

1. **Pestian et al. (2010). “Suicide Note Classification Using Natural Language Processing: A Content Analysis.”**
 - **Why it’s relevant:** One of the earliest works to apply NLP systematically to genuine suicide notes. They use machine-learning-based text classification to distinguish suicidal notes from other types of personal writings.
 - **Key contribution:** Demonstrates how text features—like sentiment indicators, word choices, and linguistic style—can be predictive of suicidality risk.
2. **Burnap, Colombo, & Scourfield (2017). “Machine Classification and Analysis of Suicide-Related Communication on Twitter.” *Health Informatics Journal*, 23(1).**
 - **Why it’s relevant:** This study focuses on suicide-related tweets, exploring machine-learning methods (including NLP-based classifiers) to detect suicidal ideation in near real time.
 - **Key contribution:** Provides insights into both the technical classification pipeline and ethical considerations around using public social media data to identify people at risk.
3. **Coppersmith et al. (2015). “Clpsych 2015 Shared Task: Depression and PTSD on Twitter.” In *Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology*.**
 - **Why it’s relevant:** Although titled with “depression” and “PTSD,” it also deals heavily with suicidal ideation as part of the shared task. Many subsequent suicide-detection studies build on methods or data from these authors.
 - **Key contribution:** Laid groundwork for standardized data and benchmark tasks—useful for comparing new NLP models.
4. **Ji, Pan, Li, Cambria, & Long (2022). “Suicidal Ideation Detection: A Review and New Directions for Multi-Modal Analysis.” *IEEE Intelligent Systems*, 37(4).**
 - **Why it’s relevant:** A more recent survey paper that synthesizes the progress of NLP-based approaches for identifying suicidal ideation in text and discusses the potential of combining text with images, audio, or other modalities.
 - **Key contribution:** Offers an organized overview of existing datasets, model architectures, and practical challenges (e.g., privacy, ethics), making it an excellent starting point for any literature review or presentation.

5. **Yaseen & Sharif (2022). “Detecting Suicidal Ideation on Social Media Using Language Models.” Knowledge-Based Systems, 253.**

- **Why it’s relevant:** Explores modern deep-learning and transformer-based language models (e.g., BERT variants) for identifying suicidal ideation. Evaluates performance on real-world social media posts.
- **Key contribution:** Demonstrates that advanced language models can surpass older machine-learning baselines by capturing context and subtle clues of suicidality (e.g., ambiguous expressions of distress).

6. **DORIS: Depression Detection on Social Media with Large Language Models**

- **Why it’s relevant:** DORIS paper presents a targeted, innovative approach with empirical results in depression detection on social media.
- **Key contribution:** DORIS is a novel system for detecting depression on social media using large language models (LLMs) and medical knowledge (e.g., DSM-V criteria). DORIS improves accuracy by combining high-risk text analysis, mood course tracking, and interpretable LLM-based diagnostics. It uses both traditional classifiers and expert-guided features for explainability and precision. Experimental results show a 0.036 AUPRC improvement over baselines, demonstrating the system’s effectiveness in early depression detection and its practical NLP application. In our project, we could use **transfer learning** technique to implement suicide detection from depression detection.

7. **Using Social Media for Mental Health Surveillance: A Review**

- **Why it’s relevant:** It provides a comprehensive overview of methodologies employed in leveraging social media data for mental health monitoring. It discusses recent trends, data collection techniques, and the application of machine learning (ML) and natural language processing (NLP) tools in this domain.
- **Key contribution:** The review discusses general applications of ML and NLP in mental health surveillance.