A Machine Learning Model to Predict Suicidal Thoughts among Adolescent Girls with Access to Social Media. A Review of Literature

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Abstract: Suicidal thoughts is one of the leading factors that cause deaths among the adolescents and young adults. Suicidal thoughts have been ranked as the major cause of deaths among adolescents in Kenya. This paper presents a systematic review of literature on prediction of suicidal thoughts among adolescent girls with access to social media. The study adopted the snowballing methodology to review the relevant literature. This involved identifying relevant and current literature on modeling of suicidal thoughts. The initial set of relevant literature was obtained by searching using keywords such as social media, suicide, mental health, adolescents, self-esteem and algorithms. The process of conducting backward and forward snowballing which entail reference tracking and citation tracking respectively followed this. Boolean operators were used to narrow down the search to at least fifty research papers relevant to the topic of study. The databases that were used to search for the literature included Google scholar, Medline, TUM university catalogue, and Project MUSE. Findings from the literature review indicated that machine learning modelling could be used to predict suicidal thoughts. The results also showed that logistic regression, decision tree, AdaBoost, artificial neural network and random forest were the commonly used algorithms in predicting suicidal thoughts among adults and youths. AdaBoost had the highest prediction accuracy of 93%. However, most studies reviewed did not mention about adolescent girls in their research thus this research paper dwelt on adolescent girls to establish how to curb suicidal thoughts among that gender.

Keywords: Prediction, Modelling, Suicidal thoughts, Machine learning, adolescent girls

1. INTRODUCTION

Suicide in adolescents has an impact on our economy as stated by the United Nations' third Sustainable and Development Goal (UN SDG); it is the second leading cause of death for adolescents between 15 to 19 years old (Shain, B., & COMMITTEE ON ADOLESCENCE., 2016).Suicide is therefore referred as a fatal mental problem according to the Kenyan report on clinical psychology. Suicidal behavior is not inherited, it is caused by clinical, psychological and biological variables (Nordin et al., 2021a). Its aim is to predict suicidal thoughts among adolescent girls of age's 13-19 with access to social media in Africa, specifically, Kenya. Factors of having electronic gadgets like phones allow them to get to social media where they are exposed to cyber stalking and cyber bullying(Lin et al., 2020).The exposure leads to spread of

Rumors and being adolescents, they do not take it lightly. At the same time, they fear asking for assistance from their guardians with the fear that they will be punished for getting to sites they were not allowed. Adolescent girls will be addressed in this study because most of the studies done covered both genders generally without looking at the female gender, and also because I am a lady and I support my gender. The literature covered a total of fifty papers each paper analyzing suicidal thoughts and what has been done to tackle the situation. Dangers of suicidal thoughts were also outlined. Some of the risks revealed in the literature include low self-esteem, offline peer support, poor body image, and emotional distress. The dangers in the literature were solved by using machine learning models to predict suicidal thoughts as they were the major cause and identifying them early so as to provide timely prevention.

2. METHODOLOGY

The study adopted the snowballing methodology to review the relevant literature. This involved identifying relevant and current literature on modeling of suicidal thoughts. The initial set of relevant literature was obtained by searching using keywords such as social media, suicide, mental health, adolescents, self-esteem and algorithms. This was followed by the process of conducting backward and forward snowballing which entail reference tracking and citation tracking respectively. Boolean operators were used to narrow down the search to at least fifty research papers relevant to the topic of study. The fifty research papers were then categorized according to the features that they used in identifying individuals with suicidal thoughts. The features were in four classifications, mental health factors, social factors, emotions and other factors. Also, the papers were further classified according to models that were used in predicting suicidal thoughts. Those that used one model were analyzed while those that used more than one model were also analyzed too, with the model having the most accurate prediction outlined. The databases that were used to search for the literature included Google scholar, Medline, TUM univesity catalogue, and Project MUSE.

3. IDENTIFYING FEATURES THAT PREDICT SUICIDAL THOUGHTS

Some of the major features analyzed to show individuals with suicidal thoughts were anxiety and depression that were captured in the literature review of (Thorisdottir et al., 2019) and (Memon et al., 2018). Self –esteem, specifically low self-esteem was used to identify adolescents with suicidal thoughts as reviewed by (Burnel al., 2019). Additionally, self-harm was identified as characteristic for individuals with suicidal thoughts in research done by (Twenge et al., 2018) and (Kelly et al., 2018). Risk exposure, post-traumatic stress and coping are characteristics that were also used to identify suicidal thoughts (McHugh et al., 2018) . In some of the reviewed literature, sleep disturbance was measured using the Pittsburgh Sleep Quality Index and the analysis showed that it was a factor identifying people with suicidal thoughts (Guo et al., 2018). Further, sociodemographic, familial characteristics, mental health and substance abuse were major features for college students having suicidal thoughts as stated by (Macalli et al., 2021b). Moreover, history of mental health problems; alienation from family and community; having a

friend who attempted suicide; weekly consumption of hard liquor; a family history of a suicide or attempt; poor self-perception of health; a history of physical abuse; female gender; and sexual abuse features was used in research to identify grade 6 to 12 students with suicidal thoughts (Grossman et al., 1991). Research on adolescents in 2015 considered diagnostic, demographic, medication, and socio economic factors predictors of suicidal thoughts due to access to social media (Walsh et al., 2018a).

Table 1. Representation of features and predictors used in the literature review and their references.

MENTAL HEALTH FACTORS	SOCIAL FACTORS	OTHER FACTORS	EMOTIONS
Anxiety (Thorisdottir et al., 2019),(Twenge et al., 2018) , (Kelly et al., 2018) , (Macalli et al., 2021b)	Risk exposure (McHugh et al., 2018)	Diagnostic factors(Walsh et al., 2018a)	Anger/sadness (Jung et al., 2019b), (Ji et al., 2020).
Depression (Thorisdottir et al., 2019),(Burnell et al., 2019),(Twenge et al., 2018) , (Kelly et al., 2018), (Memon et al., 2018), (Macalli et al., 2021b),(Heffer et al., 2019)	Substance abuse and addiction (Burnell et al., 2019), (Grossman et al.1991),(Jung et al., 2019b)	Demographic factors (Walsh et al., 2018a)	Sorrow (Ji et al., 2020).
Low self-esteem adolescents (Guo et al., 2018), (Burnell al., 2019),(Twenge et al., 2018),(Kelly et al., 2018),(Macalli et al., 2021b)	Social demographic familial characteristics (Grossman et al., 1991)	Medication history (Jiang et al., 2021), (Walsh et al., 2018a)	Hopefulness (Ji et al., 2020), (Roy et al., 2020)
Self-harm(Twenge et al., 2018) , (Kelly et al.,	Alienation from family and community	Economic factors (Walsh et al., 2018a)	Happiness (Ji et al., 2020).

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2018), (Memon et al., 2018), (Iyengar et al., 2018)	(Grossman et al., 1991)		
Poisoning/Suicidality(Twenge et al., 2018) , (Kelly et al., 2018),(Memon et al., 2018), (Iyengar et al., 2018) ,(Spiller et al., 2020)	Having a friend who attempted suicide (Grossman et al., 1991)		Peacefulness (Ji et al., 2020).
Sleep disturbance (Insomnia) (Twenge et al., 2018), (Kelly et al., 2018), (Guo et al., 2018)	Weekly consumption of hard liquor (Grossman et al., 1991)		Fear (Ji et al., 2020).
Surgeries(Twenge et al., 2018) , (Kelly et al., 2018),(Jiang et al., 2021).	Family history of suicide attempt (Grossman et al., 1991)		Pride (Ji et al., 2020).
Diagnoses(Twenge et al., 2018) , (Kelly et al., 2018)	Poor self-perception of health (Grossman et al., 1991)		Abuse (Ji et al., 2020).
Burden(Twenge et al., 2018) , (Kelly et al., 2018)	Sexual abuse features(Grossman et al., 1991)		Forgiveness (Ji et al., 2020).
Loneliness(Twenge et al., 2018) , (Kelly et al., 2018)	Religion (Nordin et al., 2021b)		
	Race (Nordin et al., 2021b)		
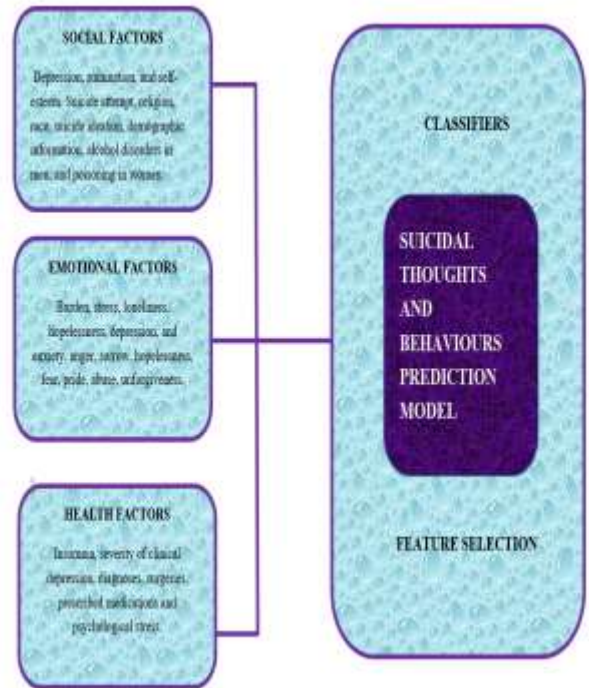
Figure 1: Theoretical framework features summary from literature review.

4. MACHINE LEARNING MODELS ON SUICIDAL THOUGHTS

Prediction of suicidal thoughts using regression models was done by researchers: (Thorisdottir et al., 2019; Guo et al., 2018; Brailovskaia et al., 2018; Mortier, Cuijpers, et al., 2018; and Auerbach, Alonso, Axinn, et al., 2018). Random forest model was used in the literature by two researchers; (Roy et al., 2020; and Jiang et al., 2021). Other researchers used more than one machine learning models to predict suicidal thoughts: (Chen et al., 2020; Lin et al., 2020; Jung et al., 2019b;Van Vuuren et al., 2021; and van Mens, de Schepper, et al., 2020b). The machine learning models used were; regular logistic regression, K-nearest neighbors, classification tree, random forests, Ada boost and support vector machine.

Table 1. Analysis of some machine learning models used to predict suicidal thoughts and references in the literature.

MODEL COMBINATION	MODEL WITH BEST RESULTS	REFERENCES
Regular logistic regression, K-nearest neighbors, classification tree, random forests, gradient boosting and support vector machine.	Random forest gave the best prediction.	(Jung et al., 2019b)
Random forest and lasso regression.	Random forest had the highest prediction of 0.79 against lasso regression of 0.76	(Van Vuuren et al., 2021).
Logistic regression (LR), random forest (RF), support vector machine (SVM), artificial neural network (ANN), and Ada boost	Extreme gradient boosting gave the best prediction of 79 percent	(Jung et al., 2019b)
Logistic regression, decision tree, random forest, Ada boost regression tree, support vector machine and multilayer perceptron	Support vector machine and multilayer perceptron provided the best prediction of almost 100 percent.	(Lin et al., 2020)

5. RESULTS

Results showed that machine learning modelling can be used to predict suicidal thoughts. It also showed that logistic regression, decision tree, AdaBoost, artificial neural network and random forest were the commonly used algorithms in predicting suicidal thoughts among adults and youths. AdaBoost had the highest prediction accuracy of 93%. Also from the findings, early detection of suicide can save many lives. Findings also confirmed that explicit content exposure, cyberbullying and sexual solicitations evoke symptoms of suicidal thoughts due to access to social media. Analysis further revealed depression was stronger for individuals with lower self-esteem than individuals with higher self-esteem. Most studies reviewed did not mention about adolescent girls in their research thus this research dwelt on adolescent girls to establish how to curb suicidal thoughts among that gender. Especially, the prediction of suicidal thoughts and behaviors using machine learning algorithms among adolescent girls in Africa, a gap that this research will fulfill.

Further research can be conducted on more emerging learning techniques, such as attention mechanism and graphical neural networks, can be introduced for suicide text representation learning. The current models may also need to be further optimized to improve accuracy. Furthermore, more research need to be done on why the female adolescents were affected more than the males from the literature.

6. DISCUSSION

From the earlier researches, most researchers identified predictors that the datasets could be fed on machine learning models. Later, the model with the best prediction could be identified after evaluation using evaluation metrics. Most researches used longitudinal data. The data collection method used by several researchers is web based surveys and interviews. From the review, some major evaluation metrics were used. They included, sensitivity, precision, Recall, Area under ROC curve and specificity.For instance in most reviewed papers, to determine how well a model recognizes a positive class, sensitivity computed the ratio of the positive class accurately detected. Illustrated on the equation:

$$Recall = \frac{True\ High}{True\ High + False\ Low}$$

Additionally, specificity yielded the ratio of real negatives to those that the models identified as true negatives or negative classes. This would yield an additional percentage of real negatives that the models would have mistakenly identified as positives, a phenomenon known as false positives. It calculates the percentage of correctly detected

negatives, such as in the following equation: (Mvurya mgala, 2016)

$$Specificity = \frac{True\ Low}{True\ Low + False\ High}$$

The area under the receiver operating characteristic curve was calculated using a graph in several reviewed papers. It plotted two parameters: the number of true positives divided by the total number of false negatives and true positives. This was referred as the True Positive Rate. The False Positive Rate, which was calculated by dividing the total number of false positives by the sum of the false positives and the true negatives, was used to describe how well the model predicts the positive class when the actual outcome is positive.
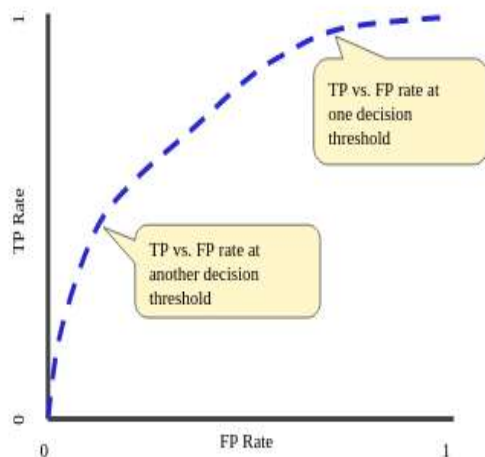

Figure 1: Area under ROC curve graph sample used in most literatures reviewed

7. GAP IDENTIFICATION

From the literature reviewed, there is no research done on prediction of suicidal thoughts and behaviors using machine learning algorithms among adolescent girls in Africa, a gap that this research will fulfill.

8. RECOMMENDATION/FUTURE WORKS

More emerging learning techniques, such as attention mechanism and graphical neural networks, can be introduced for suicide text representation learning. Also, models need to be further optimized to improve accuracy. Furthermore, more research need to be done on why the female adolescents were affected more than the males from the literature.

9. ACKNOWLEDGEMENT

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