“Suicide & Depression Detection Using Machine Learning”

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APPROVAL

The thesis paper titled **“Suicide & Depression Detection Using Machine Learning”** submitted by “**Towsif Ahmed (ID: 2019-1-50-060), Irean Hossain Poly (ID: 2019-1-52-005), Mohsina Zaman Mim (ID: 2019-1-50-001) & Md.Omar Faruk (ID: 2019-1-50-019)”** to the Department of Computer Science & Engineering, East West University, Dhaka, Bangladesh has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Information and Communications Engineering and approved as to its style and contents.

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DECLARATION

We declare that our work has not been previously submitted and approved for the award of a degree by this or any other University. As per of my knowledge and belief, this paper contains no material previously published or written by another person except where due reference is made in the paper itself. We hereby, declare that the work presented in this thesis paper is the outcome of the investigation performed by us under the supervision of Dr. Mohammad Arifuzzaman, Associate Professor, Department of Computer Science & Engineering, East West University, Dhaka, Bangladesh.

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Lastly, I thank the Almighty God, my parents, and friends for the much encouragement and support I have received during the period of this research. Their unconditional support made it possible for us to finish this thesis.

ABSTRACT

Nowadays, depression is the most common mental-health issue and the leading cause of suicide and self-injurious behavior. Due to social stigma and lack of knowledge, clinical diagnosis of various mental health conditions is costly and often disregarded. These days, people choose to communicate using online social media platforms to convey their ideas, sentiments, and emotions. As a result, non-clinical mental health screening and surveillance can be facilitated by using user-generated information from online social media platforms.

For quite some time, social media data has been utilized to automatically identify mental health problems through the use of traditional machine learning and natural language processing approaches. And the goal of our research is to examine how Machine Learning methods may be applied to the early detection and non-clinical, predictive diagnosis.

To the best of our knowledge, we did not find any systematic literature review that studies the applications of machine learning techniques in this domain. In order to address this research gap, we conducted a systematic literature review relevant research studies published until date that have applied machine learning techniques for detecting depression and suicide or self-harm behavior from social media content. Our work comprehensively covers state-of-the-art WRT. techniques, features, datasets, and performance metrics, which can be of great value to researchers. We enumerate all the available datasets in this domain and discuss their characteristics.

We also discuss the research gaps, challenges, and future research directions for advancing & catalyzing research in this domain. To the best of our knowledge, our study is the only and the most recent survey for this domain covering the latest research published until date. Based on our learnings from this review, we have also proposed a framework for mental health surveillance. We believe the findings of our work will be beneficial for researchers working in this domain.

Table of Content

Chapter One (Introduction)

Chapter Two (Literature Review)

Chapter three (Comparison between machine learning & deep learning)

Chapter Four (Research Problem)

Chapter Five (Methodology)

Chapter Six (Survey Report)

Chapter Seven (Conclusion and Future Work)

List of Tables

List of Figures

List of Diagrams

Chapter One

1.1 Introduction

Machine learning has applications in deferent area like Natural Language processing [1][2][3], cyber security [4][5][6][7], medical [8][9][10], Predicting the Success of Bank Telemarketing [11], Traffic sign recognition [12] etc .

In the current digital age, social media platforms have expanded into a vast ocean of human expression, providing a previously unheard-of window into society at large. People utilize social media platforms to share their thoughts, feelings, and experiences, making it a rich collection of textual data revealing people's deepest ideas and feelings [13][14]. Millions of individuals experience depression, a complex emotional state, among these mental health conditions that seriously impairs their quality of life and general well-being. It's critical to diagnose depression early.

However, conventional methods of identifying depressive symptoms often fail because of their intrinsic flaws, such as their reliance on subjective self-reporting or lack of scalability. Combining the strengths of machine learning (ML) offers a fresh and intriguing solution to this urgent issue. Using ML techniques, this work aims to identify the subtle language patterns and emotional clues present in textual data from social media platforms. By searching through these massive amounts of unstructured data for relevant information, we try to develop an accurate and dependable depression detection system. The scope of this study goes beyond simply classifying sentiment as good or negative.

Rather, it examines language use more closely to identify indicators of emotional distress that human observers would miss. By using this process, we want to raise the technological mist that envelops depression and deepen our knowledge of mental health in general. The framework for our ML-based approach to the identification of depression from textual social media data will be presented in this paper. We'll go over the approaches used for gathering data, preparing it, and extracting features while emphasizing the role different language cues have in categorization. We will also explain the machine learning algorithms that we used to train our prediction model and discuss their accuracy and effectiveness. We'll go through the techniques for gathering data, pre-processing it, and extracting features. We'll focus on how important different linguistic signals are to the classification process. We will also elucidate the efficacy and precision of the machine learning algorithms that were employed in the training of our predictive model. We acknowledge, though, that the analysis of personal data presents ethical issues, especially in relation to mental health.

Therefore, we emphasize the importance of privacy protection and data anonymization throughout this study to ensure the ethical and responsible implementation of our suggested approach. In summary, our research attempts to bridge the gap between digital and mental health by leveraging the transformative potential of ML to analyze vast amounts of text data from social media platforms in order to gain a better understanding of depression. By taking this action, we hope to support the worldwide effort to lower the stigma associated with depression and enhance people's quality of life.

1.2 Background

The incidence of Suicide & Depression has affected millions of people's lives globally, making it a serious public health concern. To lessen the burden associated with this mental health illness, early detection and intervention are essential. Users of social media platforms freely share their thoughts, feelings, and experiences, transforming these platforms into vast repositories of human expression. Researchers and medical professionals believe social media has the potential to be a helpful tool for developing a more thorough understanding of mental health. But it would be time-consuming and impractical to manually analyze such massive amounts of data. It has spurred the creation of novel approaches that detect depression using machine learning (ML) techniques. Following the application of ML techniques to textual data from social media platforms, researchers seek to discern emotional cues and linguistic markers linked to depression.

To create scalable and accurate depression detection models, a variety of features are extracted, including context, word usage, linguistic style, and sentiment analysis. The successful application of these models might have a significant impact. Early detection of those who are at risk may result in prompt assistance and intervention, which may lessen the intensity and length of depressive episodes. The knowledge acquired could help mental health organizations, legislators, and medical professionals create focused interventions and support networks. As promising as these methods may be, handling sensitive mental health data from social media requires careful consideration of ethical issues.

Consent, responsible use, and data privacy are essential components of any study or application in this field.

Finally, using ML techniques to diagnose depression from social media text data provides a powerful tool to learn about societal trends in mental health and individual emotional suffering. This emerging field has the potential to transform mental health services and advance society's understanding of depression.

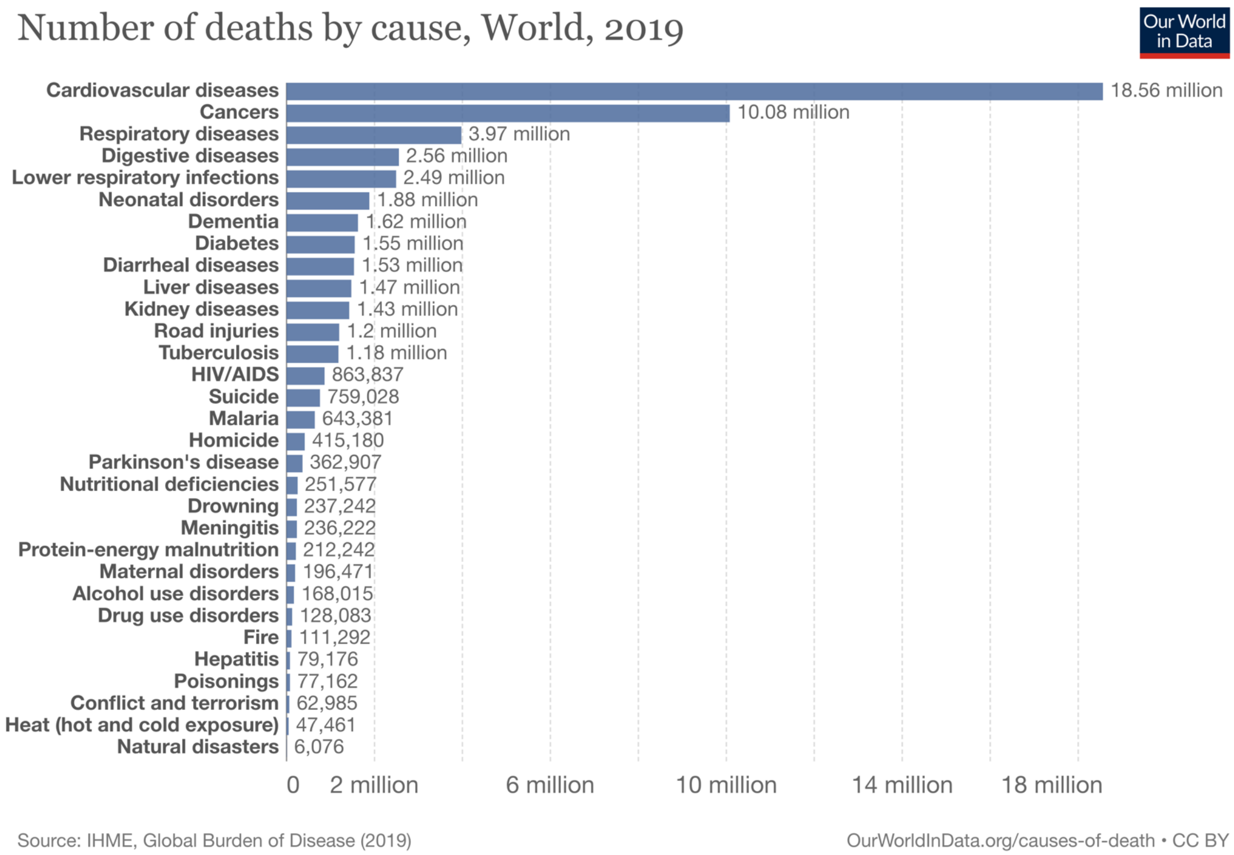


Figure 1.2: Number of deaths by cause

As the graph illustrates, the World Health Organization (WHO) and the Global Burden of Disease research project that approximately over 700,000 people commit suicide annually worldwide.

1.3 Definition

The process of automatically recognizing and categorizing instances of depression or emotional distress from the massive volume of text-based content shared by users on social media platforms is known as "depression and suicide detection textual data using machine learning" (ML). By using machine learning (ML) algorithms to learn from labeled data and identify particular language characteristics associated with depression, a predictive model can be developed that can differentiate between posts that reflect depressive symptoms and those that indicate emotional well-being.

The process typically involves several key stages:

1. Data Collection: Obtaining textual data from various social media platforms, frequently through the use of APIs or web scraping methods, while adhering to privacy and ethical considerations.

2. Data Preprocessing is the process of cleaning and transforming raw text data to remove noise, irrelevant information, and personal identifiers while retaining essential linguistic features.

3. Model Training: Using the labeled dataset, a machine learning classifier is trained to identify patterns in textual data associated with depression and emotional distress.

4. Model Evaluation: determining the trained model's accuracy, precision, recall, and F1 score to evaluate its performance, ensuring the model's dependability in detecting depression.

5. Deployment: Using the trained model to automatically classify them as indicative of depression or not.

Suicide and depression detection using ML holds great promise for mental health research and support. However, when dealing with sensitive mental health information, researchers and developers must prioritize ethical considerations such as data privacy, consent, and the responsible use of technology.

1.4 Motivation

In recent days, Depression has become a major public health concern around the world, affecting the lives of millions of people by causing suicide. Early detection and intervention are critical for mitigating the effects of this mental health condition. Users openly share their thoughts, emotions, and experiences on social media platforms, which have evolved into massive repositories of human expression. According to researchers and medical practitioners, social media has the potential to be a useful tool for understanding mental health on a larger scale. The abundance of textual data on these platforms provides an opportunity to gain insight into people's emotional well-being. Manually analyzing such massive amounts of data, on the other hand, is impractical and time-consuming. Any research or application in this domain must ensure data privacy, consent, and responsible use.

Finally, using ML approaches to diagnose depression from social media text data provides a powerful tool for gathering insightful knowledge about societal trends in mental health and personal emotional suffering. This burgeoning field has the potential to transform mental health care and advance societal understanding of depression.

1.5 Problem Statement

Depression is a widespread mental health problem that affects a significant portion of the world's population. Giving support and assistance to people in emotional distress necessitates prompt recognition and response. People are increasingly posting text-based updates about their ideas and feelings on social media platforms, providing a rare opportunity to access this vast pool of human expression. The goal of this study is to create an efficient and accurate depression detection system using Machine Learning (ML) algorithms and textual data from social media. The difficulty comes from identifying subtle linguistic patterns and emotional cues that may indicate the presence of depressive symptoms in user-generated content.

-For this investigation, we used a variety of performance measurement criteria.

-One of the most significant achievements of this research is that, if trained on a large enough dataset, the system can distinguish between text samples with the required class level.

-We used a number of data-processing techniques, such as stemming and lemmatization, before applying roughly seven machine learning classifiers. By selecting a model that can recognize depression in any English-language text sample, we can improve the accuracy of our research.

1.6 Limitations

However, there are some limitations in our research. This research will not cover all the detection techniques. We use several algorithms in our detection techniques but we will not try all the algorithms for detection techniques. Apparently, no model will give us 100% accuracy.

Moreover, in our research we will try to focus on the important techniques and features of Suicide & Depression detection.

1.7 Thesis organizations

Our thesis consists of ten chapters. These are organized as follows:

1. Chapter 1: Introduction, Background, Problem statement, Motivation, Limitations and Thesis organizations.
2. Chapter 2: Literature Review
3. Chapter 3: Comparison Between Machine Learning and Deep Learning
4. Chapter 4: Research Problem
5. Chapter 5: Methodology
6. Chapter 6: Survey report
7. Chapter 7: Conclusion and Future Work

Chapter Two

(Literature Review)

2.1 Suicidal profiles Detection in Twitter

In [15], authors address the urgent issue of suicide prevention by proposing a machine learning-based approach for identifying individuals at risk on Twitter. Analyzing a dataset of 115 suicidal and 172 non-suicidal profiles, the study employs Random Forest and Ada-boost algorithms on semantic features extracted from tweets and account information. Results demonstrate promising outcomes, with the Random Forest classifier achieving a 77% F-measure based on tweet features alone. The study underscores the significance of considering both tweets and profile data for robust analysis, presenting a Java-based prototype for detecting suicidal profiles. The authors express a commitment to refining results and expanding their approach to other platforms, highlighting the paper's substantial contribution to advancing suicide prevention through innovative machine learning applications on social media.

2.2 Machine Learning and Semantic Sentiment Analysis based Algorithms for Suicide Sentiment Prediction in Social Networks.

In [16], the authors confront the challenge of rising user-generated content related to suicide. Utilizing the Weka tool for data mining and machine learning analysis, and Twitter4J for data collection, the paper's innovation lies in integrating semantic analysis with the WordNet database. The sentiment analysis, particularly focused on suicidal acts, demonstrates notable precision (89.5% with SMO) and recall (78.8% with Naive Bayes) with a dataset of 892 tweets, identifying potential suicide-related content. The paper recommends future work for refining techniques, exploring multilingual WordNet for tweets, and adapting the methodology to big data environments. This literature provides a comprehensive methodology integrating machine learning, semantic analysis, and a specialized vocabulary for social network suicide prevention, offering valuable insights for future research in this critical domain.

2.3 Suicide Risk Assessment Using Machine Learning and Social Networks

In response to the escalating global challenge of suicide, exacerbated by the COVID-19 pandemic, Castillo-Sanchez et al. (2020) advocate the application of machine learning (ML) methods on social networks for enhanced suicide risk assessment. Their scoping review systematically delves into existing literature on ML techniques, emphasizing the extraction of features from social media content to predict and identify suicide risk. The authors employ a meticulous process, narrowing down 426 articles to 16 pertinent papers, focusing on studies that seamlessly integrate social media analysis, ML model development, and the practical application of ML techniques in suicide risk assessment. The findings underscore the predominance of linguistic analysis, particularly the Linguistic Inquiry and Word Count method, alongside the effectiveness of Python-based models and Support Vector Machines in identifying suicide risk, particularly among vulnerable groups. Beyond offering a comprehensive summary and comparison of current methods, the study charts future research trajectories, advocating for initiatives such as the creation of language-diverse annotated corpora and the development of novel ML models to further refine suicide risk estimation.

2.4 Detection of Suicidal Ideation in Clinical Interviews for Depression Using Natural Language Processing and Machine Learning

The study conducted by JC and TMHL in June 2023 contributes to the burgeoning field of suicide risk assessment within the context of depression by employing a comprehensive approach utilizing natural language processing (NLP) and machine learning (ML). Addressing the inherent challenges of assessing suicide risk, especially when patients deny ideation, the research fills a crucial gap by investigating nuanced language features extracted from clinical interviews. The study builds upon prior research linking linguistic features to suicide risk and extends the analysis beyond conventional markers such as first-person singular pronouns and negative emotion words. By categorizing participants into nonsuicidal, low-suicide-risk, and high-suicide-risk groups based on structured interviews using the Hamilton Depression Rating Scale, the study establishes a correlation between suicide risk and depression severity. The findings not only reveal significant word count differences among these groups but also underscore the potential of distinct language features associated with suicidal ideation. This model, developed for more accurate detection, contributes valuable insights to suicide risk assessment in clinical settings, paving the way for enhanced intervention strategies.

2.5 Detecting and Analyzing Suicidal Ideation on Social-Media Using Deep Learning and Machine Learning Models.

In their October 2022 paper titled "Detecting and Analyzing Suicidal Ideation on Social Media Using Deep Learning and Machine Learning Models," Aldhyani et al. contribute to the burgeoning field of mental health research by proposing a Suicidal Ideation Detection System (SIDS). Leveraging machine learning, artificial intelligence, and the LIWC-22 psycholinguistic analysis tool, the authors utilized a comprehensive Reddit dataset from SuicideWatch, comprising 232,074 posts. The results showcase the efficacy of SIDS in identifying suicidal ideation, with CNN–BiLSTM and XGBoost models achieving notable accuracies of 95% and 91.5% using textual features. Furthermore, the authors observed that while the processing of textual data with CNN–BiLSTM was more time-consuming, it outperformed XGBoost. The study also shed light on the psychological distress evident in suicidal posts, as revealed by higher LIWC feature values. The research underscores the potential of advanced computational methods in monitoring mental health signals on social media platforms.

2.6 Hierarchical Multiscale Recurrent Neural Networks for Detecting Suicide Notes.

In their 2021 paper titled "Hierarchical Multiscale Recurrent Neural Networks for Detecting Suicide Notes," Annika M Schoene, Alexander P Turner, Geeth De Mel, and Nina Dethlefs tackle the critical issue of suicide prevention through a pioneering machine learning approach. Focusing on the identification of suicide notes within the expansive realm of social media, the authors leverage recurrent neural networks, specifically introducing a dilated LSTM with attention, to analyze textual data. Notably, the study employs a diverse dataset, encompassing genuine suicide notes, depression notes from Reddit, and neutral blog posts, reflecting real-world scenarios. The proposed model achieves remarkable f1-scores of 88.26% and 96.1% in two experiments, showcasing superior performance compared to established benchmarks. The incorporation of visualizations highlights the model's adeptness at discerning crucial linguistic features, such as emotions and personal pronouns. This research, positioned within the broader context of AI for Social Good, contributes significantly to global efforts in addressing mental health challenges and aligns with the UN Sustainable Development Goals for suicide prevention. The findings underscore the effectiveness of the dilated LSTM with attention in handling sequential data with variable lengths, thereby advancing the field and providing valuable insights for future research in the realm of suicide prevention and mental health support.

2.7 Depression and Suicide Analysis Using Machine Learning and NLP.

In their 2021 study titled "Depression and Suicide Analysis Using Machine Learning and NLP," Pratyaksh Jain, Karthik Ram Srinivas, and Abhishek Vichare employed a machine learning and natural language processing (NLP) approach to discern indications of depression in individuals based on their posts from Reddit subreddits and applying machine learning models, including Logistic Regression, Naïve Bayes, Support Vector Machine, and Random Forest. Notably, their models demonstrated accuracies ranging from 74.35% to 77.29%, with Logistic Regression achieving the highest accuracy. The findings underscore the significance of platforms like "SuicideWatch" on Reddit for identifying individuals at risk, highlighting the potential of online spaces as supplementary tools for mental health assessments. The study advocates for the integration of diverse data sources and machine learning models to enhance early detection and intervention efforts in addressing depression-related concerns, emphasizing the promising role of online platforms in comprehensive mental health support.

2.8 Depression prognosis using natural language processing and machine learning from social media status.

The study by Md. Tazmim Hossain, Md. Arafat Rahman Talukder, and Nusrat Jahan (2021) addresses the urgent global concern of depression through a novel approach utilizing natural language processing (NLP) and machine learning (ML) on social media data. Collecting a dataset of 2,000 sentences from diverse platforms such as Facebook, Twitter, and Instagram, the authors employed meticulous preprocessing techniques, including tokenization, stop word removal, and lemmatization. The refined dataset was then used to train six ML classifiers, with multinomial Naive Bayes (MNB) and logistic regression (LR) demonstrating remarkable performance, achieving a notable 98% accuracy in identifying potential signs of depression from social media statuses. The research emphasizes the significance of early detection by mining textual expressions on social media platforms, showcasing the potential of ML in mental health detection. The results not only highlight the effectiveness of MNB and LR but also underscore the importance of addressing the challenge of data collection for depression detection. The study contributes to the growing body of literature supporting the integration of NLP and ML in addressing mental health issues through innovative data-driven approaches.

2.9 Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms

In the 2019 paper titled "Predicting Anxiety, Depression, and Stress in Modern Life using Machine Learning Algorithms" by Anu Priya, Shruti Garg, and Neha Prerna Tigga, the authors address the prevalence of anxiety, depression, and stress in the modern world through the application of machine learning algorithms. Employing data from employed and unemployed individuals across diverse cultures, the Depression, Anxiety, and Stress Scale questionnaire (DASS 21) was utilized for predictions of severity levels using five distinct machine learning algorithms, including Decision Tree, Random Forest Tree, Naïve Bayes, Support Vector Machine(SVM), and K-Nearest Neighbour. The study revealed imbalances in class distribution within the confusion matrix, emphasizing the importance of the f1 score in cases of classification imbalance. Notably, Naïve Bayes emerged with the highest accuracy across all scales, while Random Forest excelled in stress prediction and Naïve Bayes in depression. The research underscores the significance of employing advanced computational techniques in understanding and predicting psychological health issues in a fast-paced world, with Random Forest identified as the most accurate model for this specific study. The authors also discuss the specificity parameter's consistent high values (>90%), crucial for accurate identification of negative cases in healthcare. The paper contributes to the literature on mental health prediction, shedding light on the efficacy of various machine learning models and the importance of considering diverse evaluation metrics in addressing classification challenges.

2.10 Detection of Suicide Attempters among Suicide Ideators Using Machine Learning.

In the groundbreaking study titled "Detection of Suicide Attempters among Suicide Ideators Using Machine Learning," conducted by Seunghyong Ryu, Hyeongrae Lee, Dong-Kyun Lee, Sung-Wan Kim, and Chul-Eung Kim and published on August 21, 2019, the authors address the critical issue of suicide risk in Korea. Employing a meticulous approach, the research leverages machine learning algorithms to develop predictive models capable of identifying individuals with an elevated risk of suicide attempts. The study meticulously selected 47 relevant variables, imputing missing data using the Multiple Imputation by Chained Equations (MICE) method and addressing class imbalance through the Synthetic Minority Over-sampling Technique (SMOTE). The resulting dataset of 2,654 samples underwent normalization and was divided into training and test sets. The model, trained on factors such as "days of feeling sick or in discomfort," "AUDIT score," and "average work week," demonstrated remarkable accuracy (0.865) in the training set and exceptional performance in the test set, achieving an AUC of 0.947 for predicting suicide attempts. The feature selection process highlighted 41 key features, emphasizing the robustness of the model in efficiently screening and identifying individuals at heightened risk. The study's findings underscore its potential for facilitating targeted preventive interventions and contributing significantly to suicide prevention efforts in the broader population.

Chapter Three

(Comparison Between Machine Learning and Deep Learning)

3.1 Comparison Between Machine Learning and Deep Learning:

First of all, Machine learning refers to the use of algorithms by computers to learn from data and carry out tasks automatically without explicit programming. In contrast, Deep Learning makes use of sophisticated algorithms with a brain-inspired design. This makes it possible to process unstructured data, including text, photos, and documents.

1. Human Intervention

For machine learning to produce results, more constant human engagement is needed. Although more difficult to set up, deep learning requires less intervention once it is running.

2. Hardware

While deep learning systems demand far more powerful hardware and resources, machine learning applications are frequently less complex than deep learning algorithms and can frequently be executed on standard PCs. The rising use of graphics processing units is a result of this power consumption. Due to thread parallelism, GPUs may disguise latency (delays) in memory transfer and have high bandwidth memories (the ability of many operations to run efficiently at the same time.)

3.Time

The efficiency of machine learning systems may be limited despite their ease of setup and operation. Deep learning systems take more effort to setup but deliver results right away (although the quality is likely to improve over time as more data becomes available).

4. Approach

Machine learning frequently makes use of traditional methods like linear regression and requires well-organized data. Deep learning, which is intended to handle vast amounts of unstructured data, uses neural networks.

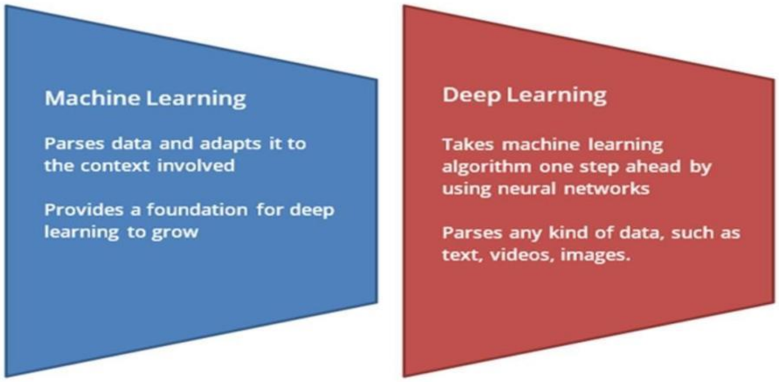


Figure 3.1: **Machine Learning and Deep Learning**

5. Applications

Machine learning is already in use in your email inbox, bank, and doctor’s office. Deep learning technology enables more complex and autonomous programs, like self-driving cars or robots that perform advanced surgery.

Machine Learning	Support Vector Machine	94.86
	Naïve Bayes Classifier	94.08
	Random Forest	96.24
	Logistic Regression	95.01
Deep Learning	Bi-LSTM	95.22

Table 3.1: Accuracy difference between machine learning and deep learning models

We can observe from the accuracy difference table that there isn't much of a difference between machine learning and deep learning models. Both models provide a decently high accuracy rate. If we compare those two models, the only accuracy difference we find is 1%.[7]

Machine Learning:

Advantages and Disadvantages of Machine Learning:

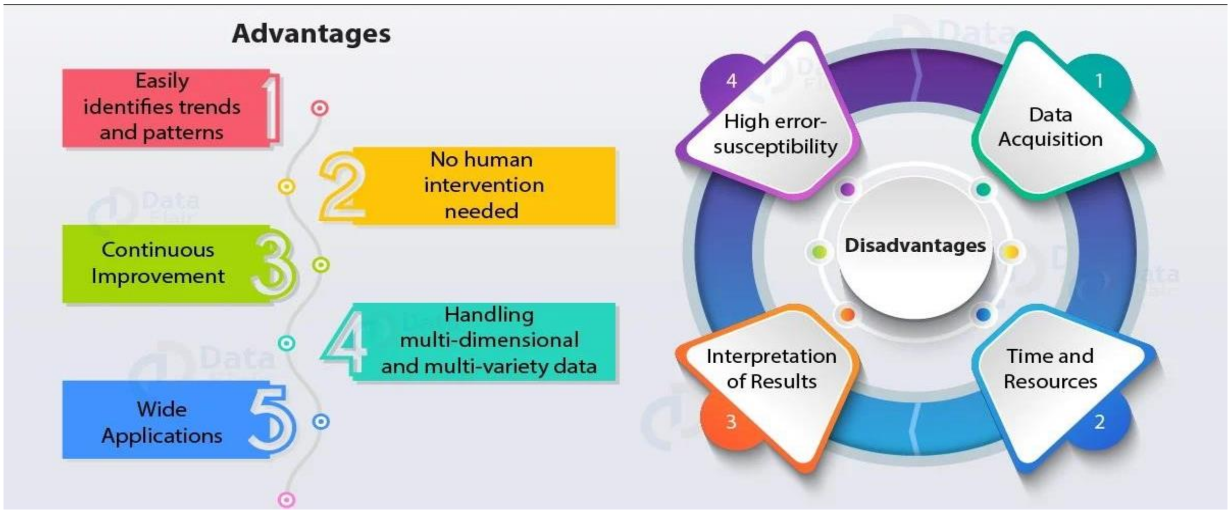


Figure 3.2: Advantages and Disadvantages of Machine Learning

3.2 Advantages of Machine learning:

1. Easily identifies trends and patterns:

Large amounts of data can be reviewed by machine learning, which can identify specific trends and patterns that humans might miss. An e-commerce site like Amazon, for example, can give its consumers the proper products, discounts, and reminders by getting to know their browsing habits and previous purchases. It uses the information to display to them relevant advertisements.

2. No human intervention needed (automation):

User no longer have to supervise your project at every stage thanks to ML. Giving computers the ability to learn enables them to make predictions and enhance algorithms on their own. Anti-virus programs are a typical illustration of this; they learn to filter new dangers as they are identified. ML is proficient at identifying spam.

3. Continuous Improvement:

ML algorithms keep becoming more accurate and effective as they gather experience. They can consequently make wiser selections. Consider developing a model for weather predictions. As your data collection grows, your algorithms get faster and more accurate at making predictions.

4. Handling multi-dimensional and multi-variety data:

In dynamic or uncertain contexts, machine learning algorithms are adept at managing data that is multidimensional and multivariate.

5. Wide Applications:

As an e-tailer or a healthcare provider, you can benefit from ML. Where it does apply, it has the ability to help in giving customers a far more individualized experience while also focusing on the right demographic. Researchers are currently creating more sophisticated computers as a result of ML. These machines are capable of handling a wide range of Machine Learning models and methods. Despite the rapid expansion of automation, we still do not entirely rely on it. With its automation, machine learning is gradually changing the sector.

6. Best for Education and Online Shopping:

The ideal educational instrument of the future would be machine learning. It offers incredibly innovative study aids for students.

A school in China just began using ML to increase pupil attentiveness. The ML model analyzes your online buying searches. It would show you ads based on your search history. This will relate to your prior searches' search preferences. The data for the model in this is derived from the search history.
This is a fantastic method to use ML to enhance e-commerce.

3.3 Disadvantages of Machine Learning:

With all those advantages to its power and popularity, Machine Learning isn’t perfect. The following factors serve to limit it:

1. Data Acquisition:

Machine learning demands large, comprehensive, unbiased, and high-quality data sets for training. They might occasionally have to wait while new data is generated.

2. Time and Resources:

The algorithms must have enough time to develop and learn sufficiently to meet their objectives with a high level of accuracy and relevance for machine learning (ML) to be effective. Also, it uses a lot of resources to function. You might need extra processing power as a result, even with a competent PC.

3. Interpretation of Results:

The capacity to correctly comprehend the information produced by the algorithms presents another significant challenge. Also, you must carefully select the algorithms for your needs.

4. High error-susceptibility:

Although autonomous, machine learning is prone to mistakes. Consider training an algorithm with data sets that are too tiny to be inclusive. You obtain biased predictions from a biased training set in the end. This results in customers seeing irrelevant advertisements. Such flaws in ML can start a cascade of mistakes that may be undiscovered for a very long time. Furthermore, it takes a while for problems to be detected, and even longer for solutions to be found.

5. Social Changes:

Machine learning is bringing numerous social changes in society. The role of machine learning-based technology in society has increased multifold. It is influencing the thought process of society and creating unwanted problems in society. Character assassination and sensitive details are disturbing the social fabric of society.

6. Elimination of Human Interface:

Human interface has been removed from some tasks by automation, AI, and machine learning. Opportunities for work have been eliminated. All of those tasks are now completed with the aid of machine learning and artificial intelligence.

7. Highly Expensive:

This software is highly expensive, and not everybody can own it. Government agencies, big private firms, and enterprises mostly own it. It needs to be made accessible to everybody for wide use.

3.4 Challenges of Machine Learning:

Figure 3.4: Challenges of Machine Learning

1: Lack of training data

Machine learning models typically require training data or details and examples of exactly what you want them to perform for your business. Let's take a simple illustration. Create a brand-new machine learning-based algorithm that can discriminate between the text is either suicidal or neither non-suicidal.

In other cases, the data required is available, but it is of very poor quality. users cannot expect to produce an algorithm that is both fully functional and efficient if you begin with data of low quality. Contrarily, it will be flawed and ineffective. Because of this, it is believed that organizing and cleansing data constitutes the great majority of the labor done by data scientists. And if it's not, no matter how extensive it may be, it's meaningless from the AI's perspective.

Tools for data quality are useful in this situation. They are made to eliminate difficulties that lower the quality of your data, such as formatting flaws, typos, redundancies, missing entries, and other problems. You may trust us that these errors happen frequently in the vast majority of businesses. More isn't always better in the area of machine learning.

3: Data over-fitting

Data over-fitting is the process of creating an overly complex machine-learning model and attempting to fit it into a small collection of data. It's referred to as over generalization in the human world. Let's utilize an example once more. Consider the possibility that a man in a black beanie recently robbed us.

Will users automatically assume that somebody sporting a black beanie is a mugger? Otherwise, people will get caught in the over-generalization trap. And in the domain of machine learning, the same thing is also possible.

As a result, your machine learning model works brilliantly on a training dataset (yes, in that particular situation, black beanie = a mugger), but in more instances and cases, it fails to generalize properly (in the real world, black beanie doesn't necessarily mean a mugger). That's data over-fitting.

4: Irrelevant features

Training data is not the only factor in machine learning algorithms. In order for our algorithm to be trained, also needs a good set of features. Let's revisit the suicidal text versus non-suicidal text comparison. Every textual data has a specific set of characteristics that are listed below: subject line, words used, links, etc. All of these qualities are important.Choosing which features in our case are irrelevant was logical and easy. You'll need to consider this matter for a while in many real-life scenarios.

5: Accessibility

In a sense, machine learning features are accessible for a relatively low cost. A lot of SaaS platforms come with built-in ML capabilities, and purchasing one is not that expensive. Yet, you must be prepared to make a significant financial commitment if you want deep learning (much alone machine learning!) system that is specifically tailored to the requirements of your business.

Since machine learning will enable the company to save a great deal of time and labor-intensive manual labor, we naturally conclude that it will be a successful long-term strategy. Nevertheless, due to the hefty upfront cost, many smaller businesses simply cannot afford to implement machine learning models, even if they wanted to. It is one of the most significant issues that have to be resolved. The good news is that this issue has already made some progress. No-code AI is one of the newest developments in artificial intelligence. We firmly believe that sooner or later, artificial intelligence will reach a level of sophistication where you can create models and algorithms using straightforward drag-and-drop builders, much like you can do today to create WordPress websites.

6: Deployment

Although it sounds funny, many machine learning experts have trouble deploying their projects correctly. Those who deal with ML occasionally have trouble understanding business issues.

Its algorithms, which in theory should address these issues, are consequently usually disproportionate or insufficient, making the entire effort useless. There is just one approach to solving this problem. You require a group of specialists who are not only qualified in machine learning but also in business. Users can only ensure having a good project will be beneficial from a business standpoint in this manner.

7: Video training data

Most machine learning models used today are trained on static data, such as texts and images. Using dynamic data to "train" machine learning algorithms is still a difficulty. When we figure out how to teach machine learning models using films, audio, and animations, just think of how advanced they will be in the future.

8: Object detection

In theory, everything is cut and dried. Mostly solely on identifying different things in photos, object detection is a feature. Two other AI-related technologies—Deep learning and computer vision— make object detection possible. Deep learning is used by computer vision-based technologies to extract picture fragments and analyze them in order to find patterns. Face identification is one of the most sophisticated methods of object detection, mainly because human faces have a variety of distinctive traits and, generally speaking, are relatively comparable.

All of these factors must be considered by the deep learning algorithms in order to correctly identify a specific person. Yet even though we are aware of and understand how this technology operates, object detection is still a difficult task for many algorithms.

3.5 Deep Learning:

Deep learning is a subset of machine learning that uses artificial neural networks (ANNs) to model and solve complex problems. It is based on the concept of creating deep neural networks, which are artificial neural networks with many layers and the ability to learn hierarchical representations of the input.

Figure 3.5: Deep Learning

3.6 Advantages of Deep Learning:

Deep learning has several advantages over traditional machine learning methods, some of the main ones include:

Deep learning has several advantages over traditional machine learning methods, some of the main ones include:

1. **Automatic feature learning:**

Deep learning algorithms don't need manually designed features because they can automatically learn them from the data. This is especially helpful for tasks like picture recognition when the features are hard to describe.

2. **Handling large and complex data:**

Large and complicated datasets that would be challenging for conventional machine learning algorithms to process can be handled by deep learning methods. This makes it a practical tool for gaining insights from large amounts of data.

3. **Improved performance:**

State-of-the-art performance on a variety of issues, such as image and speech recognition, natural language processing, and computer vision, has been demonstrated using deep learning methods.

4. **Handling non-linear relationships:**

Deep learning can uncover non-linear relationships in data that would be difficult to detect through traditional methods.

5. **Handling structured and unstructured data:**

Deep learning algorithms can handle both structured and unstructured data such as images, text, and audio.

6. **Predictive modeling:**

Deep learning can be used to make predictions about future events or trends, which can help organizations plan for the future and make strategic decisions.

7. **Handling missing data:**

Deep learning algorithms can handle missing data and still make predictions, which is useful in realworld applications where data is often incomplete.

8. **Generalization:**

Deep learning models can generalize well to new situations or contexts, as they are able to learn abstract and hierarchical representations of the data.

A few advantages of deep learning over conventional machine learning methods include automatic feature learning, handling large and complex data, improved performance, handling non-linear relationships, handling structured and unstructured data, predictive modeling, handling missing data, handling sequential data, scalability, and generalization capacity.

3.7 Disadvantages of Deep Learning:

While deep learning has many advantages, there are also some disadvantages to consider:

1. High computational cost:

Deep learning model training takes a lot of processing power, requiring strong GPUs and lots of RAM. This can be costly and time-consuming.

2. Over-fitting:

When a model is overtrained on training data and under-performs on fresh, untrained data, it is said to overfit. Deep learning frequently encounters this issue, which can be brought on by a dearth of data, complicated models, or a lack of regularization, especially when working with big neural networks.

Figure 3.7.2: Overfitting

3. Lack of interpretability:

Deep learning models can be complicated and challenging to interpret, especially those with several layers. Due to this, it may be challenging to comprehend how the model generates predictions and to spot any biases or inaccuracies in the model.

4. Dependence on data quality:

The integrity of the data that deep learning algorithms are trained on is crucial. The model's performance will suffer if the data is erroneous, lacking, or biased.

5. Data privacy and security concerns:

As deep learning models often rely on large amounts of data, there are concerns about data privacy and security. Identity theft, financial loss, and privacy invasion are just a few of the negative effects that can result from criminal actors using data improperly.

6. Unforeseen consequences:

Deep learning models can lead to unintended consequences, for example, a biased model can discriminate against certain groups of people, leading to ethical concerns.

7. Limited to the data if's trained on:

Deep learning models can only make predictions based on the data it has been trained on. They may not be able to generalize to new situations or contexts that were not represented in the training data.

8. Black box model:

Certain deep learning models are referred regarded as "black-box" models because it can be challenging to figure out how the model makes predictions and what influences those predictions.

While deep learning has many benefits, it also has some drawbacks, including high computational costs, overfitting, interpretability issues, reliance on data quality, data privacy, and security issues, a lack of domain knowledge, unanticipated outcomes, being restricted to the data it is trained on, and black-box models. When using deep learning to solve a problem, it's crucial to take these restrictions into account.

3.8 Challenges of Deep Learning:

Researchers have discussed how the benefits of deep learning outweigh those of its related domains, such as machine learning and artificial intelligence when it comes to making predictions and judgments based on data sets. But from time to time, it has also brought up a number of concerns.

However, if some algorithms are unable to comprehend a piece of data, even well gathered and cleansed data may produce incorrect findings. This problem, as well as others similar to it in deep learning, have been researched. We must examine these challenges in the near future.

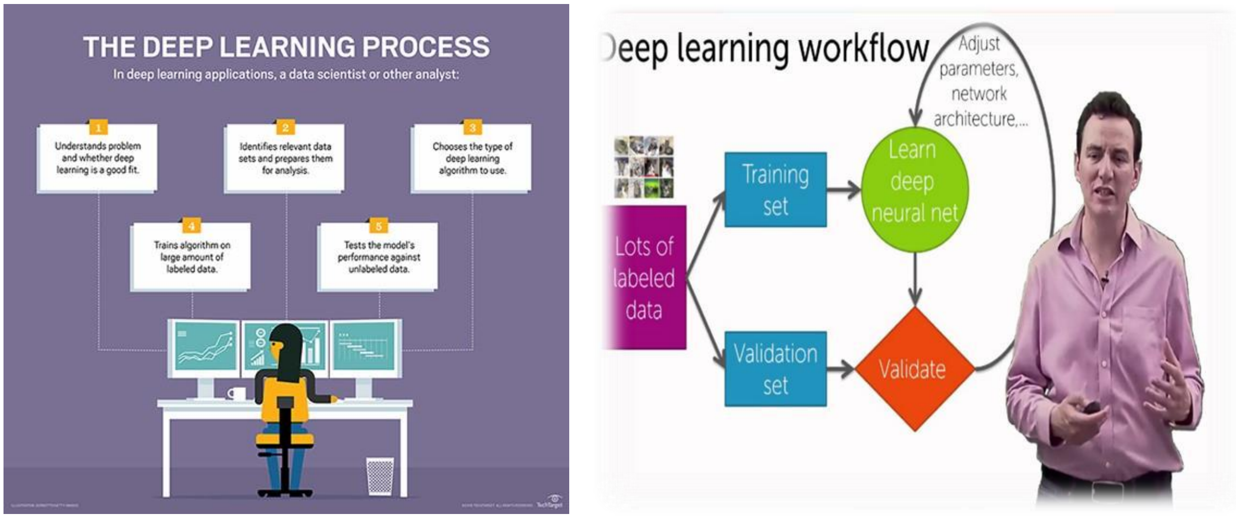


Figure 3.8: Challenges of Deep Learning

1.Deep Learning is data-hungry:

Deep learning algorithms are taught to gain knowledge incrementally from data. To ensure that the machine produces the appropriate results, large data sets are required. Similar to how the human brain needs a lot of experiences to learn and make inferences, an artificial neural network too needs a lot of information. More parameters need to be tweaked and more parameters demand more data the more sophisticated an abstraction you want. A speech recognition program, for instance, would require information from various languages, demographics, and time scales. Terabytes of data are fed to the algorithm by researchers so that it may learn just one language. This process takes a long time and requires advanced data processing skills.

The amount of data available for Deep Learning to train on will somewhat determine the breadth of a problem that it can solve. The number of parameters in a neural network can be used to describe its complexity. This number can be in the millions, tens of millions, or in some circumstances even hundreds of millions in the case of deep neural networks. Give this number the letter P. A reasonable rule of thumb for the number of data points is at least P*P since you want to be confident that the model can generalize.

2. Deep Learning Needs Enough Quality Data:

Deep learning functions best when applied to vast amounts of data and becomes better as more data is gathered. Yet, a deep learning system can perform poorly if it is not provided with enough high quality data. In 2017, researchers modified the available data by injecting "noise" in order to trick Google's deep learning systems into making mistakes. While the study team's flaws were rather minor in nature (i.e., mistaking rifles for turtles in image recognition algorithms). This article discusses how deep learning depends on having the proper kind and amount of data (to work accurately). There is a clear need to provide higher stability and accuracy in deep learning models because even slight input deviations in data quality can have such profound effects on outcomes and predictions. Furthermore, in some firms/ industries like industrial applications, sufficient data might not be available, it limits deep learning’s adoption.

Figure 3.8.2: Deep Learning Needs Enough Quality Data

3. Artificial Intelligence and its Expectations:

The uses of artificial intelligence (AI) in various applications and sectors vary from what the general public expects from these technologies. According to what print media and other media want to publish, many occupations will be replaced by extremely intelligent computers (done by human beings). Yet, the difficulty facing the computer and data science sectors is that AI is a tool to increase efficiency with minimal human functions (providing high accuracy with high productivity). AI processes and execution must have a minimal amount of mistake cases. In general, AI can work well by automating repetitive jobs, making data-driven predictions, optimizing processes, etc.

4. Overfitting in neural networks:

Sometimes, the mistakes found in the training data set and the error found in a brand-new, untested data set are very different. When there are too many parameters in relation to the number of observations in complex models, it happens. A model's effectiveness is assessed by how well it performs on a collection of untrained data, not by how well it performs on training data. Training error in blue, Validation error in red (Overfitting) as a function of the number of cycles. Credits: Wikipedia. In general, a model is typically trained by maximizing its performance on a particular training data set. The model thus memorizes the training examples but does not learn to generalize to new situations and data set.

5. Hyperparameter Optimization:

Hyperparameters are parameters whose value is established before the learning process ever begins. The performance of your model can be significantly altered by slightly altering the value of such parameters. The model performance can be significantly impacted if default settings are used and hyperparameter optimization is not performed. Another factor that affects performance is having too few hyperparameters and manually adjusting them as opposed to optimizing using tested techniques.

Figure 3.8.5: Hyperparameter Optimization

6. Requires high-performance hardware:

A large amount of data is needed to train a data set for a Deep Learning solution. The device must have sufficient processing power in order to carry out a task to address difficulties in the actual world. Data scientists migrate to multi-core, high-performance GPUs and comparable processing units to assure improved efficiency and reduced time consumption. These processing devices are expensive and use a great deal of electricity. The Oregon Data Center for Facebook. MIT Technology Review is credited. High-end data centers are needed for industry-level deep learning systems, but processing units that are compact yet effective are needed for mobile and other smart devices like drones and robots. So, deploying a Deep Learning solution in the actual world turns out to be expensive and energy intensive.

7. Neural networks are essentially a Blackbox:

We are familiar with the model's parameters, the neural networks' construction, and the known data we feed them. But, we frequently do not comprehend how people come to a given conclusion. In essence, neural networks are Blackboxes, and scientists struggle to comprehend how they draw conclusions.

High-level cognitive tasks are challenging to accomplish because neural networks lack the capacity for abstract reasoning. Also, because most of their operation is unseen to people, they are not appropriate for fields where process verification is crucial.

Chapter Four

(Research Problem)

Developing a machine learning-based suicide or non-suicide detection system presents a delicate and intricate research domain. Addressing potential challenges is crucial for our paper. We confront intricate issues in crafting a solution, navigating the sensitivity of the topic, and addressing complexities inherent in accurately detecting and preventing self-harm through advanced machine learning techniques. Here, some research problems are given below;

1. Data Privacy and Ethical Concerns:

- Obtaining a dataset that is sufficiently large and diverse while also resSecuring a comprehensive yet diverse dataset for suicide risk detection is challenging, given the sensitivity of suicide-related data. Maintaining ethical standards is imperative, particularly in ensuring the anonymity of individuals. This intricate balance underscores the need for meticulous approaches to dataset acquisition, with a commitment to upholding privacy and ethical considerations throughout the research process.

2. Imbalanced Data:

- Dealing with imbalanced data in suicide prediction, where incidents are fortunately rare, is crucial to prevent biased models. The scarcity of positive examples can skew predictions. Addressing class imbalance involves employing techniques like oversampling the minority class, under sampling the majority class, or using advanced algorithms designed to handle imbalanced datasets. These strategies ensure model accuracy and sensitivity in identifying critical instances.

3. Interpretable Models:

- In the realm of mental health, transparency and interpretability are paramount. Logistic regression, SVM, and K-Nearest Neighbors models serve as crucial tools, offering explanations for their predictions. This interpretability is vital for cultivating trust among users and healthcare professionals, ensuring a clear understanding of the decision-making process and fostering confidence in the models' outcomes.

4. Real-time Prediction:

-Implementing a real-time prediction system using the k-nearest neighbors algorithm (K-NNs) offers efficient and timely predictions, crucial for crisis intervention or support systems. However, deploying such a model in real-world scenarios, particularly integrating it with existing healthcare or support systems, introduces complexities. Addressing these challenges is essential to ensure the K-NNs model can effectively contribute to rapid decision-making and support in critical situations, optimizing its utility in dynamic, high-stakes environments.

5. Temporal Aspects:

- Suicide risk is dynamic, necessitating models attuned to temporal nuances in behavior. Accurate predictions demand the incorporation of temporal patterns through longitudinal data and time-series analysis. Understanding how risk evolves over time is critical, enhancing the precision of models and enabling timely interventions in mental health care.

6. Crisis Response and Intervention:

- Developing a system that not only predicts but also recommends appropriate interventions or support mechanisms is a significant challenge. This involves collaboration with mental health professionals and crisis response teams.

7. NLP and Sentiment Analysis in Suicide Detection:

Delving into NLP and sentiment analysis, this section scrutinizes the techniques and algorithms utilized to identify signs of suicidal thoughts in online communication. Methodologies tackle challenges like sarcasm, metaphor, and cultural nuances, acknowledging their role in textual interpretation noise.

8. Challenges in Noise and Context:

Navigating the intricacies of online communication poses challenges for precise suicide risk detection, emphasizing the critical role of comprehending noise and context. Ambiguous language, diverse cultural expressions, and the dynamic nature of online conversations present hurdles.

9. Computer Vision in Suicide Detection:

Exploring Computer Vision for Suicide Detection, this section delves into the analysis of image data. By employing techniques like facial expression analysis, image sentiment analysis, and content recognition, we gain critical insights into potential indicators of suicidal thoughts. These components are instrumental in deciphering the emotional states of users, contributing to a more nuanced and effective approach to suicide risk detection.

10. Model Integration and Fusion:

Within the Model Integration and Fusion phase, our focus intensifies on harmonizing data from various modalities into a cohesive model. Through the exploration of fusion techniques like late fusion and attention mechanisms, we aim to seamlessly amalgamate textual, visual, and auditory information. This intricate integration is pivotal for constructing a robust suicide risk detection system, enhancing our ability to discern early signs across multiple dimensions of user-generated content on social media platforms.

Chapter Five

(Methodology)

5.1 Machine Learning Techniques for Detection

Nowadays suicide & depression is a major problem in this world. So, it is necessary to detect and prevent these problems. We can use machine learning algorithms to detect suicide & depression. In our paper we use machine learning algorithm for detection.

In addition, we used supervised learning for our detection techniques. In supervised learning there is input variables denoted by (x) and output variable denoted by (y) and an algorithm is used to learn the mapping function from the input to the output. In supervised learning, the training set we feed to the algorithm contains the wanted solutions, called labels.

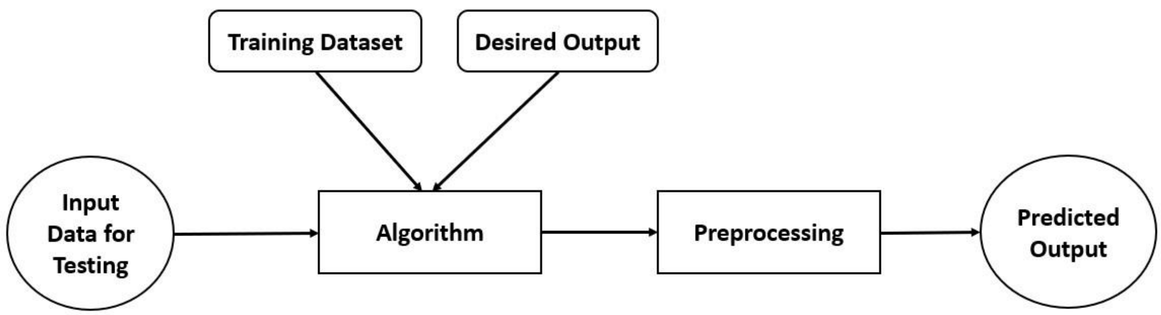


Diagram (5.1): Supervised Learning

Supervised Learning can be divided by two ways of problem solving:

1. Classification
2. Regression

Regression analysis mainly understand the relationship between dependent and independent variable and in Classification technique the algorithm learns from the input given to it and then uses this learning to classify new observation. We will use these algorithms:

- Support Vector Machine (SVM) or Support Vector Classifier (SVC)
- K- Nearest Neighbor (KNN)

- Decision Tree Algorithm
- Random Forest Classifier
- Naïve Bayes Classifier
- Logistic Regression

5.1.1 Naïve Bayes Classifier

Naïve Bayes Classifier is a supervised learning algorithm which based on bayes theorem.

Bayes theorem displays the relation between one conditional probability and its inverse.

$$P(A|B) = P(B|A). P(A) / P(B)$$

P(A|B) is referred to as posterior ratio which means the probability of occurrence of A given B

P(B|A) is referred to as likelihood ratio which measure the probability (given event A) of occurrence of B

P(A) is referred to as prior which represents the actual probability distribution of A

P(B) is referred to as prior which represents the actual probability distribution of B

This classifier works under the prediction that the measurement is mutually independent among all the features given the target class that's why it is called Naïve Bayes Classifier.

5.1.2 Support Vector Machine

Support vector machine (SVM) works for both classifier and regression technique. It is also called Support Vector Classifier (SVC) in our detection techniques. It was introduced in 1960s first then in 1990 it was refined. The way of implementation of SVM is unique than another algorithm.

SVM is a binary classifier which makes use of a hyperplane in a multidimensional space using a subset of the training data called the support vectors. Three main concepts for SVM techniques are:

- **Hyperplane** − A decision plane which is divided between a set of objects having different classes is called Hyperplane. This is also known as the decision boundary.

- **Support Vectors** − Datapoints that are closest to the hyperplane is called support vectors. Hyperplane is defined with the help of these data points.

- **Margin** − The space between two lines on the closet data points of different classes. It can be calculated as the perpendicular distance from the line to the support vectors.

SVM create hyperplanes iteratively that separates the classes in finest way. Then, it will choose the hyperplane that separates the classes correctly. This is how SVM works.

5.1.3 K Nearest Neighbour

K Nearest Neighbor algorithm classifies the new data based on a similarity measure and stores all the available possible cases. Here the number of nearest neighbors is represented by k. KNN algorithm uses ‘feature similarity’ to predict the values of output. Working of KNN model:

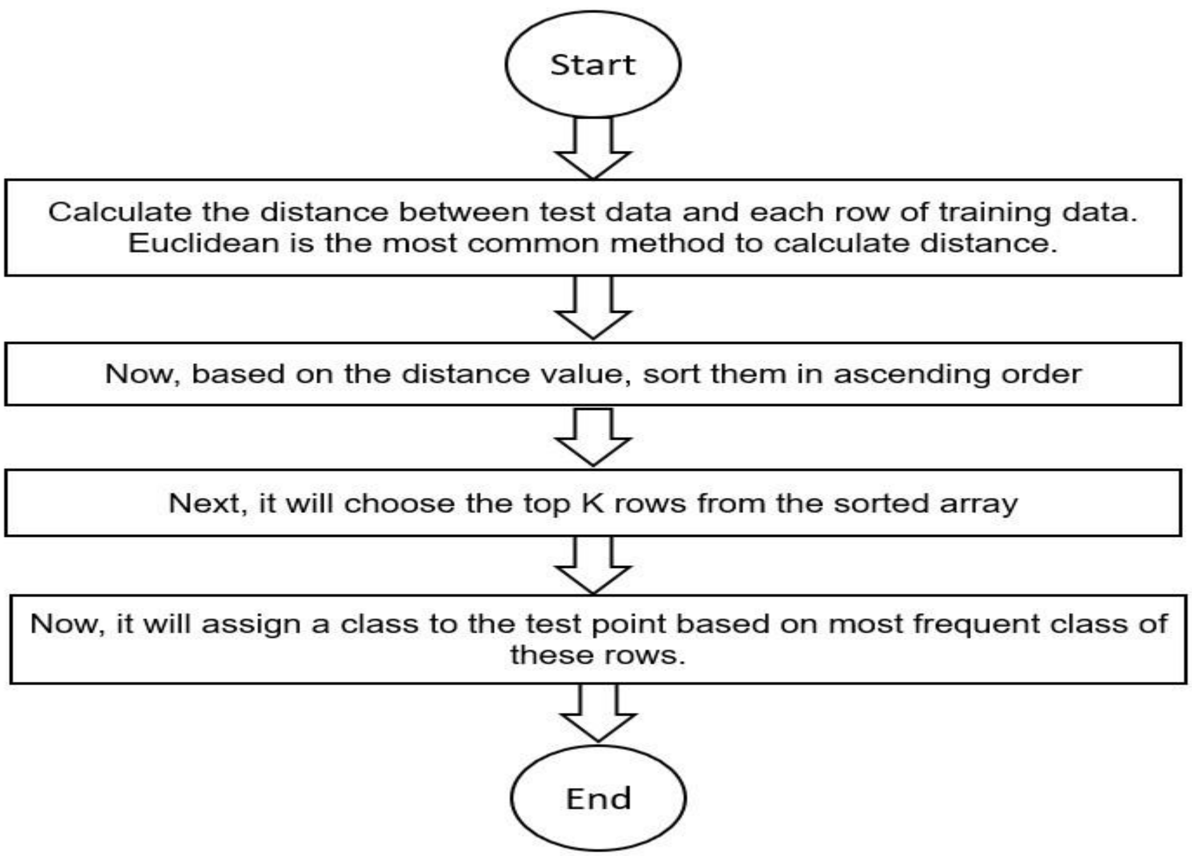


Diagram (5.2): Working Process of KNN Algorithm

5.1.4 Logistic Regression

Logistic Regression produces output in a binary format which is used to predict the outcome of a categorical dependent variable. Such as:

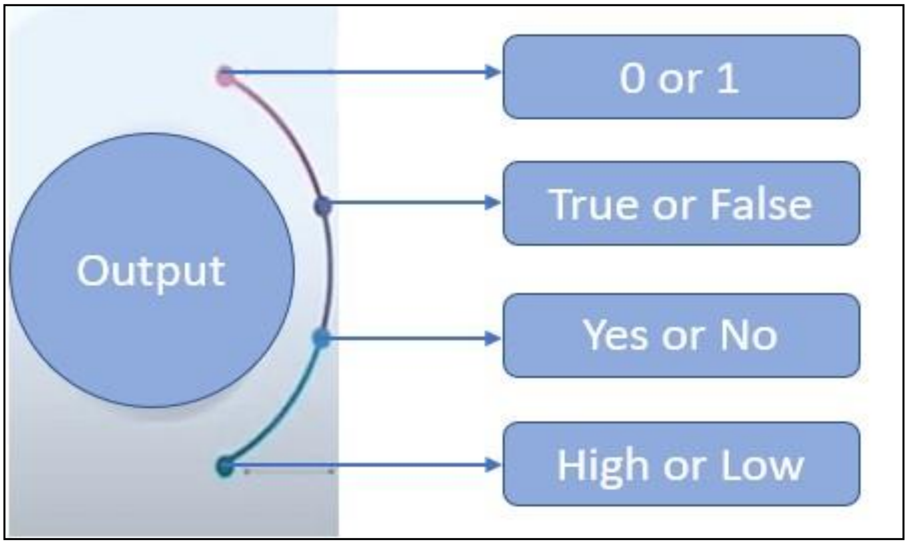


Diagram (5.3): Logistic Regression Outcome

The dependent variable is also called target variable. Logistic regression predicts the outcome probability by using log function. Normally sigmoid function is used to predict the output value.
Sigmoid function: $p = 1 / 1 + e^{-y}$.

The threshold value of sigmoid function decides the outcome (Suicide/ non-Suicide)

5.1.5 Decision Tree Algorithm

For different conditions Decision tree can spilt dataset in different ways. To formulate a set of decision rules decision tree algorithms, use training data. The classes of the test data are estimated based on the set of decision rules. This is represented as a tree structure with each non-leaf node turns as a decisionmaker and each leaf node signifies a class.

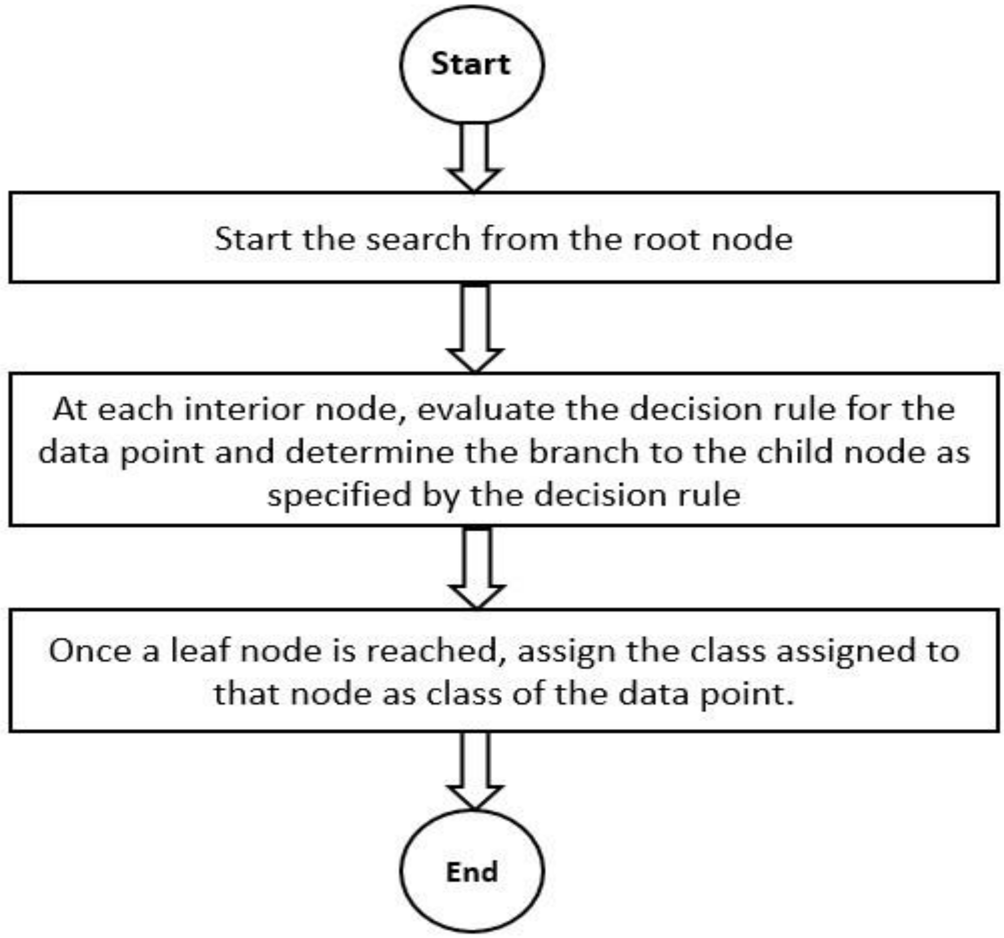


Diagram (5.4): Working Process of Decision Tree Algorithm

The stopping criteria of this algorithm:

- All the leaf nodes are labeled.
- Maximal node depth is attained.
- There is no information gain on splitting of any node **Algorithm:**

Input: Dataset file for each feature

Output: Classified samples with labels allocated

1: **if** leaf nodes do not satisfy the early stopping criteria **then**

2: Select attribute that gives the "best" split; assign it as the root node

3: **repeat**

4: Begin from the root node as the parent node

5: Split parent node at some feature xi to maximize the information gain

6: Assign training samples to new child nodes

7: **until** for each new child node

8: **end if**

5.1.6 Random Forest Classifier

Random Forest Classifier used for both classification and regression techniques. It decreases the overfitting in the region of the result. Working model of Random Forest Classifier:

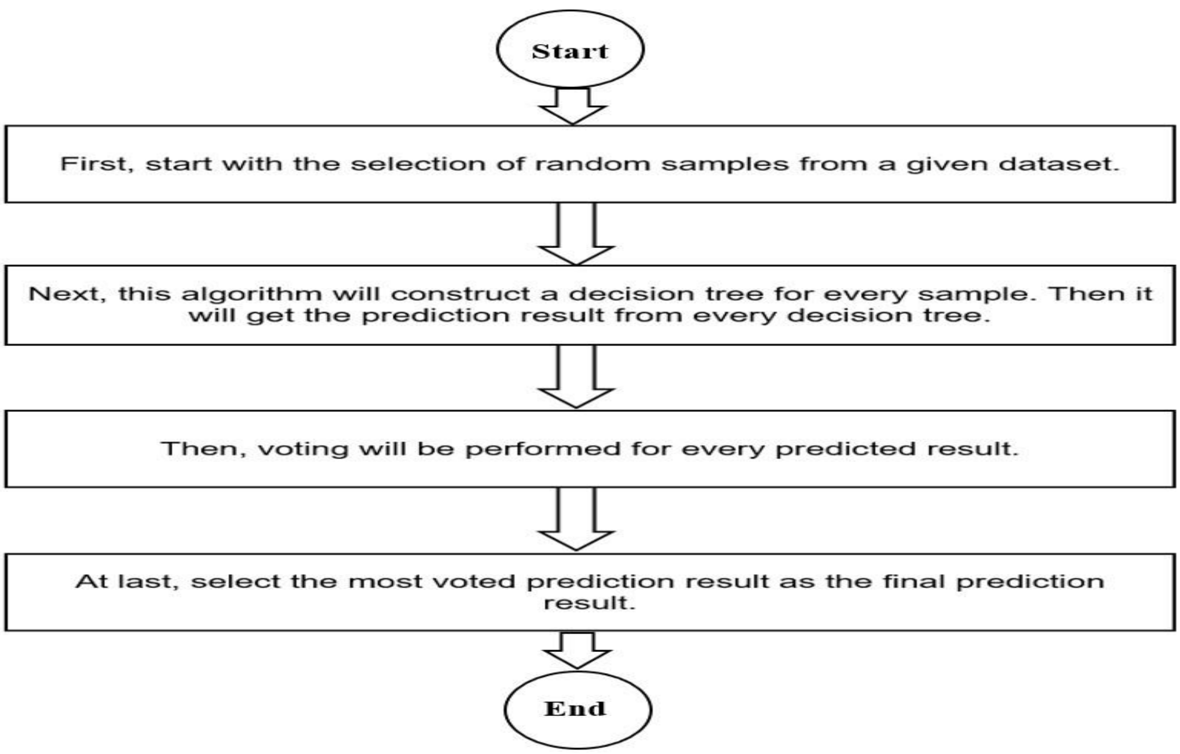


Diagram (5.5): Working Process of Random Forest Classifier

5.1.7 XGBoost Algorithm Classifier

XGBoost, or eXtreme Gradient Boosting, is a highly efficient and widely used machine learning algorithm for regression and classification tasks. Employing a gradient boosting framework, it sequentially constructs decision trees, correcting errors from previous iterations. Known for its speed, scalability, and regularization capabilities . XGBoost handles missing data, supports parallel processing, and giving more better accuracy from other methods. Its feature importance analysis aids in variable selection, and it has become a popular choice for diverse applications due to its versatility and competitive performance in predictive modeling tasks.

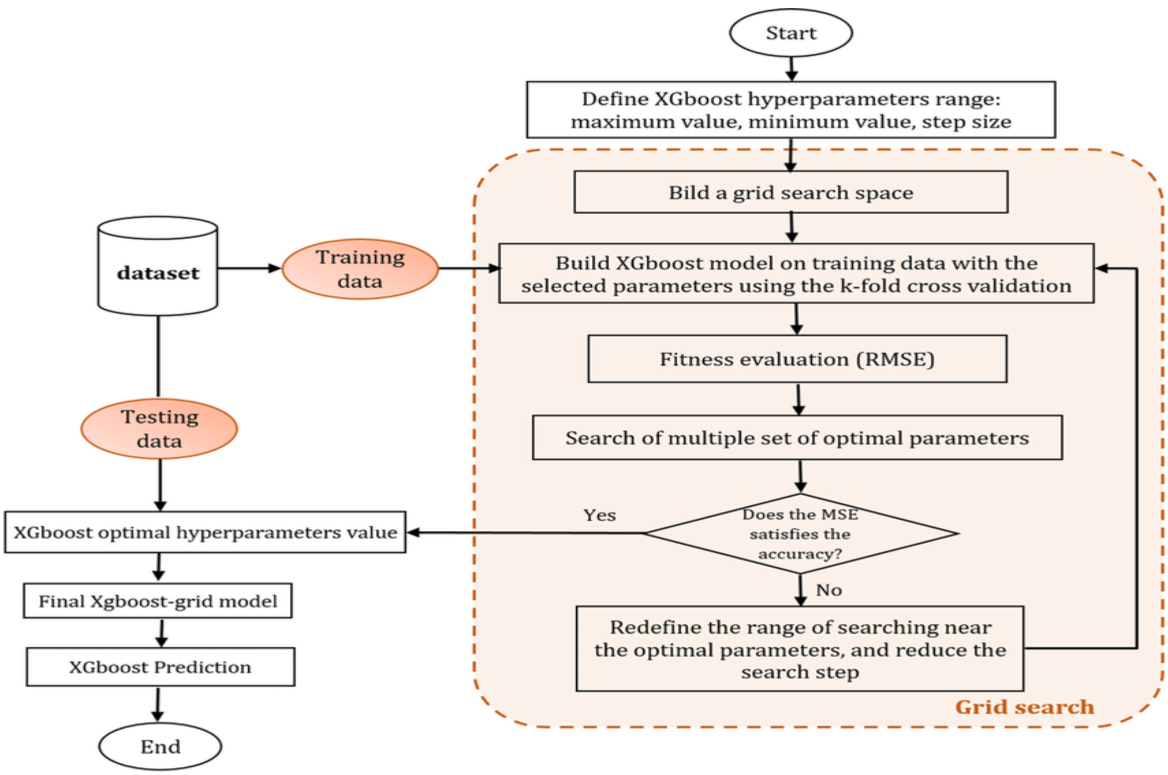


Diagram (5.6): Working Process of XGBoost Algorithm

5.2 Some important Features of Machine Learning

True Positive (TP): It characterizes the value of accurate estimations of positives out of actual positive cases.

False Positive (FP): It characterizes the value of wrong positive estimations that means the number of negatives value which gets falsely estimated as positive.

True Negative (TN): True negative characterizes the value of accurate estimations of negatives out of actual negative cases.

False Negative (FN): False negative characterizes the value of wrong negative estimations that means the number of positives value which gets falsely estimated as negative.

Confusion Matrix: The confusion matrix is used to determine the performance of the classification models for a given set of test data. It signifies a tabular representation of Actual vs Estimated values.

Precision: Precision score signifies the model's capability to correctly expect the positives out of all the positive prediction it made. It signifies the ratio of true positive to the sum of true positive and false positive.

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

Recall: Recall score signifies the model's capability to correctly expect the positives out of actual positives. It signifies the ratio of true positive to the sum of true positive and false negative.

$$\text{Recall Score} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Negative}}$$

Accuracy score: It signifies the model's ability to accurately expect both the positives and negatives out of all the predictions and it signifies the ratio of sum of true positive and true negatives out of all the predictions.

$$\text{Accuracy Score} = \frac{\text{True Positive}+\text{True Negative}}{\text{True Positive}+\text{False Negative}+\text{True Negative}+\text{False Positive}}$$

F1 Score: F1 score signifies the model score as a function of precision and recall score.

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

In our detection technique we will not detect anything manually. In python there are built in machine learning model in SKLearn’s library and we will use it. Without it we will import some necessary libraries for our detection experiment like pandas, NumPy, matplotlib, seaborn.

5.3 Experiment

We want to use methods from Machine Learning to build a computer program that will automatically flag links it thinks are phishing attempts. We can do this by studying the problem, looking at data, and learning a decision rule. We follow this step:

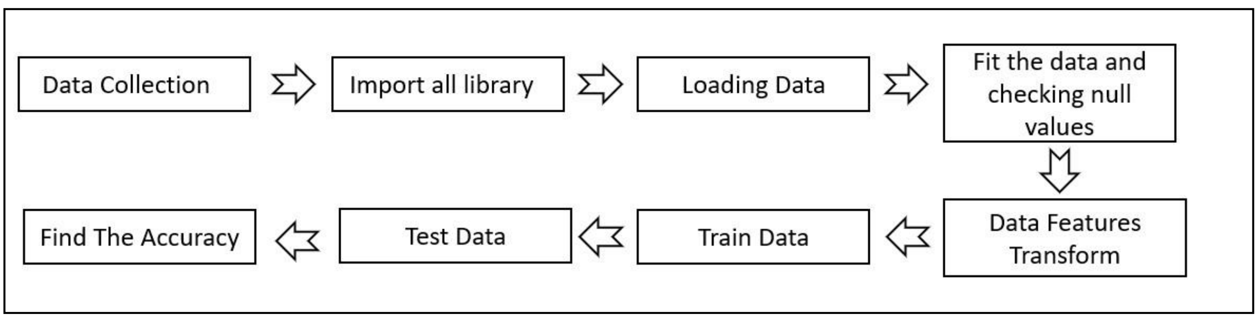


Diagram (5.7): Step of the Experiment

5.3.1 Data Collection

The first thing and most important thing is collected dataset. We collect our Suicide detection dataset. In our dataset there are 2 features. Let's take a look at the provided features on our data set.

Text: The details of a person’s condition & mental health.

Class: A class to determine whether a person is suicidal or not.

5.3.2 Import all Libraries and Loading Dataset

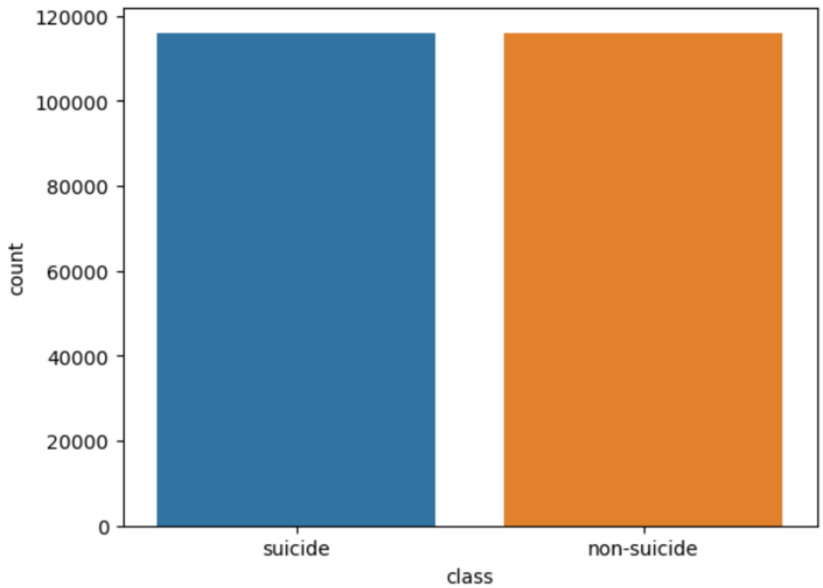
Then we import all our library and then load our dataset.

```
#load the dataset
data=pd.read_csv('Suicide_Detection.csv')
data.head(12)
```

	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’v...	suicide
5	11	Honetly idkI dont know what im even doing here...	suicide
6	12	[Trigger warning] Excuse for self inflicted bu...	suicide
7	13	It ends tonight.I can’t do it anymore. \nI quit.	suicide
8	16	Everyone wants to be "edgy" and it's making me...	non-suicide
9	18	My life is over at 20 years oldHello all. I am...	suicide
10	19	I took the rest of my sleeping pills and my pa...	suicide
11	20	Can you imagine getting old? Me neither.Wrinkl...	suicide

```python
#count
sns.countplot(x="class", data=data)
```

```
<AxesSubplot:xlabel='class', ylabel='count'>
```



Then we check our data if there is any null value or not and check the data info. In our data there are total 232074 entries. Among them we take 70% data for training and 30% data for testing.

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 232074 entries, 0 to 232073
Data columns (total 3 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   Unnamed: 0  232074 non-null  int64
 1   text        232074 non-null  object
 2   class       232074 non-null  object
dtypes: int64(1), object(2)
memory usage: 5.3+ MB
```

5.3.3 Feature Transforming, Training and Testing

Then in Data feature transformation part we check the special character, digit, entropy, subdomain etc. We train our dataset using XGBoost algorithm and drop the 'class' column of testing dataset because it is the output of our model.

Then we get our result for our testing dataset. For XGBoost algorithm the F1 Score on training dataset is 95.45 % and accuracy is 95.55 %

We also test this dataset for Random Forest Classifier Model, KNN, Naïve Bayes, Decision Tree Classifier and Logistic Regression using SKLearn's library.

Now let's see the summary of our Analysis

Method Name	**Accuracy%**
XGBoost Classifier	95.55
KNN	90.48
Naïve Bayes	88.88
Decision Tree Classifier	90.80
Logistic Regression	93.33
Random Forest Model	92.26

Table (5.2): Percentage of Accuracy of different method of suicide detection

Method Name	**F1 Score%**	**Precision%**	**Recall%**
XGBoost Classifier	95.55	94.88	95.66
KNN	90.58	90.44	91.52
Naïve Bayes	83.33	91.11	87.33
Decision Tree Classifier	91.93	93.83	93.93
Logistic Regression	93.54	90.55	92.80
Random Forest	94.36	90.17	92.26

Table (5.3): F1 score, Precision Score and Recall Score of suicide detection

A bar chart of our percentage of Accuracy:

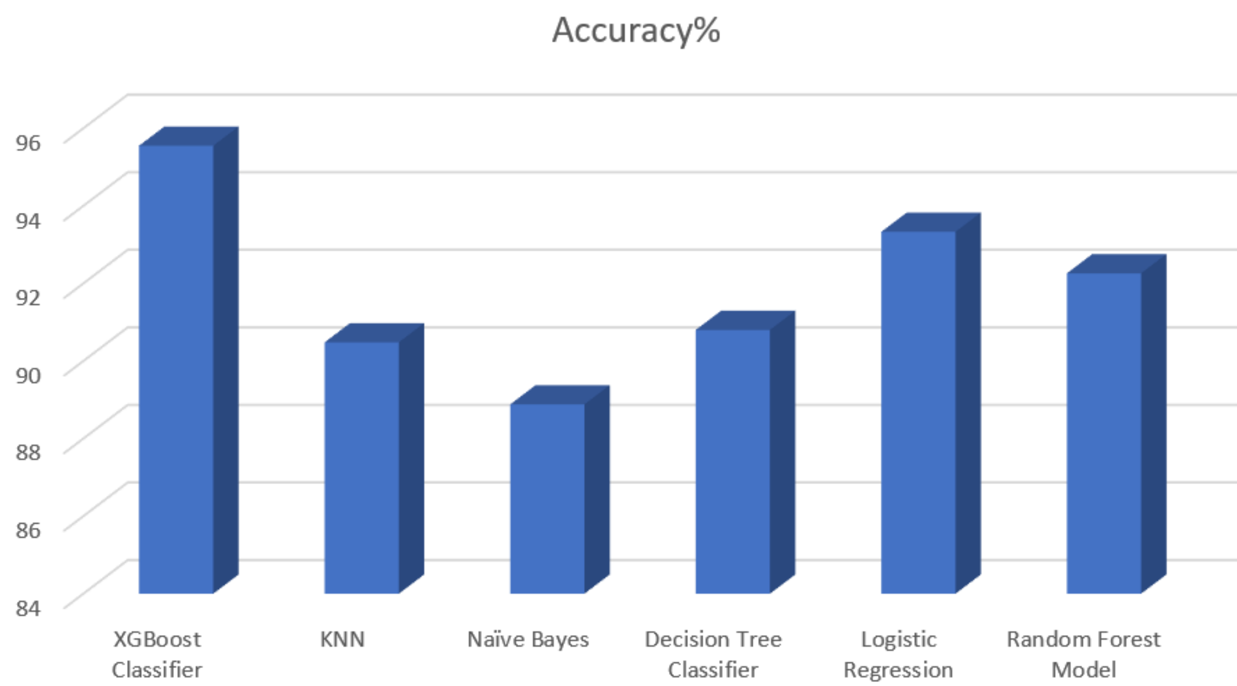


Figure (5.7): Bar Chart of the Accuracy of the different model in %

So, we can see the result that XGBoost is giving the highest accuracy of 95.55%. Logistic Regression model also gives better accuracy but it is time consuming.

5.4 Summary

We use a suicide detection model from using XGBoost algorithm. We train a suicide detection dataset for our detection and then test this model using another test dataset. For suicide detection, we mainly focused on XGBoost algorithm. Because, XGBoost algorithm is the fastest algorithm and giving more accurate result comparing others algorithm and it also gives the highest accuracy. We also test this dataset for KNN, Naïve bayes, Random forest and Decision tree algorithm for comparing the result. And, we saw the difference among the results. Comparing all results, we see that XGBoost algorithm gives the highest accuracy. There is also some model already available for SKLearn's Make_Classification dataset for big data. This result is also shown that XGBoost is fastest and more accurate.

5.5 Proposed Model

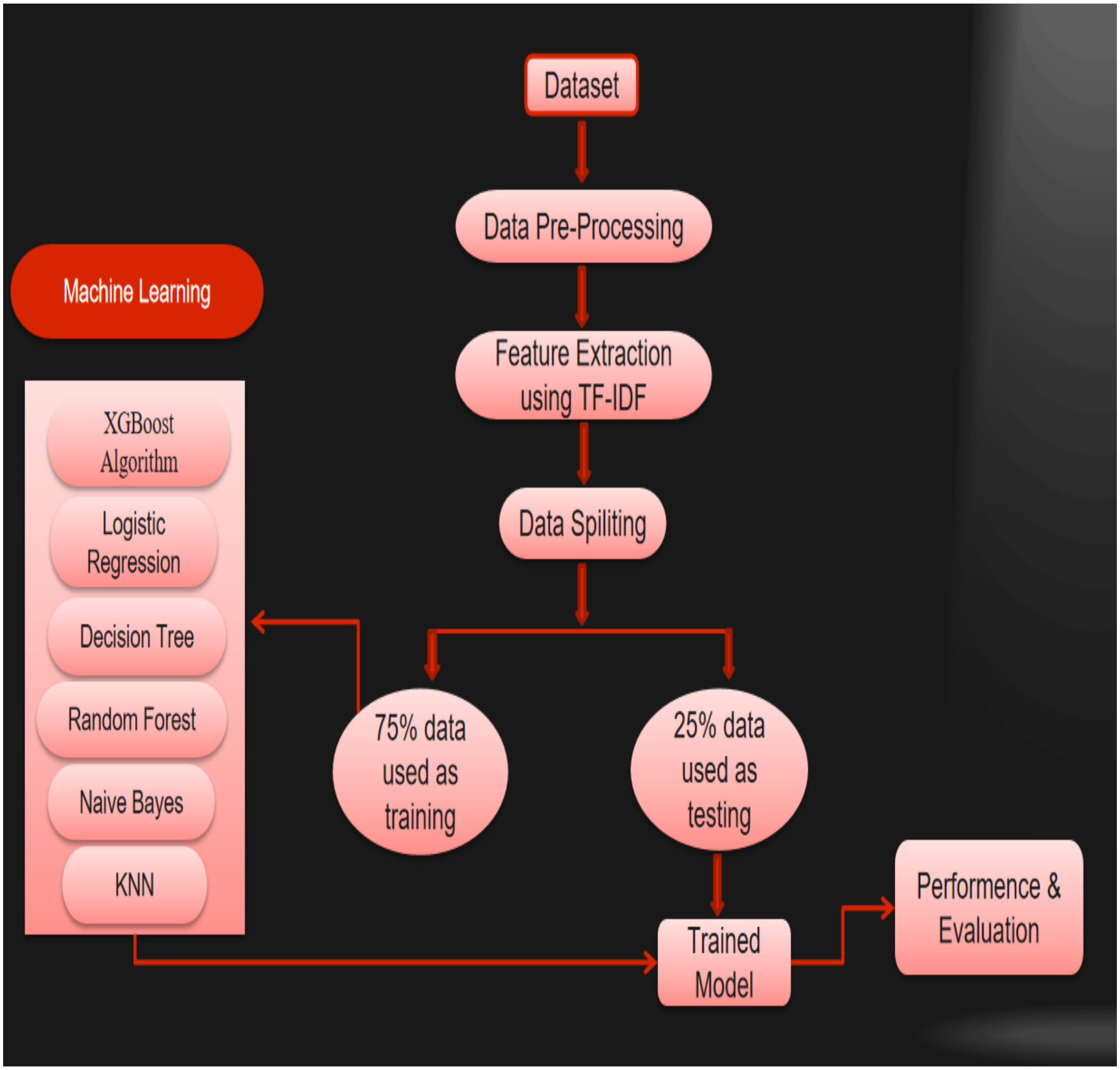


Diagram (5.8): Proposed model of suicide detection

Chapter Six

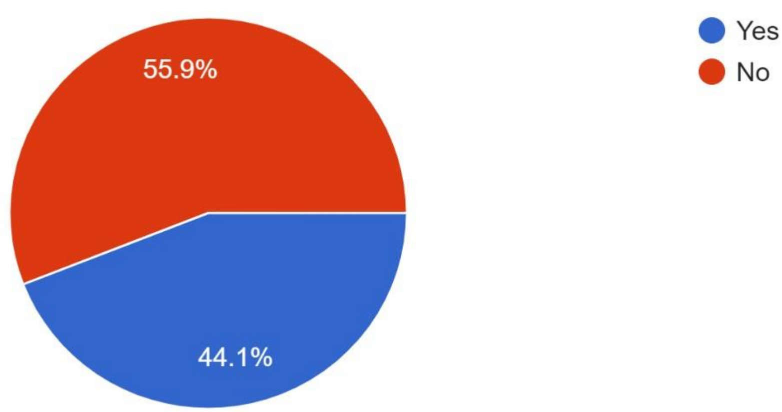
(Survey Report)

Survey Report

We did an online survey on Decemebr,2021. 80% of the participants from Bangladesh and 20% of the participants from UK, USA, India, Germany, Canada, Netherlands, Scotland and Greece. This survey is still on going and we are trying to collect more data. In our survey we find some interesting information.

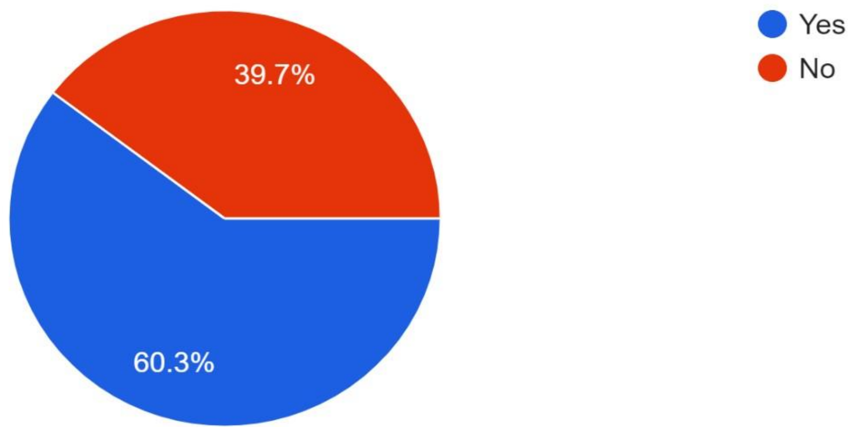
Question: Do you check the news of suicide every day on internet?

Ans: 55.9% of people don't check this.



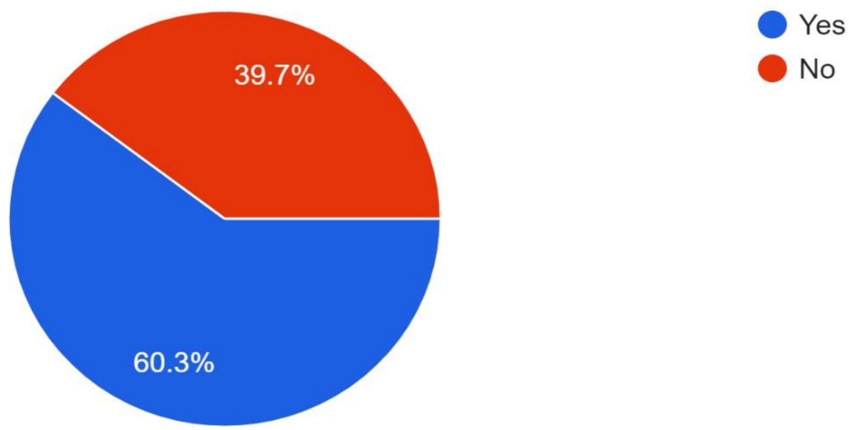
Question: Do you believe that suicide is a crime by society?

Ans: 60.3 % people agrees that.



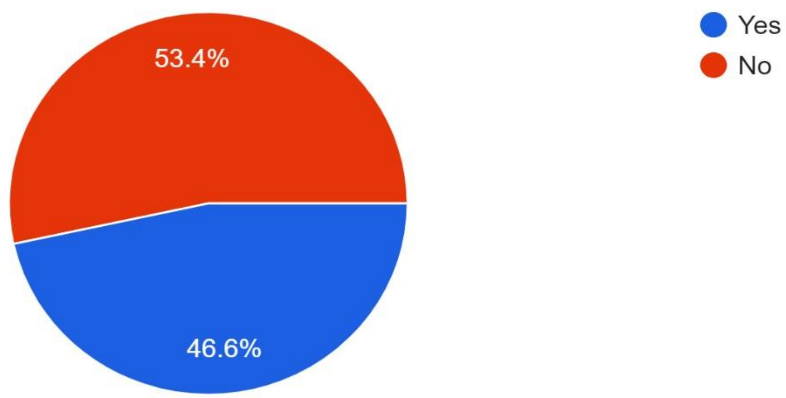
Question: **Have you ever experienced persistent feelings of sadness or hopelessness?**

Ans: 60.3% people say yes.



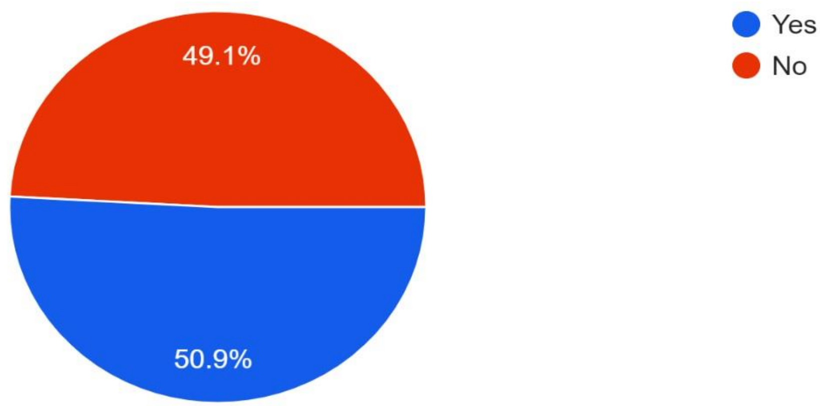
Question: **Do you find it difficult to concentrate on tasks that you used to perform easily?**

Ans: 46.6% of people faced this.



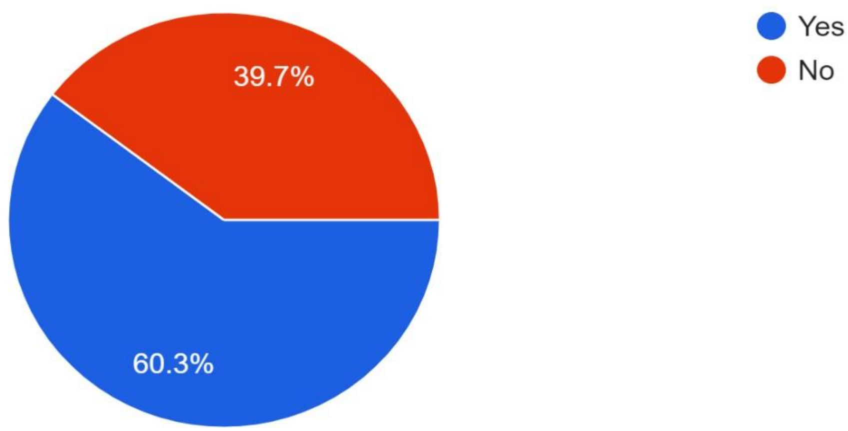
Question: **Have you lost interest in activities that you used to enjoy?**

Ans: 50.9% agreed this.



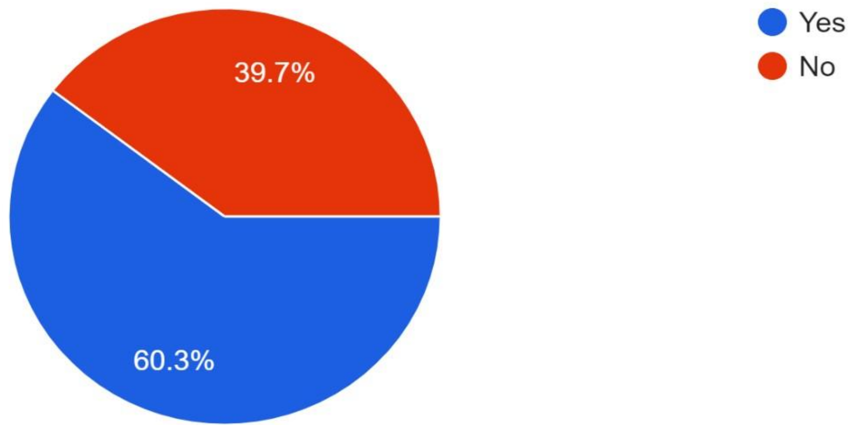
Question: **Do you frequently experience changes in appetite, either eating significantly more or less than usual?**

Ans: 39.7% People agreed this.



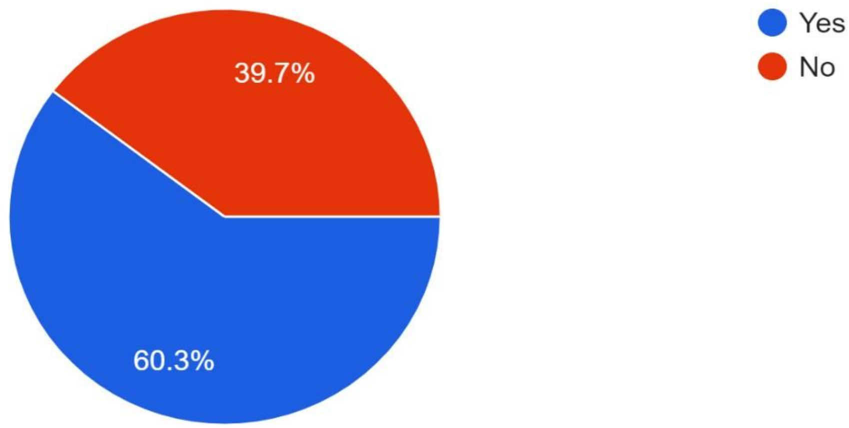
Question: **Do you often feel guilty or worthless?**

Ans: 60.3% of people felt this.



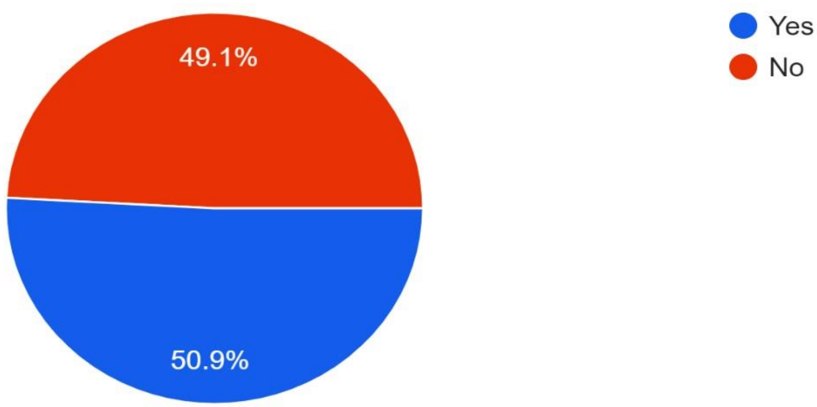
Question: **Have you had thoughts of death or suicide, even if you do not have a specific plan?**

Ans: 60.3% of people faced this.



Question: Have you engaged in self-harming behaviors or had suicidal attempts?

Ans: 50.9% of people faced this.



Chapter Seven

(Conclusion and Future work)

Conclusion

In our paper we analyzed the various characteristics of suicidal detection and its detection techniques using machine learning models. We collected lots of data from various trustworthy sources to explain our investigation report about suicide & depression detection. Using python program, we detected the text is suicidal or non-suicidal. We used various machine learning model for our detection and found the best one. With accuracy we also focused on the time, we need to train the dataset and we found that XGBoost classifier gave higher accuracy and take less time. We proposed a model for detecting suicide more accurately. We also did a survey to find out about some information from the internet users. Moreover, in our paper we try to give a clear idea about suicide & depression detection by using Machine Learning Algorithm.

Future Work:

The paper under consideration marks a groundbreaking milestone in the realm of suicide prevention within social networks using Machine Learning Techniques. Its innovative methodology, integrating machine learning, semantic analysis, and specialized vocabulary, emerges as a potent tool in addressing the critical public health issue of suicide.By acknowledging the dynamic nature of social networks, our paper advocates for a strategy that can evolve alongside the ever-changing landscape of online platforms. This adaptability is further emphasized with the integration of multilingual WordNet tailored for platforms like Twitter and Facebook, showcasing a commitment to enhancing the global applicability of suicide prevention measures.

In future work or forward-thinking move, our paper extends its methodology recognizing the real-time generation of vast amounts of data on social networks using Deep Learning Techniques. Because we know that, Deep learning techniques provide a potent and adaptable framework for detection tasks, enabling models to autonomously acquire intricate patterns and representations from data. This autonomy enhances accuracy and performance, making deep learning a transformative approach in diverse fields, from computer vision to natural language processing.

Our paper's insightful anticipation of future challenges in the realm of social media suicide prevention, coupled with its call for ongoing research, underscores its commitment to addressing the evolving dynamics of technology and social networks. Consequently, our paper not only contributes significantly to the specific domain of suicide prevention but also paves the way for advancements at the intersection of technology, mental health, and public well-being, making it a pioneering force in the field.

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