

## **Developing a Machine Learning Model for Suicide Attempt Prediction**

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**ABSTRACT\_** Because suicide contributes to many unfortunate global deaths, it is a serious issue that has to be addressed. Fewer than half of the tens of thousands of people who experience depression each year receive treatment that works. Suicidal behaviour can be viewed as a continuum that progresses from suicidal ideation to suicidal attempt to suicide. Depression is one of the factors contributing to suicide attempts. A negative attitude, an intolerance for action, and a general sensation of lethargy are all that depression is. Mental sickness, interest loss, and hopelessness are just a few of the many additional problems that depression can cause. The leading cause of disability worldwide is mental illness. The model in this research is based on the dataset analysis and understanding of numerous factors impacting suicide attempts utilising various visualisations. It is now possible to foresee suicide attempts and respond accordingly thanks to machine learning. Using a number of machine learning techniques, we can classify suicide as either Yes or No.

### **1.INTRODUCTION**

The World Health Organization ranks suicide as the 18th leading cause of death worldwide. Suicide was the tenth leading cause of death in the United States in 2018, accounting for 48,344 deaths. It also contributed to a decline in the average life

expectancy. Lastly, the classification task that is the first step in suicide prevention can be thought of as a way to accurately identify people who are at risk of suicide within a certain time frame and allow for preventative intervention. The largest meta-analysis of suicide prediction, on the other hand, looked at 365 studies and

found that predictions based on individual risk or protective factors had poor predictive accuracy and showed little change over time.

There are many factors that contributed to this prediction's failure. Most importantly, suicide is uncommon, even among high-risk individuals like those who have been in a psychiatric hospital, making it hard to predict. In addition, suicide is the result of a complex interaction of numerous factors, each of which makes a small but significant contribution, as opposed to a small number of strong, stable predictors. Even more troubling is the fact that many suicide drivers are time-varying. Some, like major depressive episodes, can change slowly, while others, like being intoxicated quickly with alcohol or another substance or feeling rejected after a relationship ends, can change quickly. Prior research typically utilized small samples, examined a limited number of characteristics, quantified at a single time point, and primarily focused on components that remained stable or enduring. As a result, previous studies lacked a large enough sample to collect complete chronic and transitory risk variables over time for effective prediction models.

Another issue arises with conventional suicide data analysis. Up to this point, customary factual philosophies prevailed,

zeroed in generally on derivation, which includes model boundary evaluations and speculation testing. It is not well-suited to working with data that contains numerous correlated, interacting components or to being programmed to include new data in order to repeatedly update the models because it produces very basic models and prioritizes interpretability over prediction accuracy.

However, the landscape of suicide prediction has been altered by two recent developments. First, massive, sophisticated, longitudinal databases, which are frequently referred to as "big data," have been created. Reception of electronic wellbeing record (EHR) frameworks, for instance, has become far reaching, bringing about a remarkable information development: Through 2020, an estimated 2,314 exabytes (an exabyte is equal to one billion gigabytes) will be produced <sup>3</sup>. EHR data is longitudinal, can be linked to other sources like vital statistics and census data, and it can include both structured and unstructured (text) data from various sources. Researchers are able to overcome low incidence rates thanks to access to huge, comprehensive datasets containing a large number of suicide cases. As a result, prevention efforts are enhanced because it is now possible to conduct a more in-depth

analysis of risk factors and potential interventions.

Additionally, individuals who are at a high risk for suicide can be identified and targeted interventions can be provided with the assistance of EHR data. Using EHR data can also make it easier to keep track of a patient's mental health over time, making it possible to catch suicidal thoughts or actions early and treat them. The use of telehealth services can also improve patient access to mental health care in isolated or underserved areas, lowering the risk of suicide among these populations. In the end, this may result in better patient outcomes and lower medical costs. In addition, this strategy may provide patients with more adaptable and practical options for receiving treatment, potentially enhancing treatment compliance and mental health outcomes as a whole.

Also, versatile numerical and measurable models, by and large known as AI, have developed, showing guarantee in conquering a significant number of the issues inborn in earlier procedures. Machine learning is well-suited for making large-scale analyses feasible, simpler, and less expensive by taking advantage of the growing amount of big data and improved computer processing power.

## **2.LITERATURE SURVEY**

**2.1 M. C. Podlogar, A. R. Gai, M. Schneider, C. R. Hagan, and T. E. Joiner, "Advancing the Prediction and Prevention of Murder-Suicide," Journal of Aggression, Conflict and Peace Research, vol. 10, no. 3, pp: 223-234, 2018.**

Suicide rate is one of the most significant issues in the world. With each year that goes by, there are an increasing number of people who commit suicide. It is estimated that 8,000 people will die while attempting suicide this year due to a variety of factors. This problem has a big impact on the families and communities of those who commit suicide in addition to the people who actually commit suicide. It is imperative to deal with the root causes of suicide and offer assistance and resources to those who are dealing with mental health problems.

**2.2 J. D. Ribeiro, X. Huang, K. R. Fox, and J. C. Franklin, “Depression and Hopelessness as Risk Factors for Suicide Ideation, Attempts and Death: Meta-Analysis of Longitudinal studies,” The British Journal of Psychiatry, vol. 212, no. 5, pp: 279-286, 2018.**

An integrated machine learning framework for the prediction of suicide risks was proposed by a researcher. The proposed structure essentially consists of three parts. 1) Extraction of temporal characteristics 2) Risk Control 3) An ensemble loop for ordinal categorization and feature selection. The framework examines temporal data patterns, controls risk factors, and chooses pertinent features for prediction in an effort to improve suicide prevention. It could be a useful tool for mental health professionals to spot people who are at high risk of suicide.

**2.3 S. Ayat, H. A. Farahani, M. Aghamohamadi, M. Alian, S.Aghamohamadi, and Z. Kazemi, “A Comparison of Artificial neural Networks Learning Algorithms in Predicting Tendency for Suicide,” Neural Computing and Applications, vol. 23, no. 5, pp. 1381–1386, 2013.**

Another researcher suggests a method for calculating the suicide rate. He suggests using the information currently available for suicides that have been reported in order to estimate individual suicidal behaviour. He claims that Sentiment Investigation, one of the most recent machine learning experiments, can play a significant role because social networking systems present a significant amount of information that is generated and collected by users. By examining the mechanism of the thought process, which is based on the opinion, view, and sentiments provided by the user, he is of

### **3.PROPOSED SYSTEM**

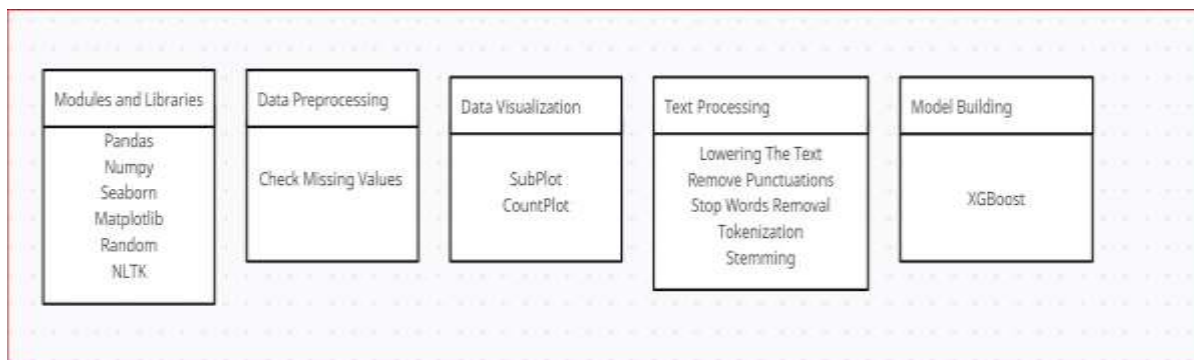
Under this proposed system, we would be creating a model that can predict whether or not a person will commit suicide. We will use XGBoost to predict the user's suicide using the text that most accurately sums up their

current predicament. The ultimate goal is to intervene and help those who are in immediate danger of suicide before it is too late. The use of this technology can help crisis hotlines and mental health professionals recognise at-risk people and offer them specialised support. However, since suicide prediction is a complex issue that needs a multifaceted approach, it is crucial to use this technology with caution and sensitivity.

### 3.1IMPLEMENTATION

A particular type of diagram that

displays the modules, components, and connections in a system is a module diagram. Modules are frequently used to group related functionality and can contain classes, interfaces, or other modules. Module diagrams are often used to explain module dependencies and the structure of the code. By identifying potential issues and visualising the dependencies between modules, developers can enhance the overall structure of the code. Module diagrams can also improve member collaboration and communication.



**Fig 1 Modules**

It involves the following modules:

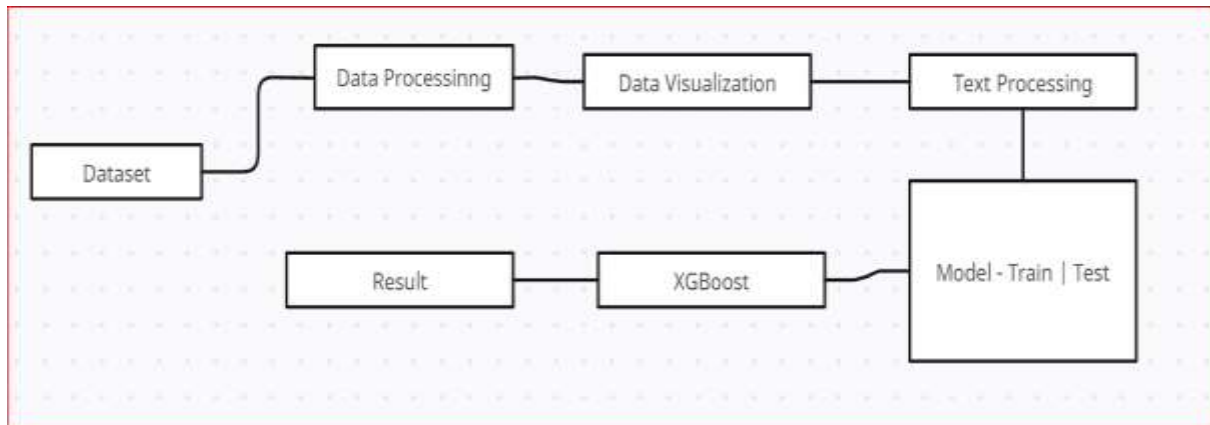
- Exporting the library's data
- Data pre-processing
- Data visualisation
- Text processing
- Building Model

The conceptual model, also known as the system architecture, of a system determines its structure, behaviour, and other characteristics. An

architecture description is a formal description and representation of a system that is designed to make it easier to analyse its structures and behaviours. System architecture and architecture descriptions are crucial to software engineering because they improve stakeholder communication, spot potential issues, and give a clear understanding of the system's design.

More efficient system development, maintenance, and evolution can be achieved with an effective system

architecture and architecture description.



**Fig 2: System Architecture**

## 5.RESULTS AND DISCUSSION

The screenshot shows a web application interface for uploading a dataset. The top bar includes a logo, the title 'Copy of Suicide Prediction', and a star icon. Below the title is a menu bar with 'File', 'Edit', 'View', 'Insert', 'Runtime', 'Tools', and 'Help'. The main area is divided into a left sidebar and a right pane. The sidebar shows a file explorer with a folder named 'sample\_data' containing a file 'Suicide\_Detection.csv'. The right pane shows a code editor with the following Python code:

```
dataset = pd.read_csv('/content/Suicide_Detection.csv')
dataset.head()
```

Below the code editor, a table displays the first five rows of the dataset. The table has three columns: 'Unnamed: 0', 'text', and 'class'.

Unnamed: 0	text	class
0	2 Ex Wife Threatening SuicideRecently I left my ...	suicide
1	3 Am I weird I don't get affected by compliments...	non-suicide
2	4 Finally 2020 is almost over... So I can never ...	non-suicide
3	8 i need helpjust help me im crying so hard	suicide
4	9 I'm so lostHello, my name is Adam (16) and I've...	suicide

**Fig 3: Dataset Upload Screen**

This picture represents the uploaded dataset from suicide cases and non-suicide cases for the analysis of the suicides and predictions of the suicide using machine learning.



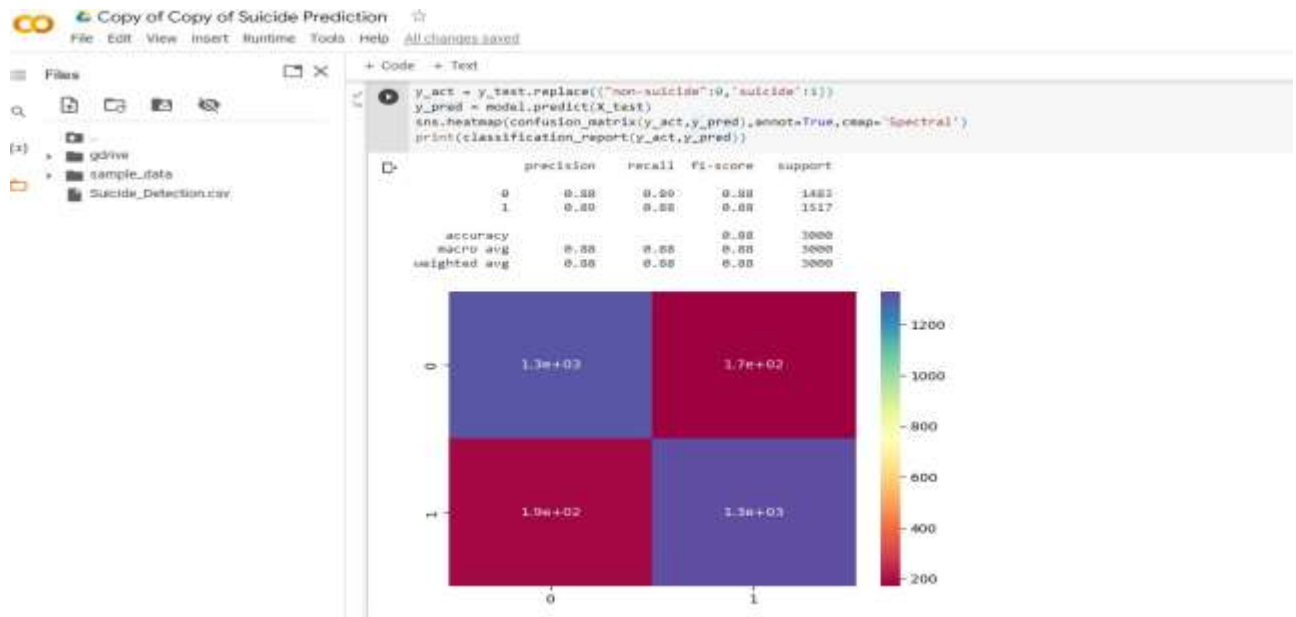
**Fig 4: Data Visualization Screen**

This picture represents the data visualization with the rates of suicide cases and non-suicide cases for the analysis of the suicides and predictions of the suicide using machine learning.



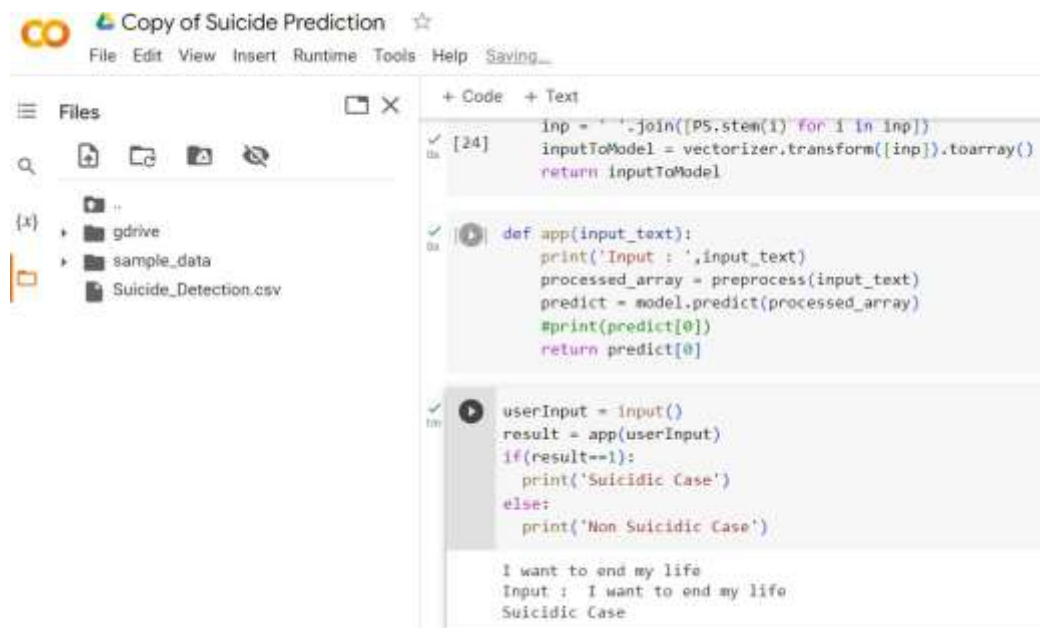
**Fig 5: Model Selection Screen**

This picture represents the model selection with the suicide cases and non-suicide cases for the analysis of the suicides and predictions of the suicide using machine learning.



**Fig 6: Classification Report Screen**

This picture represents the classification report with the suicide cases and non-suicide cases for the analysis of the suicides and predictions of the suicide using machine learning.



**Fig 7: Input and Output Screen**

This picture represents the input and output with the suicide cases and non-suicide cases for the analysis of the suicides and predictions of the suicide using machine learning.

## 5. CONCLUSION

Suicide is a deeply personal and individual matter. If you or someone



you know is in immediate danger or crisis, please reach out to emergency services or a helpline in your country right away. They can provide the necessary assistance and support. We have carefully examined the research that has been done in the field of suicide prediction. Although there have been many successful high accuracy models developed, there is still room for growth. Preliminary data analysis uncovered a number of unexpected findings, including the effect of GDP on suicides, the link between introversion and depression, and the higher suicide risk among teenage boys. The analysis conducted will also inform the government and other suicide prevention and counselling organisations about areas that need improvement so that appropriate action can be taken. Gradient boosted decision trees, one type of machine learning algorithm, consistently outperformed others and had the highest accuracy and precision.

## REFERENCES

1. M. C. Podlogar, A. R. Gai, M. Schneider, C. R. Hagan, and T. E. Joiner, "Advancing the Prediction and Prevention of Murder-Suicide," *Journal of Aggression, Conflict and Peace Research*, vol. 10, no. 3, pp:

223-234, 2018.

2. J. D. Ribeiro, X. Huang, K. R. Fox, and J. C. Franklin, "Depression and Hopelessness as Risk Factors for Suicide Ideation, Attempts and Death: Meta-Analysis of Longitudinal studies," *The British Journal of Psychiatry*, vol. 212, no. 5, pp: 279-286, 2018.

3. S. Ayat, H. A. Farahani, M. Aghamohamadi, M. Alian, S. Aghamohamadi, and Z. Kazemi, "A Comparison of Artificial neural Networks Learning Algorithms in Predicting Tendency for Suicide," *Neural Computing and Applications*, vol. 23, no. 5, pp. 1381–1386, 2013.

4. Pragya Prashar; Tanupriya Choudhury; Praveen Kumar; Karshin Khatri, Analysis & Counter Measures paradigm associated with Suicide, 2018 International Conference on Advances in Computing and Communication Engineering (ICACCE), June 2018.

5. Tarun Agarwal et. al., "Analysis and Prediction of Suicide Attempts", 2019 International Conference on Computing, Power and

Communication Technologies  
(GUCON), IEEE 2019.

6. Gen-Min Lin, Masanori Nagamine, Szu-Nian Yang, Yueh-Ming Tai, Chin Lin, Hiroshi Sato, Machine Learning Based Suicide Ideation Prediction for Military Personnel, IEEE Journal of Biomedical and Health Informatics, vol. 24, issue: 7, July 2020.
7. L. K. Richardson, B. C. Frueh, and R. Acierno, Prevalence estimates of combat-related PTSD: critical review, Australian and New Zealand Journal of Psychiatry, vol. 44, no. 1, pp.4-19, January 2010.
8. Ji-Won Baek and Kyungyong Chung, Context Deep Neural Network Model for Predicting Depression Risk Using Multiple Regression, IEEE Access, vol. 8, January 2020.
9. S.A.S.A. Kulasinghe; A. Jayasinghe; R.M.A. Rathnayaka;  
  
P.B.M.M.D. Karunarathne; P.D. Suranjini Silva; J.A.D.C. Anuradha Jayakodi, AI Based Depression and Suicide Prevention System, IEEE, 2019 International Conference on Advancements in Computing (ICAC), December 2019.

10. Jun Shen; Shihui Zhao; Mingzi Ye, Suicide Prediction Analysis with Generalized Addictive Model, 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), October 2019.
11. Shaoxiong Ji; Shirui Pan; Xue Li; Erik Cambria; Guodong Long; Zi Huang, Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications, IEEE Transactions on Computational Social Systems, September 2020.
12. Ranjitha Korrapati, Kranthi Nuthalapati, S. Thenmalar, A Survey Paper on Suicide Analysis, International Journal of Pure and Applied Mathematics, Volume 118 No. 22 2018, 239-244.

### **AUTHOR PROFILES**