Boamente

Subjects: Others
Contributor: Ariel Teles, José Fontenele, Adonias OLIVEIRA, Victor Hugo Bastos, Silmar Teixeira, Ricardo Rabelo, RENATO DOS SANTOS

People at risk of suicide tend to be isolated and cannot share their thoughts. For this reason, suicidal ideation monitoring becomes a hard task. Therefore, people at risk of suicide need to be monitored in a manner capable of identifying if and when they have a suicidal ideation, enabling professionals to perform timely interventions. This entry aimed to develop the *Boamente* tool, a solution that collects textual data from users' smartphones and identifies the existence of suicidal ideation.

Keywords: artificial intelligence ; deep learning ; eHealth ; mental health

1. Background

Suicide is one of the main causes of death in the world [1]. In 2019, Brazil was among ten countries where the most suicides occurred in the world, and the second among countries of the Americas, with 14,540 suicide cases [2]. According to the World Health Organization (WHO), 703,000 people committed suicide in 2019 in the world. As an aggravating factor, the current COVID-19 pandemic has changed people's well-being and mental health due to different events, such as deaths, social isolation, and job closures, which can also cause an increase in the number of people at risk of suicide [3][4].

Several factors can influence individuals to make the decision to end their lives (for example, emotional pain, marital problems, and biological, genetic, psychological, social, cultural, financial, and environmental factors) [5][6][7]. According to the WHO, when people are mentally healthy, they are able to be productive, contribute to the community, and recover from the stress they experience daily [1]. In contrast, mental disorders can negatively impact people's lives, in addition to affecting relationships with friends, family, and health systems. Anyone can have suicidal ideation [8].

To prevent suicide, there has been rapid growth in the development and use of digital technologies [9], such as mobile applications [10][11], which can identify, monitor, and support individuals at risk. In particular, mobile applications for digital phenotyping aim at collecting information to objectively contribute to the identification of symptoms and behaviors of interest to mental health professionals (for example, psychologists and psychiatrists) [12][13]. According to Torous et al. [14], the term "digital phenotyping" refers to a "moment-by-moment quantification of the individual-level human phenotype in-situ using data from smartphones and other personal digital devices". Digital phenotyping mobile applications use people's interactions with smartphone applications in everyday environments to facilitate remote monitoring of their behaviors and habits, requiring little or no direct interaction for data collection.

Usually, people at risk of suicide tend to be isolated and cannot share their suicidal thoughts with their family, friends, or even mental health professionals [15]. At the same time, people may express their emotions, thoughts, and feelings in a variety of ways, including through text messages on social media (for example, Twitter, Facebook, Instagram, and Reddit) [16]. These texts, obtained from online social media, may be defined as non-clinical texts [17], as they are not annotated by health professionals. Non-clinical texts can be obtained from different sources, but social media can produce large quantities available at any time. Such a characteristic (the high availability at any time) enables non-clinical texts to be explored in studies that use machine/deep learning (ML/DL) and natural language processing (NLP) techniques to identify suicidal ideation [18]. Such techniques have demonstrated their potential to perform different tasks in the healthcare field [19][20].

2. Related Work

Suicide is an intriguing form of human death, and its motivations are complex [21]. Therefore, the timely identification of an individual at risk of suicide is a hard task. For this reason, different studies have taken advantage of information and communication technologies (ICT), such as ML/DL techniques [22][23][24] and mobile applications [10][25][26], to identify suicidal patterns and behaviors. Such studies seek to propose computer solutions enabled for the early identification of people at risk of suicide. Thus, solutions are proposed to prevent suicide from happening.

Most mobile applications for suicide prevention provide features for ecological momentary assessment (EMA) [27] and ecological momentary intervention (EMI) [28], such as *emma* [29], and coping tools, such as *CALMA* [30]. There are a few digital phenotyping applications for suicide prevention and, specifically, solutions focused on detecting suicidal ideation. *Strength Within Me* [31][32] is a digital phenotyping mobile application developed to sense data that are useful for predicting suicidality. It collects contextual information, usually gathered from smartphone sensors, such as sleep behavior, mood, and steps, to be correlated with user answers obtained from a suicide severity rating scale. The collected data are used as inputs to test ML models for predicting suicide risk. Studies using this digital phenotyping application [31][32] demonstrated its feasibility to detect risk of suicidality.

Another proposed digital phenotyping mobile application for monitoring suicidal ideation is *SIMON* [33]. This solution is composed of two parts: *SIMON-SELF*, which is an EMA application that uses a conversational agent (a chatbot) to request self-reports from users; and *SIMON-SENSE*, a sensing application used to passively collect contextual data from the user's smartphone (for example, data produced by an accelerometer, GPS, Bluetooth, Wi-Fi) and identify situations of interest (for example, physical activity, location, and social connectedness). Collected data will be used as inputs to develop ML models for predicting suicidal ideation and psychiatric hospital re-admission.

Studies focusing on developing ML/DL models may use non-clinical texts to identify harmful content related to suicide. Burnap et al. [34] used non-clinical texts related to suicide to train several ML algorithms. This study aimed at classifying texts relating to suicide on Twitter. The study motivation is based on the fact that suicide-related posts can represent a risk to the users of online social networks, who could encourage them to hurt themselves. Classifiers were trained to distinguish between suicidal ideation and other suicide-related content (for example, suicide reports, memorials, campaigning, and support).

Psychiatric stressors (see [35] for definition) related to suicide were detected by Du et al. in [36]. For this purpose, the authors used user posts (non-clinical texts) obtained from Twitter and a convolutional neural network (CNN) to classify them into positive (that is, related to suicide or suicide ideation) and negative (that is, unrelated to suicide or suicide ideation) classes. Next, psychiatric stressors were annotated in the tweets labeled as positive, and a recurrent neural network (RNN) was used to extract stressors from positive tweets. Models created using different ML/DL algorithms were compared to identify the best one. This study achieved promising results in the process of identifying psychiatric stressors.

In the work by Ophir et al. [37], two deep neural network models using the Facebook posts of users to predict suicide risk were developed. The first model was able to predict suicide risk from posts. The second one was focused on predicting a hierarchical combination of multiple factors (for example, personality traits, psychosocial risks, and psychiatric disorders) to mediate the link between Facebook posts and suicide risk.

Most of the works have developed models using the English language as input. Carvalho et al. [38] started the study for suicidal ideation detection using texts written in Brazilian Portuguese (PT-BR). This work used texts obtained from Twitter to develop and compare three different ML/DL models. Posts were labeled using two approaches: three classes (safe to ignore, possibly worrying, and strongly worrying) and two classes (safe to ignore and possibly worrying). Results demonstrated that the bidirectional encoder representations from transformers (BERT) model [39] obtained the best performance in the two approaches; researchers have considered the models developed in Carvalho et al.'s study to compare with model.

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