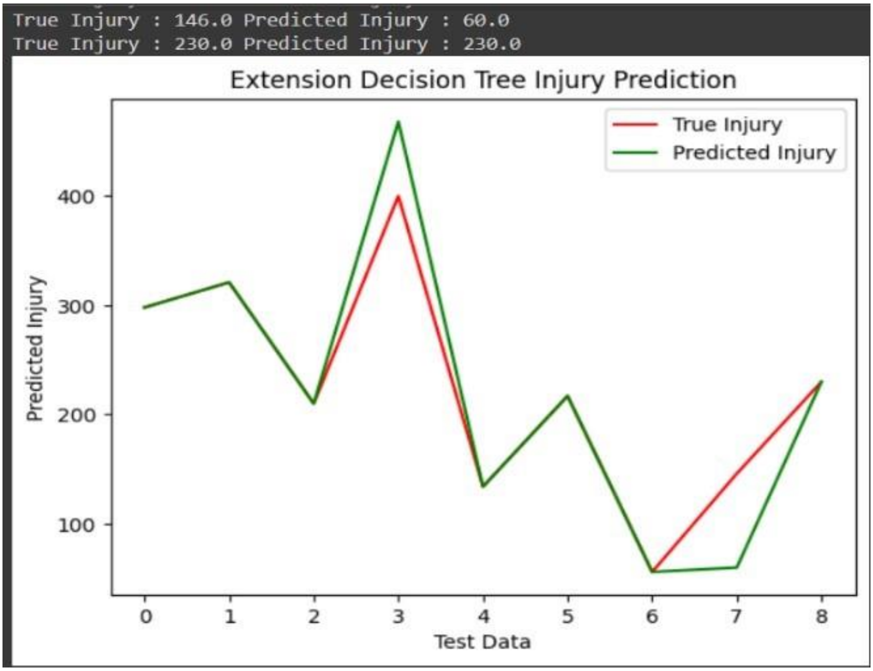

Fig.7. Extension Decision Tree injury prediction graph

Fig.8. Extension Decision Tree death prediction graph

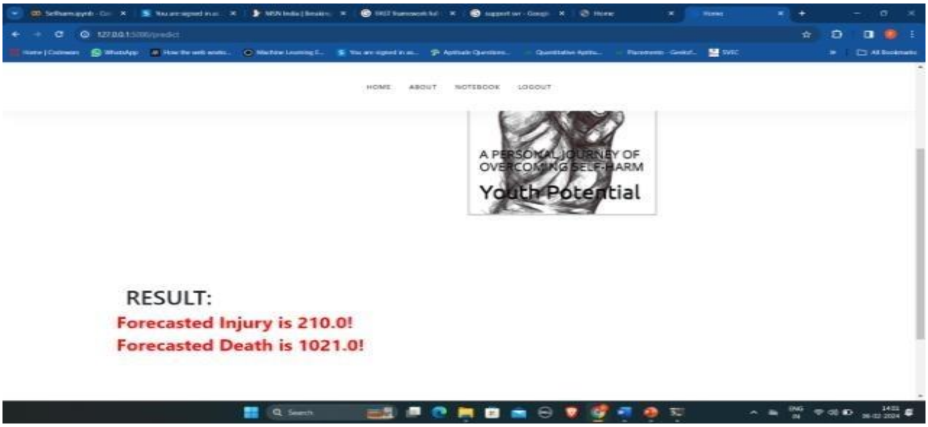

Fig.9. Predict result for forecasted injury is 210.0 and forecasted death is 1021.0

5 Conclusion and Future Scope

This study ends with the introduction of FAST, a new way to predict trends in self-harm across a whole community by using mental cues taken from a lot of social media data. The study looks at the problems that come up when ground-truth data aren't available, aren't enough, or are delayed in some countries. This makes it harder to keep an eye on things quickly enough to make smart policy decisions. Twelve mental cues taken from tweets are used in the framework to show that it can better predict self-harm death and injury cases in Thailand. Notably, FAST does better than the standard ARIMA baseline by 43.56% and 36.48% on average when it comes to Mean Absolute Percentage Error (MAPE). The new method of using bulk social media data to predict and nowcast self-harm cases at the national level shows that lawmakers and public health groups may be able to step in quickly and effectively. Even though the testing results look good, the study admits that more work needs to be done to make them even better. We are looking into more ways to use other techniques, like Decision Tree and Voting Regressor, to make the framework better all the time and help with the ongoing work to stop the rising trend of self-harm that comes with new technologies and fast urbanization in developing countries.

In the future, researchers could broaden their study by looking at different types of online media, such as news stories, different social media sites, and multimedia material like photos and videos. This would add to the collection and make the predictions more accurate. When deep learning methods are added to the data, they may reveal even more complex trends. Looking into self-harm incidents on a more specific level, like a regional or demographic level, could help in customizing management strategies. This would allow the creation of targeted interventions that are specific to certain areas and groups of people, which would improve the accuracy of prevention plans.

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