

Review

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A Comprehensive Review of Automatic Methods for Suicidal Ideation Detection

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Article

A Comprehensive Review of Automatic Methods for Suicidal Ideation Detection

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Abstract: Suicide is a complex health concern that affects not only individuals but society as a whole. Its prevention is possible but to be effective it has to consider the medical and technological resources available for its evaluation. Nowadays, computational advancements have enabled new forms of study of this phenomenon. Particularly, the study of suicidal ideation using computer-based techniques primarily involves two main technical approaches: *text-based classification* and *deep learning*. Furthermore, it heavily relies on creating and using custom datasets with social media textual data. However, some publications have utilized public information (e.g. records from a particular healthcare provider) in their studies. In this paper, a comprehensive overview of current advancements in automatic suicidal ideation detection, focusing on computer science techniques from 2020 to 2024, is provided. Particularly, it evaluates existing and innovative methodologies, datasets, and limitations in the field to give a proper analysis based on the PRISMA methodology of the current state-of-the-art of this specific task.

Keywords: Suicidal Ideation; Deep Learning; Natural Language Processing; Mental Health

1. Introduction

Suicide, despite not being considered a disease, it can be classified as a convoluted global health concern [1,2]. As revealed by the World Health Organization, an estimate of over 700,000 suicides per year happen worldwide [3]. Particularly, in 2019 over one in every 100 deaths was the result of suicide [4]. Moreover, in that year, around 77% of global self-murders occurred in low- and middle-income regions, like the Southern Cone of the American continent [4,5]. Namely, countries within this sub-territory such as Argentina, Chile, or Uruguay, despite the availability of intervention techniques to prevent suicide, still have a high suicide mortality rate with an average of 20,046 deaths from 2015 to 2019 [5].

Despite being one of the most investigated causes of human mortality with a huge volume of literature and mortality statistics, very little is still understood about suicide [6,7]. Namely, such an important health complication lacks a universally accepted definition in current research (*eidem*). For instance, Émile Durkheim, one of the first individuals to study this phenomenon, defined it as a classification of all deaths resulting from the victim's own actions, distinguishing them from the notion of attempt due to the direct or indirect accomplishment of the expected mortal result [8]. Moreover, Bailey explains it as *the intentional act of causing a human being's own death* [9]. In contrast, Douglas interprets it as *a strategic solution by an individual to existential problems*, whereas Chávez-Hernández and Leenaars perceive suicide as a universal and tangible manifestation of the struggles between human passions, biological basis, and cultural environment [8,10]. These final rationales suggest that this is a multidimensional problem whose complexity is influenced and determined by various causes, such as physiological, intrapsychic, historical, political, philosophical, and socio-cultural contexts [8,11,12]. Moreover, such risk factors hint at a general rationality and intentionality of meaning for these actions due to the establishment of a set of common detectable characteristics that shape how communities

and individuals respond to the issue [8,13]. However, these may not be universal since the motivation for a convoluted outcome such as suicide depends on varied components that act together, which vary from one individual to another [14,15]. Particularly, the lack of a common suicide victim model makes these fail to capture the emergence of a suicide crisis [16,17]. Thus, the necessary, but insufficient, nature of the influence of risk factors in suicide suggests that there is still a lack of a mechanism for explaining how these general elements are linked to suicidal mortality [15,18].

For this reason, suicide is considered a multidimensional and multifaceted complex event whose understanding involves knowledge and insights drawn from multiple disciplines [12]. For instance, mixed research (qualitative and quantitative approaches), large-scale epidemiological surveys, and problem-solving therapy are examples of techniques from Suicidology, Epidemiology, and Psychology, respectively, that, in conjunction, have explored in recent times the origin, development, and outcome of suicidal activity [17,19,20]. Moreover, the broader perceptions of suicide derived from the contribution of different fields of study have expanded empirical evidence and knowledge of the phenomenon since its proper interpretation results complicated due to the multiple phenotypes that must be considered across the suicide spectrum [1,17,19]. These phenotypes include [1]:

- **Suicidal ideation:** Commonly defined as thoughts about ending one's own life. Further, literature has acknowledged its broad conceptualization by contemplating it as a set of contemplations and behaviors within a continuum of suicide potential [16,21,22].
- **Suicide attempt:** Defined as a self-injurious behavior with inferred or actual intent to die. In addition, Yerly highlights the multifaceted nature of suicide by illustrating this concept as the intentional actions of ending one's own life without achieving a fatal result [23].
- **Death by suicide:** Defined as the mortal outcome of a suicide attempt.

Notably, suicidal ideation is cataloged as one of the strongest predictors of suicide attempts as it logically precedes a mortal endeavor or completed suicide [24,25]. However, literature still fails to determine when ideation is transformed into action since there is a lack of consensus about this transition [26,27]. Particularly, some studies suggest that this progression is facilitated by co-occurring psychiatric conditions that increase distress (eg. panic disorder or post-traumatic stress disorder) [1]. Other theories emphasize suicidality as a single phenomenon in need of a single overarching explanation [27]. Neither the approach, there is yet a loose collection of empirical facts unconnected by theory that need to illuminate the likelihood of suicidal behavior based on the attempter-ideator distinction [15,18,27].

Moreover, it exists limited progress derived from the paucity of research on the basic phenomenology of suicidal ideation [25]. Contemporary investigations couched it within the distinction between active (a latent intention that leads to the creation of specific plans to commit suicide) and passive (formulation of suicidal thinking without a particular plan) deliberation. Because of this, it is important to highlight the nuanced differences between suicidal thoughts and suicidal ideation since many studies have a limited empirical basis founded on the interchangeability of these concepts derived from the few explorations of the latent structure of explicit rationalizations (*eidem*). Suicidal thoughts are any episodic, with a quick onset and short duration, ideas or ruminations about the possibility of ending one's own life [28]. Alternatively, suicidal ideation results in a conceptualization with a more generalized scope since it implies the progression of these contemplations to consolidate a two-factor structure based on suicidal desire and resolved planning/preparation [25,27]. Thus, a clear differentiation between notions, as well as improved knowledge of suicidality's meta-analysis, are critical for more robustly designed prevention strategies [19,27].

Notably, current prevention strategies flaw to identify which subjects with suicidal behavior are at risk of acting on their thoughts and which ones aren't since literature has prioritized the quantification of suicide rather than its understanding [7,17,26]. Particularly, the methodologies derived from diverse understandings about suicide (highlighting suicidal ideation phenotype) like ideation-to-action frameworks such as: the Interpersonal Theory of Suicide, the Integrated Motivational-Volitional Model, and the Three-Step Theory) have pushed techniques for researching and practically assessing

the phenomenon with varying degrees of success [1,27,29]. For instance, self-reports and clinical interviews based on scales (e.g. Scale for Suicide Ideation from 1979 [24] and the Columbia–Suicide Severity Rating Scale from 2011 [30]) are the most common methods employed in the field and yet there is the need for improved strategies for its assessment [14,31,32]. Moreover, with human life shaping into digital interactions, these evaluations have not been able to suit the online context due to the need for the analysis of clinical professionals, costly research efforts, and an overall lack of comprehension of the full spectrum of suicidal ideation [32,33].

Therefore, efforts such as the SIDA scale have tried to adapt these traditional approaches to the web-based era [32]. Nonetheless, in recent times the more observable changes in suicidal ideation research have been done by the application of artificial intelligence (AI) since its identification relies on both: traditional and advanced statistical methods [34,35]. Namely, the usage of methods within the branches of Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) on large datasets provides the ability to detect new patterns of factors regarding the phenomenon by the inclusion of a wider array of factors/variables to, in the future, automatically monitor and respond to harmful behaviors in real time [36,37]. In particular, the application of these advanced methods is currently based on [38]:

- **Text-based Classification:** Based on Feature Engineering, the goal of this approach is to determine, via text-based interactions (e.g. social media posts), if a person has suicidal ideation. Such task is tackled using:
 - *Tabular Features:* This is structured data (statistical information or questionnaire responses) that can be employed as features for regression or classification analysis.
 - *General Text Features:* To handle unstructured data -that with no systematic order [39]- general features like N-gram features, knowledge-based features, syntactic features, context features, and class-specific features, are extracted via self-made vocabulary or dictionaries.
 - *Affective Characteristics:* Probably the most experimental approach since it combines specific psychological techniques (e.g. manual emotion categories) with the previous computational methods to perform a fine-grained sentiment analysis over suicide notes or blog streams. As a consequence of this, it is expected to better distinguish between a potentially suicidal person and a healthy one.
- **Deep Learning:** Taking advantage of automatic feature learning, this approach utilizes advanced methods based on Neural Networks to boost predictive performance. Consequently, these techniques indicate a more robust preliminary success in suicidal ideation understanding compared to traditional statistical methodologies as demonstrated by Haque R, Islam N., et al [40].

Hence, these technologies have highlighted their value in predicting suicide risk by enabling low-cost and efficient alternatives to conventional techniques [41,42].

Acknowledging the broader nature of this phenomenon, the present paper aims to develop a systematic assessment of current limitations, approaches, and the impact that computational techniques have in suicidal ideation detection. Namely, this research has the objective to: **(i)** provide valuable recommendations or insights for future studies from the synthesis and analysis of contemporary efforts focused on a technological perspective, and **(ii)** explore the diversification of this topic's literature based on the language of the data employed to assess different AI-based methodologies, predicting English as the most popular and suggesting that the subject should be further explored in more vocabularies, specifically in Spanish. Consequently, this document is organized as follows: **Section 2** introduces the methodology employed for collecting investigations. **Section 3** institutes a concise summary of the selected research's characteristics, methods, metrics, and results. Moreover, **Section 4** institutes a discussion of these works to understand the current state of computer-based approaches for automatic suicidal ideation detection. Finally, **Section 5** establishes the author's comment on feasible technological trends for this problem and opportunities to conclude the compilation.

2. Methodology

The scoping review of investigations utilizing Natural Language Processing technologies, alongside other computational-based techniques, to detect individuals with suicidal ideation was conducted adhering to the standards of the PRISMA Statement [43]. Notably, this approach aided the present qualitative study in increasing transparency and the quality of the reporting of publications (*eidem*).

2.1. Search Strategy

For this systematic review, the collection of scientific efforts related to suicidal ideation detection using computational-based approaches was made using a search query with the following filter criteria:

- Limitation to peer-reviewed journal publications/articles.
- Publication date between 2020 and 2024 (inclusive).
- Use of a similar syntax based on the PICO framework applied by Arowosegbe., et al, for the searched index terms [42], making a special inquiry in the top 6 most popular languages according to Webber [44]:

((("Machine Learning" OR ML OR "Deep Learning" OR DL OR "Natural Language Processing" OR NLP OR "Artificial Intelligence" OR AI) AND (Suicidality OR "Suicidal Ideation" OR Ideation OR Suicide) AND (English OR Spanish OR French OR Russian OR Arabic OR Chinese))

2.2. Databases

The search for suitable literature for this research was made using five scientific databases: **1)** Springer Link; **2)** Scopus; **3)** Science Direct; **4)** IEEE; and **5)** MDPI. The main reason behind the election of such repositories is because of the grand Computer Science content available and the author's ease of access.

2.3. Eligibility and Inclusion criteria

All peer-reviewed journal publications published between 2020 and 2024 were included. This range was chosen because, as mentioned by Eiberg., et al, the manifestation of this phenomenon online is constantly evolving due to technological developments [45]. Additional inclusion criteria were: **1)** presentation of comparative studies between methods for suicidal ideation detection, **2)** introduction of new AI-based detection methodologies, and **3)** discussion of original frameworks applicable to real-life scenarios and supplemented by one or more AI-based techniques. Excluded from this review were conference papers, conference proceedings, conference reviews, books, book chapters, and reviews. Furthermore, literature related to measuring the effect of an intervention, presenting guidelines, case reports, and clinical studies, was removed as it did not include any computational-based approaches. Finally, research with full-text submissions available in languages other than English or Spanish was omitted.

2.4. Screening

A single reviewer screened titles, abstracts, and conclusions for eligibility. In particular, to meet the inclusion criteria defined above, the author briefly analyzed the abstract of each article using tools like Elicit, Scispace, and ChatPDF. When eligibility could not be determined with the obtained information, a full-text analysis was performed. Moreover, articles that appeared more than once in the complete collection were removed.

2.5. Analysis

As suggested by Arowosegbe., et al, a reflective thematic analysis (RTA) was adopted for this paper to generate a grounded discussion based on the findings from the collected studies [42]. Further, the assessment literature based on RTA, as exemplified by Byrne, resulted beneficial to the declared

objective of the present research since it facilitated a flexible interpretation of qualitative data due to the identification and analysis of themes in the compiled information [42,46].

3. Results

3.1. Study Selection

As seen in the PRISMA flow diagram depicted in Figure 1, 49 publications were identified in the selected databases. Originally, the preliminary search with the criteria described in Section 2 produced 317 results. After an initial screening using each article’s title and abstract, 256 records were excluded due to 3 main reasons: **1)** wrong study (not being associated with computer-based approaches); **2)** wrong theme of investigation; and **3)** not being publicly available for a complete individual assessment. Finally, a full review of 49 studies was developed once duplicated entries (12) were removed.

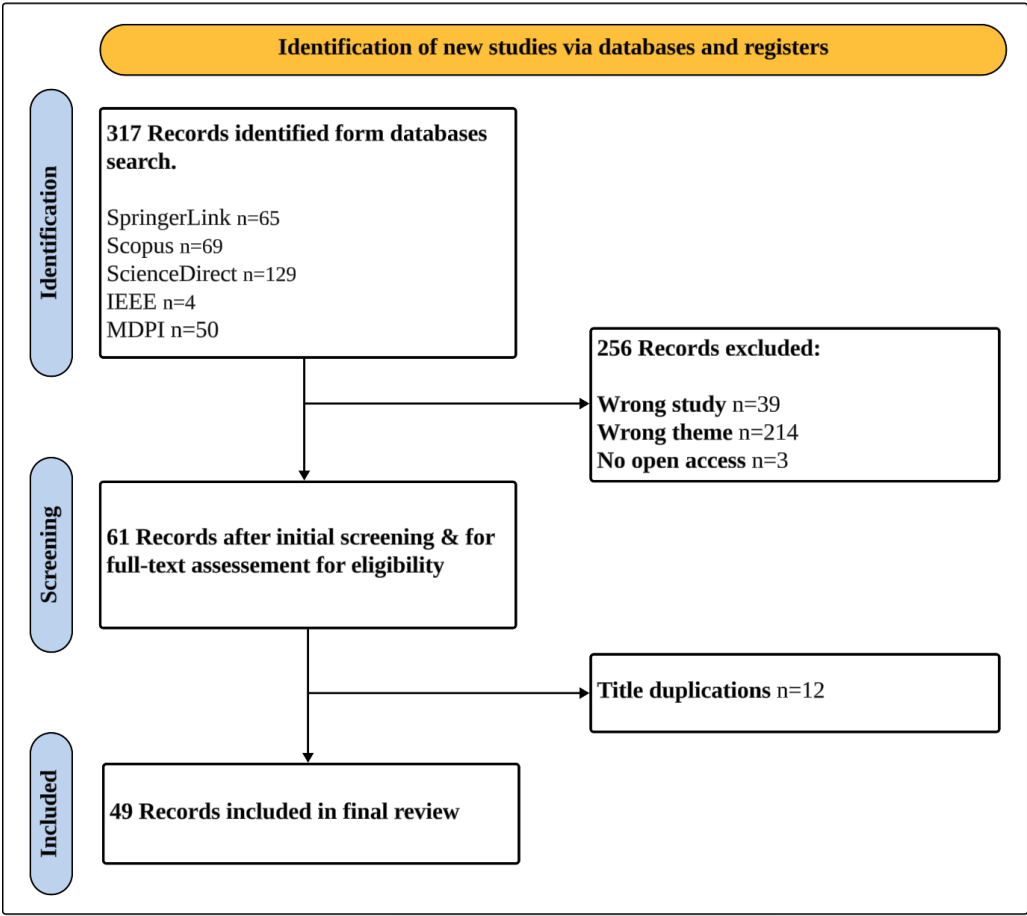


Figure 1. PRISMA Flow Diagram for identification of studies related to suicidal ideation

3.2. Study Characteristics

Since this research focused more on the language in which each dataset was originally written for the selected publications, an origin country analysis was omitted. In this sense, most investigations ($n = 33, 67.3\%$) utilized information written in English as seen in Figure 2.

A few exceptions, as seen in Figure 3, employed a combination of English and another language ($n = 3$ in total: $n = 2, 4.1\%$ for English/Spanish; and $n = 1, 2.0\%$ for English/Thai). Further, both figures highlight the fact that Chinese was the second most used language in the utilized sets ($n = 5, 10.2\%$) whereas both, Arab and Spanish, were the third most popular language ($n = 3, 6.1\%$). From the language popularity list from Webber [44], Russian and French did not appear nor were mentioned in any of the obtained literature ($n = 0, 0\%$).

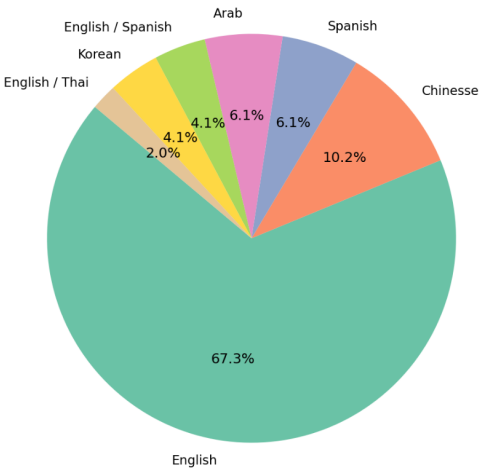


Figure 2. Language popularity in datasets used in collected literature

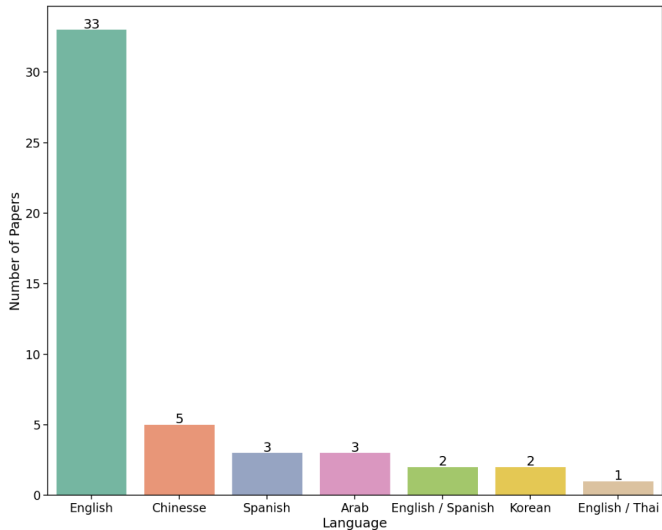


Figure 3. Collected literature count based on Language

As shown in Figure 4, recent literature was mainly based on ML approaches ($n = 20, 40.8\%$) or a combination of ML and DL techniques ($n = 16, 32.7\%$). However, despite the recent public consciousness of DL [47], a limited amount of publications focused their efforts on exploiting it ($n = 12, 24.5\%$). In addition, a single paper employed evolutionary algorithms (EA) for researching suicidal ideation ($n = 1, 2.0\%$).

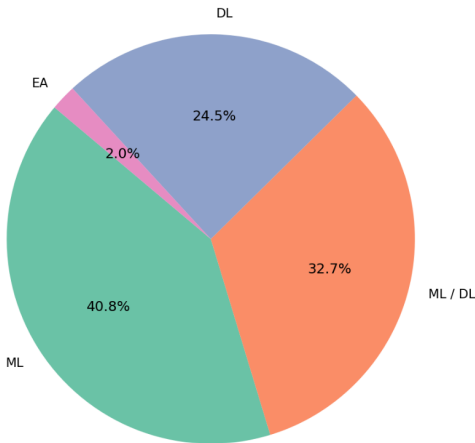


Figure 4. Technical approach popularity in collected literature

Moreover, Figure 5 shows that most of the literature used Twitter as their primary source of data ($n = 13, 27\%$), followed by Reddit ($n = 9, 19\%$), custom sets ($n = 7, 14\%$), clinical or clinically-reviewed sets ($n = 5, 10\%$), and a combination of Reddit and Twitter ($n = 3, 6\%$).

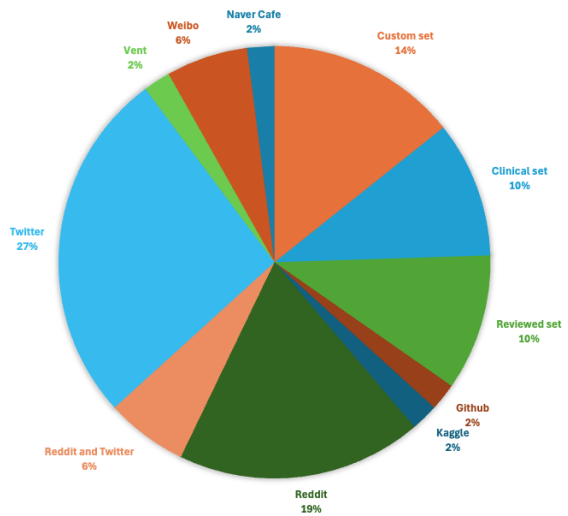


Figure 5. Dataset origin popularity in collected literature

Finally, almost every publication had *classification* as the main task to accomplish. Only a single document had *message assessment* as its main technical objective. However, Figure 6 highlights that 10 investigations focused on specific tasks apart from the generalized classification concept.

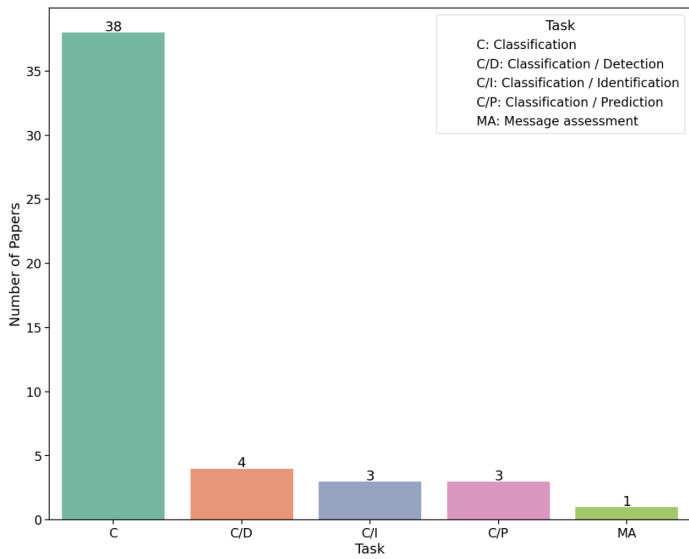


Figure 6. Main task counting per publication

A more detailed summary of the characteristics of each included study ($n = 49$) is outlined in Table 1. Some information presents acronyms for some of the techniques employed. Hence, the following glossary is provided:

- LR (ML Classifier): Logistic Regression
- RF (ML Classifier): Random Forest
- NB (ML Classifier): Naïve Bayes
- GB (ML Classifier): Gradient Boosting
- DT (ML Classifier): Decision Tree
- SVM (ML Classifier): Support Vector Machine
- SVC (ML Classifier): Support Vector Classifier
- KNN (ML Classifier): K-Nearest Neighbor
- MNB (ML Classifier): Multinomial Naive Bayes
- SGD (ML Classifier): Stochastic Gradient Descent
- ANN (ML Classifier): Artificial Neural Network
- MLP (DL Classifier): Multilayer Perceptron
- CNN (DL Classifier): Convolutional Neural Network
- RNN (DL Classifier): Recurrent Neural Network
- GRU (DL Classifier): Gated Recurrent Unit
- LSTM (DL Classifier): Long Short-Term Memory
- BERT (DL Classifier): Bidirectional Encoder Representation from Transformers

Table 1. Summary of studies for detecting suicidal ideation using AI tools

Reference	Language of Dataset	Classifiers	Results
[48]	English	DT, SVM	SVM outperforms DT with a 91.89% overall score (average of all metrics)
[40]	English	RF, SVC, SGD, LR, MNB; BiLSTM, LSTM, BiGRU, CLSTM	The best ML model was RF, which achieved a 93% accuracy and 0.92 F1 Score. The best DL model was BiLSTM, which achieved 93.6% of accuracy and 0.93 F1 Score
[49]	English	RF	The model applied within S-Care achieved 84.15% of accuracy. The model performed better in classifying 'Risk' scenarios than 'No Risk'

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[50]	English	CNN, RNN, ANN, RF, HACNN-LSTM	The proposed method obtained a 96.84% score in accuracy, surpassing any technique in suicidal ideation detection. In addition, the model performed better in the rest of the metrics
[51]	English	CNN, LSTM	The proposed method combined with the Glove embedding achieved the highest Accuracy, Precision, and F1 Score (88.48%, 87.36%, and 90.82%, respectively), whereas the ACL with Random embedding achieved the highest Recall (94.94%)
[52]	Spanish	NB, LOGIT, SVM, RF, KNN	1) The proposed predictor model detected 122 depression cases out of 140. 2) The model based on ML detected 179 depression cases out of 280 patients. 3) The best ML model in terms of Recall was NB with 92%
[53]	English	RF, Ripper, MLP	The proposed interestingness metric enhanced classification accuracy and prediction for every classification approach
[54]	English	BiLSTM, CNN, C-BiLSTM, BERT, GPT	The proposed model achieved the best accuracy and F1 Score among other DL models (94.95% for both cases). However, it was surpassed by the optimal GPT2 LLM, which achieved 97.69% for both scores.

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[55]	English	SVM, CNN, LSTM, LSTM-CNN, LSTM-Attention-CNN combined	The proposed model achieved a 90.3% accuracy and 92.6% scores, surpassing baseline ML models
[56]	English	SVM, Gradient Boosting, Bernoulli NB, Gaussian NB, DT, KNN, RF	SVM was the most useful algorithm for suicide detection with an accuracy of 88.6%
[57]	Arab	USE-M, USE-MQA, USE-M (Tuned), USE-MQA (Tuned), BERT-BV2, BERT-BV02T, BERT-LV2, BERT-LV02T, AraELECTRA	USE models obtained a max WSM at 80.2% whereas Arabic BERT models at 95.26%
[58]	English	LR, DT, RF, SVM, Perceptron, XGBoost	RF performed the best with an accuracy, F-1 Score and AUC over 97%
[59]	Arab	mBERT, GigaBERT, XLM-RoBERTa, AraBERT, AraELECTRA, Arabic BERT, Arabic ALBERT, ARBERT, MARBERT, AraGPT2, AraT5,	The model that achieved the highest accuracy in predicting depression and suicide was MARBERT with 91.2%
[60]	English / Spanish	28 different ML-based classifiers like: Kstar, RandomCommittee, RandomFiltClass, LMT, PART, RF, BayesNet, and AdaBoostM1	Kstar, along with the POS-SYNSETS-NUM features, achieved the best results with a ROC AUC value of 0.81 and F-measure of 0.71
[61]	English	CNN, XGBoost	CNN was the model that obtained better results with 0.88, 0.87, 0.88, 0.87, and 0.86 of accuracy, F1 Score, precision, recall, and AUC, respectively
[62]	English	J48, NB, Bayes Net, LMT, CNN, BiLSTM, BiLSTMAttention, DLSTMAttention, TransformerRNN	The proposed model achieved the best accuracy and F1 Score among other DL models (94.95% for both cases). However, it was surpassed by the optimal GPT2 LLM, which achieved 97.69% for both scores.

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[63]	English	KNN, Multinomial LR, Bagging, DT	The proposed approach had an accuracy of 97.64% in detecting suicide ideation
[64]	Korean	ML (monolingual model), ML-refined, CL-mixed (cross-lingual model), CL-ours	The model achieved a high accuracy with 87%
[65]	English	Custom Evolutionary Algorithm	The proposed approach detected suicidal cases with 95% sensitivity and 92% specificity
[66]	Chinesse	DPCNN, FastText, TextCNN	The model achieved a high accuracy and F1 Score of 93.11% and 89.62%, respectively
[67]	Chinesse	KNN, RF, SVM, TextCNN, TextRNN, TextRCNN, TCNN-MF-LA	The model outperformed any of the baseline models with an accuracy of 86.75% and a precision of 89.73%
[68]	English	XGBoost, CNN-BiLSTM	CNN-BiLSTM was the model that achieved the highest accuracy in detecting suicidal ideation with textual features at 95%
[69]	Arab	NB, SVM, KNN, RF, XGBoost, AraBERT, AraELECTRA, AraGPT2	AraBERT outperformed all of the models used to test the dataset with an accuracy of 91% and F1 Score of 88%
[70]	English	SVM, RF, XGBoost	The model with the best accuracy was XGB-EFASRI with 96.33%
[71]	English	LSTM	The used model achieved 93.34% of accuracy
[72]	English / Spanish	LR, SVM, GP, QDA	The methodology showed an effective result with an F1 Score of 0.95 in every classifier employed

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[73]	Spanish	RF, MLP, LR, SVM, CNN	The study identified statistical differences between textual and behavioral attributes for suicide risk detection. Further, the models employed outperformed the Bag-of-words based baseline models by 8%
[74]	Spanish	LR, SVM	The LR reached a maximum accuracy of 0.79
[75]	English	RF, SVM, NB, XGBoost, LSTM, CNN, LSTM-CNN	The proposed model combined with word embeddings achieved the best accuracy with 93.8%
[76]	English	TransformerRNN, MHA-BCNN, ABLSTM, CMA-MemNet, CNN w/GA, SENN, LSTM-Attention-CNN, COMV, VC, VCPCNN, CoDyn-BMHSA-CNN	The model accurately detected emotions from text sequences with a 98.2% effective rate in social media posts and 97.4% in suicide notes
[77]	English	LR, RF, CNN	The proposed approach outperformed in Recall, Accuracy and F1 Score models trained with Word2Vec, DistilBERT and GLoVe
[78]	Chinese	LR, Gradient Boosting, SVM, RF, DT, LR	LR and SVM models outperformed the rest by achieving an AUC of 0.57 and a p-value lower than 0.05
[79]	Chinese	Custom neural network	The proposed method distinguished 1356 out of 1916 patients (achieving 70.68% and 67.09% of sensitivity and specificity, respectively), as well as an accuracy of 70.08% and an AUC of 0.76

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[80]	English	SVM, LR, RF, XGBoost, VGGish-Z, VGGish-L	RF model exhibits robustness for major depressive disorders and persecutory thoughts dataset by showing positive values in effective robustness (0.23= and relative robustness (0.36)
[81]	English / Thai	SVM, LaBSE, BERT, MNB, BiLSTM, RoBERTa	The proposed framework demonstrated a cross-correlation between social media and clinical data, showing stronger indicators (like mental signals from social media) for this assessment. Further, the best performing model was LaBSE with 0.68 and 0.95 for F1 and both, Specificity and NPV values
[82]	Chinese	LR	The correlation between actual and predicted suicidal ideation was significant (p-value less than 0.001), suggesting that the analysis of features (like affection, positive emotion, or negative emotion) in the text is efficient for depression and suicidal ideation detection
[83]	English	LR, SBERT	Models demonstrate that message similarity is positively associated with signs of suicidal ideation and is stronger in users who post negative content

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[84]	English	SVM, RF, KNN	The proposed framework achieved F1, sensitivity, and specificity scores of 0.766, 0.750, and 0.79, respectively for the depression task, whereas 0.84, 0.86, and 0.72 for the suicidal ideation task
[85]	English	CMD-1	The proposed model reduced the daily triage time from 9 hours to 8-13 minutes. Additionally, the model achieved AUC, sensitivity, and PPV values of 0.82, 0.99, and 0.35, respectively in the retrospective test set, whereas 0.98 and 0.66 in the prospective test set
[86]	Korean	XGBoost-based proprietary model	The model that combined both: the brain magnetic resonance imaging and clinical notes achieved a higher AUC (0.79) compared to those that only included clinical notes (0.74) and brain magnetic resonance imaging (0.73)
[87]	English	SVM, Logistic Regression, RF, Multinomial NB	LR and SVM models outperformed the rest in accuracy by achieving 0.76 and 0.72, respectively
[88]	English	ScANER	The proposed model achieved a macro-weighted F1 Score of 0.83 for suicidal behavior identification, a macro-weighted F1 Score of 0.78 and 0.60 for classification of suicide attempts and suicide ideation, respectively

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[89]	English	ALBERT, DistilBERT	The evaluation of methods with synthetic data consistently offered F1 scores of 0.82, suggesting that the richness of topics within this data can bridge the performance gap. Furthermore, the F1 Score improved to 0.88 when the data was combined with a mere 30% of a real-world set
[90]	English	DT, RF, GB, Ensemble, AdaBoost, XGBoost, CNN, LSTM, 2-Layer LSTM, CNN-LSTM, Stacked CNN + 2-layer LSTM	The Stacked CNN + 2-layer LSTM model achieved an accuracy of 93.93%, outperforming any model compared
[91]	English	FastText, CNN, LSTM, BiLSTM, RCNN, SSA, Custom RN	The proposed model shows the best accuracy of all the models employed with a score of 0.83, proving its effectiveness
[92]	English	NB, LR, SVM, LSTM, BiLSTM, GRU, BiGRU	The proposed model outperformed state-of-the-art models with an F1-micro score of 0.30 when combined with a BiGRU classifier
[93]	English	SVM, LR, RF, MNB, AdaBoost, XGBoost, Max Voting Ensemble classifier	The proposed model yielded an improved precision of 01.39% with an accuracy of 87.5%, highlighting promising outcomes of ensemble models
[94]	English	LR, RF, SVM, XGBoost	When combined with LR, the proposed model outperformed other baselines by achieving an accuracy of 87%

Table 1. Cont.

Reference	Language of Dataset	Classifiers	Results
[95]	English	BERT, STL-EMO, CMSEKI, STL-INT, SPANMLC, VAD-BERT	The model performs better than single-task systems for emotion recognition with an overall mean recall of 65.25%

* Tables may have a footer.

3.3. Discussion

AI and its different areas of study (ML, DL, NLP) have impacted how various fields study suicide by aiding in the application and development of sophisticated statistical methods for the identification of potential suicide risk and suicidal ideation [35]. Thus, literature constantly tries to improve prediction accuracy to refine suicide care overall [36,37]. In that sense, and as demonstrated in Section 3, most investigations related to the topic employ canonical NLP features, like TF-IDF, in conjunction with ML classifiers, such as SVM or Logistic Regression, to perform an analysis based on extracted features [38]. For instance, Valeriano K, Condori-Larico A., et al, one of the few recent research focused on the use of Spanish data and the first to use these technical approaches in such language, prepared a phrase classification model to detect suicidal ideation in social networks automatically via TF-IDF and Word2vec, for pre-processing, and SVM and Logistic Regression classifiers [74].

Furthermore, automatic detection of suicidal ideation has started to explore automatic feature learning with deep learning models, in particular, CNN and LSTM [38]. For example, Fabra J, Martínez A., et al, created a new platform that enables the detection of suicide risk by combining emotional processing systems, clustering techniques, and the LSTM classification technique [71].

However, as suggested by Table 1, as well as by Figure 7, a significant amount of research has focused on employing both of these approaches (ML and DL classifiers). Notably, Abdulsalam A, Alhothali A., et al, recently created a new Arabic suicidal tweet dataset to evaluate ML and DL techniques for suicide detection in Arabic, satisfying the need for corpora in such language [69].

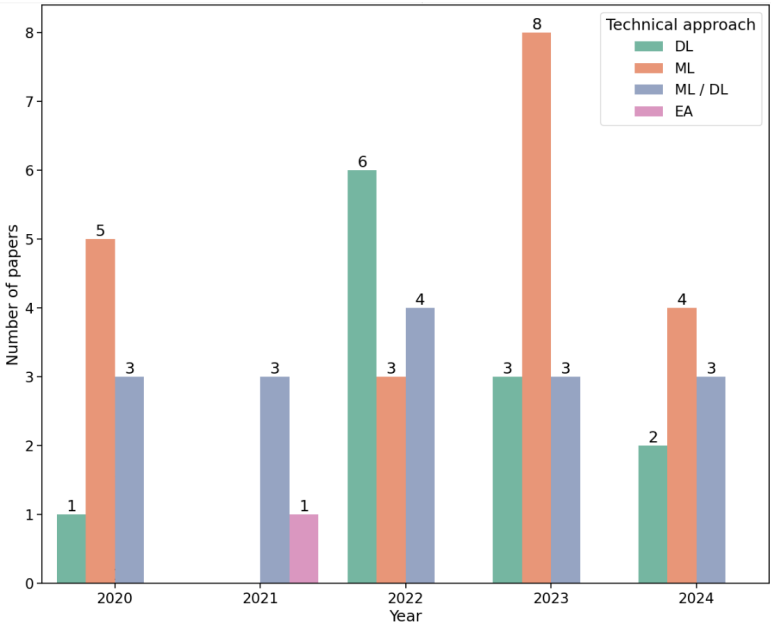


Figure 7. Main task counting per publication

Notably, by making a special inquiry in the presence of research in the top 6 most popular languages according to Webber [44], English is still the predominant language in which suicide is being analyzed as it has access to ample ground truth information derived from expert diagnostics

of individuals with suicidal ideation or depression [96]. As seen in Figure 8, throughout 2020 and 2024, such language was predominantly used in the datasets employed to classify this condition automatically with an outstanding difference between other languages. Multilingual approaches, as those proposed by Noraset T, Chatrinan K., et al; Wellington R, Gómez J., et al; and Pool-Cen J, Martínez H., et al [60,72,81], have used Anglo-Saxon data, along with language-specific information to detect this phenomenon in other linguistic contexts (Spanish or Thai). However, these approaches are not easily feasible due to costly effort derived from the excessive features needed for semantic representation of multiple linguistic resources [97].

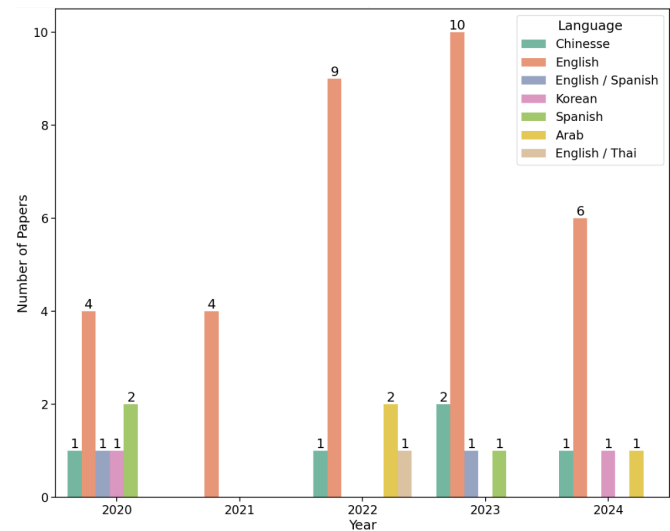


Figure 8. Number of publications per year by language

In contrast, Chinese, the second most popular language for this particular task and the most spoken language in the world [98], presents a vast discrepancy to English when the amount and constancy of publications are compared over the years. Similarly, the Spanish and Arab idioms suffer from this absence of representation with even less presence in recent literature than its Asian counterpart. This deficiency, as well as the limited exploitation of techniques in languages highlighted in Figure 9, suggest the existence of several potential research branches yet to be acknowledged that would benefit extensive non-explored numerous geographic and digital linguistic populations, as is the case of the Spanish language.

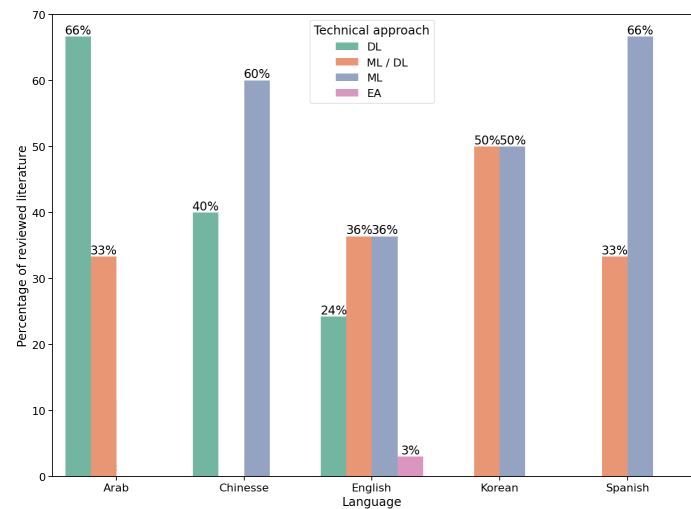


Figure 9. Percentage of usage of different technological approaches (ML & DL) for suicide and suicidal ideation detection in different languages

Moreover, as suggested by the works included in Section 3, as a whole, the utilization of these advanced techniques has allowed the expansion of methodologies in which suicide is studied from a computer-based perspective.

Namely, from 2020 to 2024, as shown in Figure 10, the utilization of advanced technical tools in research years has facilitated the development of custom datasets, frameworks, models and specialized solutions to enhance comprehension in the efficacy of practical applications of automatic suicidal ideation detection systems. For example, Rentz D, Heckler W., et al, created a proprietary system (S-Care) for suicidal ideation detection and assistance that integrated external data sources (like hardware information and social media information) for enabling a daily tracking of a user [49]. Other examples are the works presented by Renjith S, Abraham A., et al; and Pillai A, Nepal S., et al, where they: **i)** explored new technological improvements for suicide detection by the application of social media data and a novel LSTM-Attention-CNN model; and **ii)** performed experiments to explore the generalizability of speech-based suicidal ideation detection, evaluating at the same time unsupervised (UDA) and semi-supervised (SSDA) domain adaptation to assess performance mitigation due to distribution shifts, respectively [55,80].

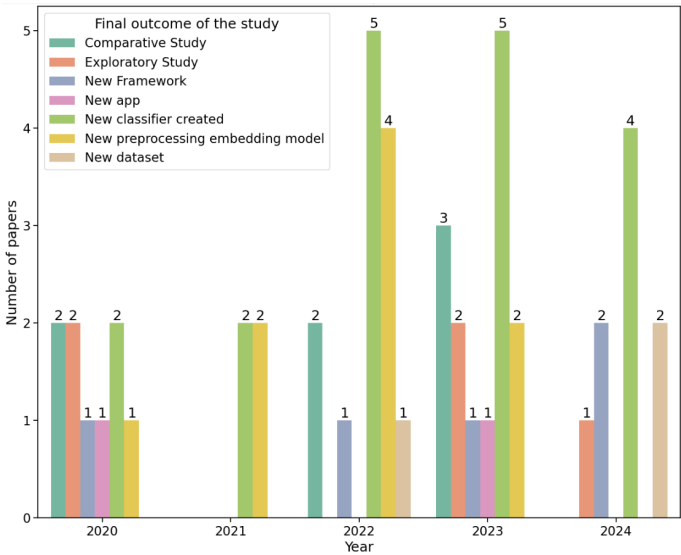


Figure 10. Principal research outcomes per year

Additionally, as hinted in Section 3, the understanding of the current state-of-the-art of how literature studies suicide as a computationally detectable phenomenon via the application of such techniques can be expanded under the constant investigation of two main research themes: **i)** Suicidal ideation & Suicide; and **ii)** Depression & other Mental Disorders.

3.4. Suicidal Ideation & Suicide

As previously mentioned, suicide is a complex multifaceted event with multiple phenotypes that can and must be considered across its spectrum, such as suicidal ideation [1,12]. The focused study on the manifestations of the phenomenon [mainly done by technological methods] is a legitimate avenue that has increased its understanding [12].

Notably, ML and DL techniques have aided in the identification of suicide risk factors and expressions not only in isolation but also while integrating complex interactions across variables [35]. Significantly, researchers have exploited the vast amount of data passively and actively created by social media users to: **i)** present new classifiers based on modern pre-processing and ensemble techniques for suicidal ideation detection [50,67,93]; **ii)** Enhance the accuracy of detection by fine-tuning specific parameters or mechanisms of existing models [57,70,92,94]; **iii)** Compare and identify which techniques are the most effective for the identification of suicidal ideation [48,56,68,90]; **iv)**

Create new sets that could expand the research of the phenomenon on more languages or expand current ones with synthetic information [59,69,89].

Moreover, clinical data has also been used (with less frequency than social media information) to endorse and refine suicide predictive algorithms according to a specific population, like Guíñazú M, González M., et al approach that validated a custom model (PDRM) for specific Chilean characteristics [35,52]. Furthermore, this type of data source has enabled a more diverse exploration of suicide as a phenomenon as it allows the analysis of speech-based manifestation, the evaluation of physiological characteristics (e.g. brain magnetic resonance imaging) of potentially suicidal patients, as well as the identification of linguistic features that could indicate suicidal ideation in clinical transcripts of a specific language [78,80,86].

Consequently, it can be said that the predictive analysis derived from these approaches has enabled the recognition of at-risk individuals, their likelihood of a future suicide attempt, and, overall, improved suicide management in areas of prevention, evaluation, diagnostics, treatment, and follow-up strategies [35].

3.5. Depression & other Mental Disorders

Currently, as complex as the phenomenon itself, some literature about suicide has suggested equating it to a cause, namely disorder of the mind [7]. Meaning that death by suicide is a consequence of a particular mental illness (e.g. Depression) and, thus its prevention revolves around the interpretation of a peculiar clinical condition (*eidem*). Furthermore, this specific approach categorizes and emphasizes the understanding of the type of factors that contribute to suicide risk¹, as these might facilitate or increase vulnerability for developing suicidal ideation or behavior [1]. Namely, medical factors such as anxiety, depression, impulse-control disorders, self-harm, eating disorders, or post-traumatic stress disorder have become relevant risk factors for suicide, making its consideration a relevant research opportunity for automatic evaluation of data [1,8].

In that sense, more recent literature regarding the automatic detection of suicidal ideation has been complemented by the analysis of these particular disorders. Namely, the identification of relevant terms in common social posts has been improved by the utilization of domain-specific corpora from mental health issues [77]. Additionally, from this perspective, computer-based investigations have expanded beyond the basic textual analysis of data to incorporate more complex relations via the assessment of temporal information of individual users in social media [61]. Also, it has enabled the creation of sophisticated intervention strategies to assure instantaneous mood evaluation or to improve response time to crisis messages, as the ones proposed by Dogrucu A, Perucic A., et al, and Swaminathan A, López I., et al, respectively [84,85].

Nonetheless, risk factors are not universal as an individual who experiences either suicidal ideation or attempted suicide, does not necessarily die by suicide [1,14]. This suggests that approaching the automatic detection of suicide cannot be solely dependent on the evaluation of a mental disorder as these are not the same [7]. Thus, research should also be complemented with culturally informed insights to avoid the exacerbation of this phenomenon and ultimately develop robust methodologies for improved preventive strategies [7,14].

3.6. Limitations

From 2020 to 2024, each research presented unique limitations that affected their development as the complexity of automatically assessing suicidal ideation is recently being studied. However, it was possible to summarize what the most common constraints are currently being discussed in ongoing literature, and that represent a valuable insight for further research regarding this particular theme:

- Limited dataset size for more robust experimentation development like expanded statistical analysis or the application of cross-validation [62,90,94].

¹ The biopsychosocial model of suicide risk introduces a comprehensive review of the factors that may contribute to suicide risk [1]

- Created custom models lacked interpretability in clinical-based scenarios, affecting their reproducibility and real-life applications [58,79,89].
- Datasets contained insufficient and imbalanced data that made it harder for some models to capture semantic relationships and affected the detection [66,67,76].
- Datasets that used social media data lacked ground truth values and, as a whole, the source can affect reliability. This approach was mainly made due to the restrained access to clinical-assessed data [51,69,73].
- Data did not consider demographic or culturally specific characteristics of the language [59,64,83].
- Absence of domain-specific corpora in languages apart from English [63,64,74].

Despite being external constraints, each of the presented limitations is and should still be addressed in future investigations exploiting new technologies and methodologies to continue the development of solutions for this phenomenon. For example, more recent research, like the one presented by Ghanadian H, Nejadgholi I., et al, focuses on the expansion of data with the implementation of IA-based content created with Large Language Models [89]. Another example is the application of curated datasets that have been previously used or collected in past related studies to continue the exploration of new approaches [54,56,68,93], or the use of specific regional data to comprehend suicide [52] particularly.

4. Conclusion

Suicide, and more particularly Suicidal Ideation, is an issue whose understanding relies on the exploitation of different strategies ranging in numerous fields [99]. Particularly, the identification of potential suicide risk and suicidal ideation relies on traditional and advanced statistical methods [35]. Hence, it is through technology-driven approaches that literature is allowed to encompass different and more complex manifestations of suicidal ideation in a more digital era by enabling efficient alternatives to conventional techniques [35].

Currently, the most popular techniques in related publications during the last years have been: 1) *text-based classification*, with ML models like SVM, ANN, CRF, Logistic Regression, Naïve Bayes, Random Forest, XGBoost, Decision Trees and KNN; and 2) *deep learning*, with models like DNN, LSTM, CNN, BERT and Ensemble Learning (learning based on the combination of two or more models [100]). Each of these advanced statistical methods has enabled the computational study of suicide through its broad spectrum considering phenotypes like suicidal ideation and potential risk factors such as mental illnesses, depression being the most studied. Moreover, these applications derived in the creation of solutions ranging from custom ML or DL models for classification; to former applications and proto-frameworks for testing its potential effectiveness in real-life scenarios.

Nonetheless, before AI can be integrated into clinical practice and more robust predictive frameworks, there are still limitations to be addressed [35]. Namely, current literature is mostly centered in Anglo-Saxon contexts, leaving the implementation of these novel methods out of other languages. As highlighted in Figure 8 and in Figure 9, there is a considerable gap in research that exploits ML or DL for detecting suicidal ideation in the most popular languages of the world according to Webber [44]. This also highlights the impediment of not having investigations that explore the influence of cultural characteristics manifested in a particular idiom. Another barrier that constrains modern-day investigations is the limited access to ground-truth data and the reliability of social media information. This has affected the overall amount of entries in datasets for robustness and more accurate results in experimentation processes.

Hence, to aid in the constant tackling of knowledge gaps to improve the treatment and prevention strategies of this phenomenon, this document suggests that future research, based on the analysis elaborated in this investigation, should be focused on:

- Detecting implicit suicidal manifestations and ambiguous emotions in sentences.
- Improve the integration of user-profiles and linguistic features for social media data to improve suicide ideation detection.

- Expand the inclusion of parameters that add demographic context to data such as gender and location.
- Data from social media should include images, videos, and emoticons in its analysis to provide a complete assessment of potential suicidal risk.
- Explore language diversity beyond English in models, as well as cross-lingual frameworks.
- Address data sparsity and imbalance challenges.
- Validate results through large-scale research with larger datasets, ground-truth clinical data, and specialized vocabulary.
- Continue the exploration of the impact of risk factors in the detection of suicidal ideation automatically.
- Test models generalization for potential clinical detection applications.
- Continue exploring the performance of novel techniques and datasets from various social media sites for this task.
- Continue incorporating a timeline analysis in social media data to improve the identification of individual risk cases.

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