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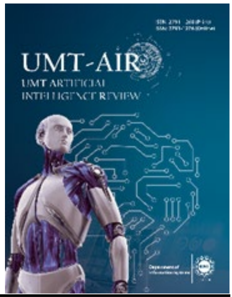

Title:	**Machine Learning-Based Suicide Risk Assessment and Intervention Strategies for Depression**
Author (s):	Muhammad Yousif[1], Arfan Ali Nagra[2], Muhammad Abubakar[2], Shoaib Saleem[1], Farman Ali[1], Hamza Wazir Khan[3]
Affiliation (s):	[1]Minhaj University, Lahore, Pakistan [2]Lahore Garrison University, Lahore, Pakistan [3]Namal University, Mianwali, Pakistan
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Machine Learning-Based Suicide Risk Assessment and Intervention Strategies for Depression

Muhammad Yousif[1]* , Arfan Ali Nagra[2], Muhammad Abubakar[2], Farman Ali[1], Shoaib Saleem[1], Hamza Wazir Khan[3], and Muhammad Hasham Haider[1]

[1]School of Computer Science, Minhaj University, Lahore, Pakistan
[2]Department of Computer Science, Lahore Garrison University, Pakistan
[3]Department of Business Studies, Namal University, Mianwali, Pakistan

ABSTRACT Suicide is a global issue, primarily caused by depression. Over the past three decades, the World Health Organization reports that a considerable number of people have died by suicide. This study uses machine-learning models like Naive Bayes and logistic regression, to predict suicide risk using a dataset of social media posts. Previous research has used SVM and random forest, but deep learning techniques could improve accuracy by analyzing visual and auditory data. This would simplify mental health professionals' work and move away from traditional methods. In today's digital world, leveraging digital tools can make significant progress in suicide prevention and mental health support. Moreover, future developments may include refined clinical reports with human experts, providing researchers with more effective tools for improving mental health outcomes.

INDEX TERMS machine learning, ML-based suicide for depression, suicide risk assessment

I. INTRODUCTION

Depression is a complex mental disorder characterized by persistent sadness, loss of interest or pleasure, and a range of cognitive, emotional, and physical symptoms. It affects people of different ages and significantly impairs their quality of life. Increased suicide risk is one of the severe consequences of depression. It is one of the significant public health concerns globally, with divesting consequences among individual families and communities. As it is, the most widespread mental health disorder in older persons is depression. According to a WHO report, 7% of older individuals worldwide experience depressive disorders [1]. Additionally, depression is frequently linked to a higher risk of various illnesses, heart diseases, and fatalities in older adults. Depression has become a significant health concern since the COVID-19 pandemic; therefore, the assessment and intervention of suicide risk in individuals with depression are of paramount importance.

Nowadays, depression impacts many children and adults all over the world. If depression is not recognized early and individuals do not receive timely counselling, it can lead to severe issues, including an increased risk of suicide. However, because our culture still stigmatizes mental illness, many depressed people go unrecognized and untreated.

As depression is a common mental disorder, characterized by a depressed mood or loss of interest in daily life activities for an extended period. It affects various aspects of life, including relationships, school, and work, and is more common in individuals who experience abuse, loss, or stress.

*Corresponding Author: myousif.cs@mul.edu.pk

Women are more likely to experience depression than men. Some critical facts related to suicide and depression given by WHO at different stages are given below.

Depression has a significant impact on society, affecting adults, both men and women, as well as children. Effective treatments are available for mild, moderate, and severe forms of depression.

In this century, this factor has remained uncontrolled, resulting in approximately seven million people being severely impacted, with teenagers being predominantly affected.

3rd by 4th global suicides occur in low- and middle-income countries. Various methods of suicide, such as pesticide ingestion, hanging, and firearms, are commonly encountered in public cases.

From these critical facts, it is clear that the root cause of suicide is depression. Factors such as unemployment, broken marriages or personal tragedies in life can lead to depression, which causes emotionally weak people to attempt suicide. Mental health experts identify various symptoms and patterns that can indicate a person is experiencing depression.

- Poor concentration.
- Feelings of excessive guilt or low self-worth.
- Hopelessness about the future.
- Thoughts about dying or suicide.
- Disrupted sleep.
- Changes in appetite or weight.
- Feeling very tired or low in energy.

Single-episode depressive disorder: This refers to a person experiencing their first and only depressive episode.

Recurrent depressive disorder: In this pattern, the person has a history of at least two depressive episodes.

Bipolar disorder: This condition involves depressive episodes alternate with periods of manic symptoms, which include euphoria or irritability, increased activity or energy, and other symptoms such as increased talkativeness, racing thoughts, increased self-esteem, decreased need for sleep, distractibility, and impulsive, reckless behavior.

From these patterns and behaviors, the state of depression can be identified. At times, these symptoms are not obvious in some individuals, which may lead to increased risk of suicide. Therefore, these things lead machine learning to intervene to identify depression and the level of suicide, enabling timely treatment and preventing the loss of a precious life. Suicide mainly occurs in countries that have low or middle-level income, but it is a global phenomenon as suicide is a serious public health issue. It is also preventable with timely, evidence-based, and low-cost interventions.

According to 2019 data from the World Health Organization, the country with the highest rate of suicide deaths is Lesotho at 87.5, and Barbados has the lowest at 0.3, as per 2019 data. The data is per 100,000 people. This trend suggests that suicide rates are lower in Islamic countries while more in non-Muslim majority countries. Suicide by pesticides or self-poisoning is 20% in agricultural or low-middle areas; other standard methods are hanging or firearms. To combat depression and suicidal thoughts, WHO has proposed various prevention strategies. As artificial intelligence advances, machine learning algorithms could be employed to identify at-risk individuals and connect them with authorities, such as police or health professionals. This approach could help reduce depression and suicide rates across high-, middle-, and low-risk areas.

A. BACKGROUND

Depression is widespread, affecting around 264 million people globally (World Health Organization, 2020) [1]. It often links to suicidal thoughts, with up to 15% of those with depression dying by suicide [2]. Depression increases suicide risk due to various factors. Risk factors for suicide include previous attempts, family history, mental health disorders, substance abuse, easy access to lethal means, social isolation, recent stressors, and lack of social support [3]. Standard depression assessments often do not assess suicide risk well. They prioritize symptom severity and miss important indicators like hopelessness, impulsivity, and suicidal thoughts. Specialized tools are needed to identify high-risk individuals [4].

B. SIGNIFICANCE

As depression is the leading cause of death globally, its early detection can help in preventing unnecessary loss of life. Incorporating an evaluation of suicide risk into depression management can help identify individuals who are particularly sensitive and initiate effective measures.

Suicide risk assessment provides critical information for tailoring treatment approaches, identifying suicide risk factors in individuals with depression, and enabling healthcare professionals to develop personalized treatment that addresses depressive symptoms and the underlying suicide risk factors.

It helps in allocating healthcare resources effectively depending on the level of depression and suicide risk.

It promotes patients' safety as regular monitoring of suicide risk reduces the risk of self-harm or suicide attempts.

C. OVERVIEW OF LIMITATIONS IN TRADITIONAL APPROACHES:

Traditional tools used for assessing depression have notable shortcomings. Instead of evaluating suicide risk factors, these tools often only focus on symptoms of depression. Additionally, they have limited accuracy when it comes to predicting suicide rates and rely heavily on self-report measures. Moreover, their ability to provide longitudinal assessment is also restricted due to limited data availability. Furthermore, the training and knowledge required to use these tools are also often inadequate.

Although helpful, conventional approaches to suicide risk assessment and prevention have drawbacks such as subjective assessment, reliance on sparse data, and resource limits. Although machine learning (ML) offers a promising way to overcome these obstacles, applying ML requires careful evaluation of the ethical implications.

D. POTENTIAL BENEFITS OF ML

1) IMPROVED PREDICTION ACCURACY

Machine learning (ML) algorithms are more accurate than traditional approaches in identifying potential risk factors. As they can analyze large datasets, such as social media activity, medical records, and behavior patterns.

This may result in earlier risk assessment of vulnerable individuals and more focused interventions [5].

2) PERSONALIZED RISK ASSESEMENT

More individualized risk assessments and customized treatments can result from ML models' ability to account for unique situations and a variety of risk factors [6].

This can increase the efficacy of preventative measures and save low-risk individuals from needless procedures.

3) REAL-TIME MONITORING AND SUPPORT

Chatbots and virtual assistants with machine learning capabilities can offer emergency assistance and real-time support to people who are contemplating suicide, helping to prevent potential crisis [7].

These systems can also monitor online activity and identify any warning signs that could call for human intervention.

II. LITERATURE REVIEW

There has been previous research on suicide assessment using machine learning models, but that was limited to only a few machine learning models known as a support vector machine (SVM) with an accuracy achieved of 67%, and random forests with an accuracy of 85%. This research was limited to data only from Twitter (now known as X). While this research encompasses data from various social media platforms, including Reddit. Navies Bayes classifiers and logistic regression models are applied with an accuracy of 87% and 92%. Detailed results are mentioned in the coming chapters.

A. CRITIQUE OF TRADITIONAL APPROACHES AND THEIR CHALLENGES

Although conventional methods for determining the probability of suicide and providing depression care have been beneficial, machine learning (ML) has the potential to overcome some of their shortcomings [8]. This is an in-depth analysis of the challenges associated with traditional approaches:

- Subjectivity and bias
- Limited data
- Reliance on static tools
- Resource constraint
- Stigma and dependency to seek help

1) SUBJECTIVITY AND BIAS

The foundation of traditional methodologies, clinical judgment, is subject to biases due to various factors such as personal opinions, training, and experience of the clinician. Inaccurate evaluations and missing intervention opportunities could arise from this.

2) LIMITED DATA

Traditional methods depend on clinical assessments, questionnaires, and interviews and provide a limited understanding of a person's complicated mental state. This narrow perspective may overlook important risk indicators, causing the risk of suicide to be overestimated or exaggerated.

3) RELIANCE ON STATIC TOOLS

Over time, mood swings, external stresses, and social support can substantially impact risk, which static instruments cannot fully take into account.

4) RESOURCE CONSTRAINT

Conventional techniques make it difficult to deliver prompt and comprehensive evaluations to everyone in need since they demand a significant investment of time and money from mental health specialists. This may result in missed opportunities for preventing suicides and delays in obtaining intervention.

5) STIGMA AND RELIANCE TO SEEK HELP

The stigma associated with mental illness and suicide could discourage people from getting treatment, which makes appropriate risk assessment and intervention a challenge.

B. CHALLENGES IN ML-BASED STRATEGIES:

Following are the challenges faced by machine learning-based strategies:

- Data privacy and bias
- Algorithm transparency and explainability
- Generalizability and external validity

1) DATA PRIVACY AND BIAS

There are still moral inquiries about data storage, gathering, and the potential for distortions in training datasets. These prejudices tend to maintain inequalities and provide unfair or inaccurate risk assessments for marginalized groups.

2) ALGORITHM TRANSPARENCY AND EXPLAINABILITY

It might be challenging to figure out how particular machine learning models arrive at their projections due to their "black box" nature. Inadequate transparency has the potential to undermine confidence and approval from both medical professionals as well as those in need of assistance.

3) GENERALIZABILITY AND EXTERNAL VALIDITY

Machine learning models developed for specific datasets were not able to adapt effectively to various populations or novel situations. This calls for inquiry into the accuracy and usefulness of risk predictions in real-world problems.

C. OPPORTUNITIES FOR IMPROVEMENT

The following considerations should be made in competing machine learning-based challenges [9].

1) EMPHASIZE HUMAN-IN-THE-LOOP AND EXPLICABLE ARTIFICIAL INTELLIGENCE METHODS

Developing transparent models and including human review can help mitigate bias concerns and improve confidence in ML-based evaluations.

2) INCLUDE A VARIETY OF DATA SOURCES

Clinical data can be integrated with social media activity, wearable device readings, and other pertinent data to create a broader understanding of the context and individual risk factors.

3) PRIORITIZE ETHICAL DATA GOVERNANCE AND CONFIDENTIALITY

Ensuring informed consent and establishing strong data security measures in place will help mitigate privacy concerns and promote responsible implementation of ML in mental health.

D. EXPLORATION OF THE USE OF MACHINE LEARNING IN MENTAL HEALTH RESEARCH AND SUICIDE PREVENTION

The intersection of machine learning and mental health research holds immense potential for addressing and understanding complex issues like suicide prevention.

1) UNLOCKING INSIGHTS THROUGH ML

Machine learning can help overcome challenges faced by mental health professionals in the following ways:

2) PERSONALIZED TREATMENT PLANS:

Machine learning (ML) can assist in enhancing treatment strategies for depression and other mental health challenges by analyzing individual data, leading to more successful and efficient interventions [10].

3) PREDICTIVE MODELING

Massive databases containing medical facts and ML algorithms to find early warning indicators of possible suicide risk can analyze social media posts and behavioral patterns. This may result in focused interventions and individualized help before the occurrence of a crisis.

4) REAL-TIME SUPPORT AND MONITORING

Chatbots and virtual assistants with machine learning capabilities can offer round-the-clock assistance and crisis intervention to people who are thinking about suicide. These systems can also monitor online activity and identify any warning signs that might require human action.

Depression, a common mental illness, significantly raises the chance of suicide. Though helpful, traditional methods of risk assessment and intervention have drawbacks. Machine learning (ML) presents an opportunity for transforming our approach to this critical issue.

5) ENVISIONING A FUTURE WITH ML

- Early identification
- Personalized risk assessment
- Real-time support and monitoring

III. PROPOSED METHODOLOGY

The data set is collected from Kaagle, the most popular website for gathering data sets for artificial intelligence, machine learning, and data science projects. The data set for this research contains posts from the Reddit platform, which is a social news collection, discussion, and content rating website based in the USA. The content is generated by registered users and includes text entries, all of which are voted on by the community. The data in the dataset is a compilation of overall all social media posts from different platforms. Table 1 shows the performance comparisons between accuracy and intractability.

A. MACHINE LEARNING TECHNIQUES EMPLOYED FOR SUICIDE RISK ASSESSMENT

The following machine learning techniques were used for assessing suicide risk with good accuracy results and classification reports, which will be detailed in the upcoming chapter

- Naive Bayes Classifiers
- Logistic Regression

As the model used is a classification model, this study has employed the above-mentioned techniques. While this case study used SVM and a random forest model, it was limited to Twitter data only. The flow diagram of the model is given below to make a working machine-learning model graphically

B. TRADITIONAL ASSESSMENT METHODS

- Clinical interviews and questionnaires
- Behavioral observations
- Medical records

TABLE I

PERFORMANCE COMPARISON

Method	Accuracy	Interpretability
Traditional Assessment Methods	0.7-0.8	High
Naïve Bayes classifiers	0.7-0.85	Moderate
Logistic regression	Variable (0.6-0.8)	Low-moderate

IV. SIMULATIONS AND RESULTS

A. INTERVENTION STRATEGIES FOR DEPRESSION BASED ON MACHINE LEARNING PREDICTIONS

Depression, a prevalent mental health condition, affects millions of lives. Even though conventional therapy has advanced significantly, it still frequently adopts a one-size-fits-all approach. This is where machine learning's (ML) potential becomes valuable. Through comprehensive data analysis, machine learning (ML) may more accurately forecast depression and recommend targeted intervention strategies.

B. INTERVENTION STRATEGIES FOR DEPRESSION

In a variety of ways, algorithms based on machine learning can be quite helpful in supporting and encouraging people who are depressed. Here are some ways that ML models can contribute:

- Tailored Approaches Guided by Machine Learning
- Unlocking the Power of Prediction
- Tailoring the Treatment
- Beyond the Algorithm

1) TAILORED APPROACHES GUIDED BY MACHINE LEARNING

Figure 1 shows the proposed methodology of this article.

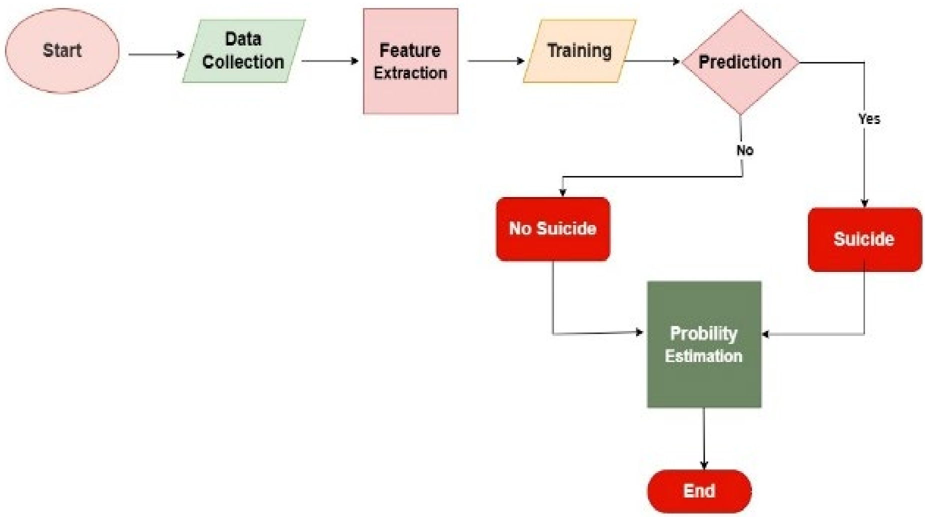


FIGURE 1. Proposed Methodology

Depression, a widespread mental health condition, impacts millions of lives. Although traditional treatments have advanced significantly, they often take a one-size-fits-all approach. This is where the potential of machine learning (ML) offers new possibilities. By analyzing vast amounts of data, ML can predict depression and suggest personalized intervention strategies with greater precision.

2) UNLOCKING THE POWER OF PREDICTION

To identify individuals who are at risk of depression and to facilitate early interventions and better long-term results, machine learning (ML) algorithms may utilize information from social media, medical records, and behavioural patterns.

3) TAILORING THE TREATMENT

Machine learning goes beyond prediction and can be used to personalize treatments [11], [12]. Considering the following approaches can be beneficial:

- Cognitive Behavioral Therapy (CBT)
- Medication Management
- Lifestyle Adjustments

ML might suggest particular CBT modules for focused therapy based on an individual's unique mental processes and recognized maladaptive suggestions.

By examining genetic characteristics and individual responses to various drugs, machine learning (ML) can assist doctors in choosing the best therapy with a minimum of side effects.

ML can recommend tailored lifestyle adjustments for improved health by identifying the specific sleep patterns, exercise routines, and interactions with others that each person experiences as contributing reasons to depression.

C. SIMULATIONS AND RESULTS

In this section, the results of the machine learning models used for this research will be presented, which include Naive Bayes classifiers and logistic regression. The accuracy and classification report of these models will be discussed, along with visualizations, mathematical workings, and confusion matrix. Additionally, a sample of predicted posts from the data set will be included. The purpose of this demonstration is to illustrate the performance of the models which involved evaluating suicide risk through social media posts highlighting their effectiveness in identifying at-risk individuals. Table 2 shows the classification report between different classes and their precision, recall, F1-score and support.

1) NAIVE BAYES CLASSIFIERS

The accuracy and classification report, along with visualizations, mathematical workings, and confusion matrix of naïve Bayes classifiers, are shown below

Accuracy: 0.8718086825379726

TABLEII

CLASSIFICATION REPORT

Class	Precision	Recall	F1-score	Support
Non-Suicide	0.92	0.81	0.86	23287
Suicide	0.83	0.93	0.88	23128
Accuracy			0.87	46415
Macro Avg	0.88	0.87	0.87	46415
Weighted Avg	0.88	0.87	0.87	46415

To apply Bayes' Theorem to the scenario of predicting suicide based on certain features, let's denote:

- A: The event of suicide (class A).
- B: The features indicating non-suicide (class B).
- P(A|B): The probability of suicide given the features indicating non-suicide.
- P(B|A): The probability of non-suicide given suicide.
- P(A): The overall probability of suicide.
- P(B): The overall probability of non-suicide.

The formula becomes:

P(A|B) =$\frac{P(B|A)\ x\ P(A)}{P(B)}$.

Now, let's assume you have some independent features denoted as $P(F_1, F_2, \ldots, F_n)$ that are indicative of suicide or non-suicide. You can modify the formula using these features:

$$P(F_1, F_2, \ldots, F_n) = \frac{P(F_1, F_2, \ldots, F_n|A)xP(A)}{P(F_1, F_2, \ldots, F_n)}$$

where, $P(F_1, F_2, \ldots, F_n|A)$is the probability of observing features $F_1, F_2, \ldots, F_n$ given that the person has committed suicide, and $F_1, F_2, \ldots, F_n$is the overall probability of observing these features.

To implement a Naive Bayes classifier, you would typically assume that the features are conditionally independent given the class label (suicide or non-suicide). This simplifies the calculation:

$$P(F_1, F_2, \ldots, F_n|A) \approx P(F_1|A) \times P(F_2|A) \times \ldots \times P(F_n|A)$$

In addition, for non-suicide:

$$P(F_1, F_2, \ldots, F_n|A) \approx P(F_1|B) \times P(F_2|B) \times \ldots \times P(F_n|B)$$

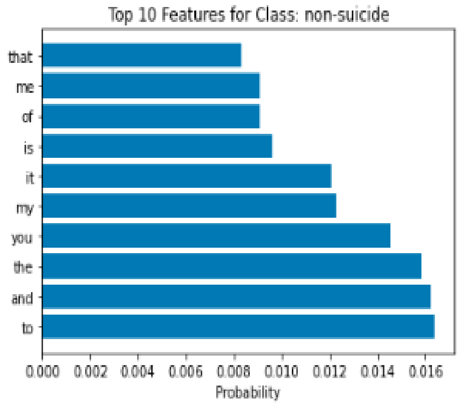
Then, compare the two probabilities and classify the instance accordingly.

Confusion matrix:

[18973 4314]

[1636 21492]

Visualizations:



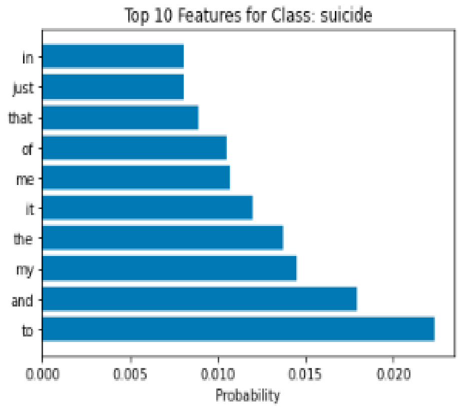


FIGURE 2. Visualization

Figure 2 shows the different visualization between probability and features. Figure 3 shows predicted probability and Figure 4 shows the confusion matrix. Figure 5 explains the ROC Curve for regression and in the end, figure 6 shows the confusion matrix against the logistic regression.

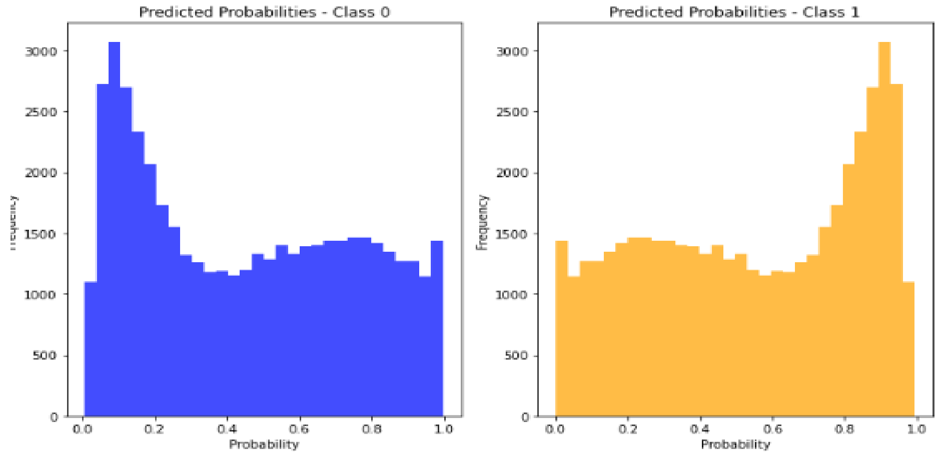


FIGURE 3. Predicted Probabilities

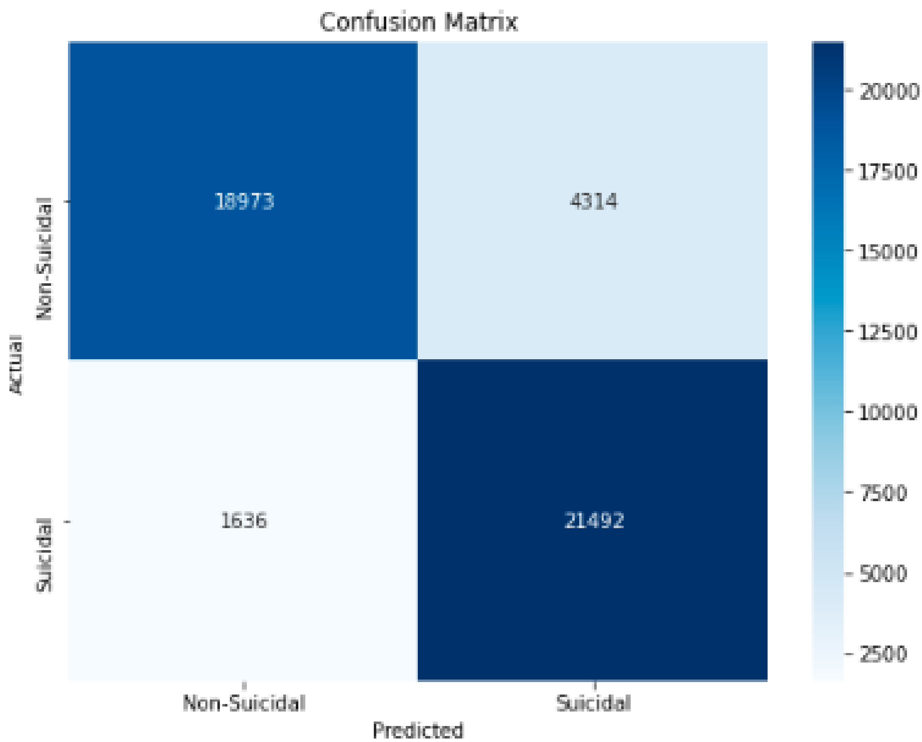


FIGURE 4. Confusion Matrix

2) PREDICTED POST SAMPLES FROM THE DATA SET

Sample 1:

Text: I don’t know. 7 Months of self-harm and, the urge just gets stronger and stronger every day. The past few days, I've just been shit...

My family stresses me out, especially my nephew (he's 12) My mum has full custody of him and he's told me to go kill myself numerous times. I wish it was that easy.

My partner’s family has stressed me out significantly over the past few days.

Stress is my trigger

I just want to scream and cry.

I live near the woods so I could go out and scream till I can't possibly scream anymore but the cops will probably get called...

My OH knows about my depression, but he doesn't know how I'm feeling at the moment. He would want to come over and make sure I'm OK, but he's fucking annoying. He annoys me all the time by doing small stupid things. I don't even know where I'm going with the post. Table 3 shows the classification chart for precision, recall, F1-score.

Predicted Label: suicide

Sample 2:

Text: A poem (haiku) for u/Me-Game-Dev hi, hello hello

Stop fucking saying hello

I know where you live

Predicted Label: non-suicide

Logistic regression:

The accuracy and classification report, along with visualizations, mathematical workings, and confusion matrix of Logistic regression and predicted text, are shown below

Accuracy:

Accuracy: 0.9332360228374448

Classification report:

TABLE III

CLASSIFICATION REPORT FOR PRECISION| RECALL| F1-SCORE

Class	Precision	Recall	F1-score	Support
Non-Suicide	0.92	0.93	0.92	23287
Suicide	0.93	0.91	0.92	23128
Accuracy			0.93	46415
Macro Avg	0.93	0.93	0.93	46415
Weighted Avg	0.93	0.93	0.93	46415

Mathematical working:

To apply logistic regression to predict suicide (0) or non-suicide (1) based on input features, you would have a set of features denoted as, $x_1, x_2, \dots, x_n$ weights $w_1, w_2, \dots, w_n$, and a bias term b.

$\sigma(z) = \frac{1}{1+e^{-z}}$,

where z is a linear combination of the input features and weights plus the bias term:

$Z = w_1x_1 + w_2x_2 + \cdots + w_nx_n + b$

Now, let us denote:

$P(Y = 1)$ the probability of the instance belonging to the non-suicide class.

$P(Y = 0)$: The probability of the instance belonging to the suicide class.

The logistic regression model predicts $P(Y = 1)$ using the logistic function:

$P(Y = 1) = \sigma(z) = \frac{1}{1+e^{-z}}$

The decision boundary is typically set at 0.5. If $P(Y = 1) \geq 0.5$, the instance is predicted as non-suicide (1); otherwise, it is predicted as suicide (0).

Confusion matrix:

[21705 1582]

[1981 21147]]

Visualization:

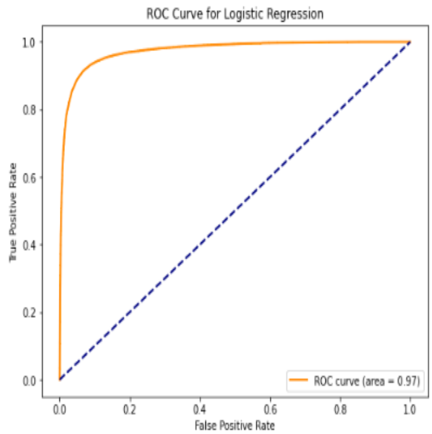


FIGURE 5. ROC curve for Logistic Regression

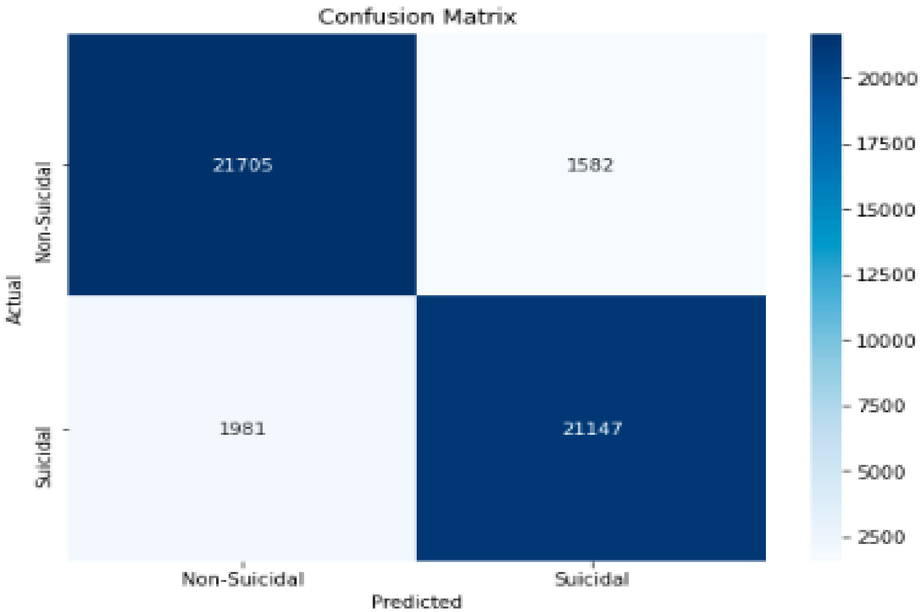


FIGURE 6. Confusion Matrix

Sensitivity

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

Precision

$$\frac{TP}{TP + FP}$$

Accuracy

$$\frac{TP + TN}{TP + TN + FP + FN}$$

3) SAMPLE PREDICTED TEXT

1 Sample1:

Text: I've honestly got no idea what to do anymore. It feels as if everyone was fake, I feel like I'm back talked and annoying. I can sometimes like hear my brain speaking to me "hey. Hey those people are fake don't talk to them". So far the only thing that helps is music, but that's kind of stopping to work. I have 2 really fucking good friends, and I don't deserve them. Nobody needs a suicidal fucktard who can't help you, who just pushes you away. What use am I to anyone? I barely do anything useful with my life. People say "what about your loved ones?" well if I've been fucking abused I don't really think that makes a difference except for my father who's actually fine, out of all my family he is the only one I'd feel about for having to suffer. I don't see a point in hanging on anymore. I'll never get better and I don't want to feel guilty by committing suicide. It is very hard for me to get help, and I really don't see how I'm going to get out of this. I feel like I'm just going to off myself before I'm even 18. I don't want anyone to feel bad for me, I deserve all of this regardless.

4) PREDICTED LABEL: SUICIDE

Sample 2:

Text: Guys, I'm scared of social interaction. Tomorrow I'm doing something with mates, and I don't know what to do or say; I don't want to say no, though; how do I fight the awkwardness

5) PREDICTED LABEL: NON-SUICIDE

Ethical Considerations

It is undeniable that machine learning (ML) has the potential to be used to estimate suicide risk utilizing data from social media. This promise is accompanied by major ethical issues and difficulties that we must appropriately handle. Let us analyze the key points:

Privacy and Consent Data collection and storage: Privacy concerns are raised when personal information is collected via social media platforms. You must obtain proper authorization and make sure that data management processes are transparent [13].

Anonymization and de-identification: While anonymizing data reduces dangers, remaining information can enable people to be re-identified. It takes excellent thought to balance model training requirements and privacy [14].

Bias and Fairness:

Algorithmic bias: Auditing and reducing bias in data and algorithms is essential since ML models trained on biased data can maintain inequalities and misclassify persons from marginalized groups**.**

False positives and false negatives: While underestimating the risk of suicide can miss those who are actually in danger, overestimating it can result in needless measures. Careful calibration is needed to achieve a balance between sensitivity and specificity**.**

Impact on Vulnerable Populations:

Stigmatization and discrimination: When risk assessment models are misused, those at risk may become discriminated against or subjected to unfair favors from authorities, insurance, or employers.

Accessibility and equity: Various ethnic groups may have different access to technology and mental health resources, which may worsen already-existing disparities in outcomes [15].

Implications for Mental Health Care Providers:

Role of clinicians: machine learning (ML) needs to be considered as an aid to clinical judgment and empathy, not as a replacement for them. In terms of assessing and intervening against suicide risk, clinicians ought to continue to be the significant decision-makers [5].

Transparency and trust: It's essential to be open and honest with patients about the limitations of machine learning models and how they're employed. Patients should be in charge of their data and have agency over its usage.

V. CONCLUSION

This research focuses on detecting suicide risk among individuals based on their social media posts. It suggests various intervention strategies for addressing depression, aiming to prevent suicide globally, as this issue is increasingly prevalent. The goal is to advance the field of psychology and make it easier for mental health professionals to provide effective support and treatment. This worked on text-based social media post data based on limited platforms like Twitter, now known as X, while the proposed work was from the Reddit data set. In addition, different models were implemented to achieve results to prevent suicide risk and detect depression in individuals at an early stage to prevent suicide and make work more accessible for mental health workers. The following are the limitations that the proposed idea should consider: It is only text-based data. It may only succeed if professionals are trained according to technology. In the future, we need to implement more machine and deep learning techniques to work on image and video to detect suicide risk from facial emotions and audio-based detection so suicide can be prevented and provide mental health assistance. So, that's how mental health professionals can detect depression among individuals and to avoid suicide. In the future data privacy will be the first consideration for mental health and legalized patterns applied with machine learning algorithms which will enhance the accuracy of depression rate outcomes.

CONFLICT OF INTEREST

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVALIABILITY STATEMENT

The data associated with this study will be provided by the corresponding author upon request.

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