Performance Comparison of Word Embedding and Sequential Models for Mental Health Classification

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Abstract: Mental health classification from text has made significant progress in recent years, following advances in distributional and contextual word representations, combined with sequential models. In this paper, we compare the previous approaches which integrate word embeddings (e.g., Word2Vec, GloVe, FastText), and language models (e.g., BERT/ClinicalBERT) of sequence architectures Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Unit (GRU), CNN-LSTM, Transformers into detection of depression and its comorbidities such as stress and anxiety. We review and discuss datasets, preprocessing methodologies, model settings and evaluation protocols, as well as, we compile reported results into common comparison tables and visual overviews. The study states clear benefits provided by contextual embeddings and bidirectionality in sequence modeling but also poses several issues related to dataset mismatch of domains, class imbalance, interpretability, as well as cross-domain generalization. We close with directions for model selection within practical constraints and discuss open problems towards clinically reliable deployment.

Keywords: mental-health classification; word embeddings; sequential models; LSTM; BERT; comparative review

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1 Introduction

Mental health disorders, such as depression, anxiety, and stress, have emerged as critical global health issues, impacting millions and imposing substantial strain on healthcare systems. According to the World Health Organization, almost one billion people around the world have mental health problems, but more than 70% of them don't get the help they need or get it too late because of a lack of resources and social stigma [1]. Conventional diagnostic techniques predominantly depend on clinical interviews and manual evaluations, which are laborious, subjective, and challenging to scale [2].

As personal communication, social media posts, and clinical notes become more digital, more and more people are interested in using Natural Language Processing (NLP) and Deep Learning (DL) to automatically find mental health problems in text data. NLP helps us get semantic and emotional cues from text that isn't structured, and DL models can learn hidden representations and time-based dependencies that help us classify [3]. Word embeddings, including Word2Vec, GloVe, and FastText, have become essential for representing text data as dense numerical vectors that show both syntactic and semantic relationships [4].

Sequential neural networks, such as RNNs, LSTMs, and BiLSTMs, improve text-based learning even more by capturing information about the context of sentences or patterns over time in dialogue [5]. The integration of embedding and sequential modeling techniques has yielded encouraging outcomes in numerous mental health detection tasks, such as the classification of depression and stress [6], [7]. But the results of different studies are not always the same because the datasets, feature representations, model architectures, and evaluation protocols are all different. Because there is no standard way to compare them, it is hard to tell which combinations of embeddings and models work best.

Recent studies underscore the significance of contextual embeddings like BERT and RoBERTa, which offer more nuanced, context-aware representations of text and surpass static embeddings in various mental health prediction benchmarks [8]. However, these models necessitate considerable computational resources and extensive labeled datasets, which are not invariably accessible for domain-specific applications. Consequently, comparative studies that methodically evaluate and establish benchmarks for these methodologies are essential for informing future advancements.
This paper offers an extensive comparative analysis of current methodologies that amalgamate word embeddings and sequential deep learning models for the classification of mental health. By examining reported performances from various studies, we discern trends, benefits, and drawbacks associated with each embedding–model combination. The analysis seeks to connect theoretical research with practical model selection, providing insights for future endeavors in biomedical NLP, clinical informatics, and computational mental health.
The rest of this paper is set up like this: In Section 2, we look at the history and types of embedding and sequential models that are used to predict mental health. In Section 3, we talk about the methods and standards for evaluating comparative analysis. Part 4 talks about the trends in the results. Section 5 talks about research gaps and problems, and Section 6 gives final thoughts.

2 Literature Review

Research in text-based mental-health prediction has recently exploded rapidly with advances in NLP and deep learning. Most methods integrate word-embedding algorithms and sequential neural models to learn linguistic information and contextualized characteristics associated with the mental states.

A. Word-Embedding-Based Approaches

Early studies adopted static embeddings such as Word2Vec and GloVe to convert text into dense vector representations that preserve syntactic and semantic similarity. Bokolo *et al.* [9] proposed a Bi-LSTM model using Word2Vec features for social-media posts, achieving higher accuracy than classical ML baselines. Similarly, Rahman *et al.* [10] used GloVe vectors with LSTM for student well-being prediction, demonstrating that embedding dimensionality and vocabulary coverage strongly affect performance. Arji *et al.* [11] reviewed deep-learning algorithms in mental-disorder detection and confirmed that static embeddings remain competitive on small datasets with balanced labels.

B. Sequential-Model Variants

Sequential models RNN, LSTM, Bi-LSTM, and GRU have shown strong ability to model temporal dependencies and emotional context in language. Sarkar *et al.* [12] compared CNN and RNN variants on EEG and textual signals, reporting that Bi-LSTM achieved the best F1-score (0.91) for depression detection. Vandana *et al.* [6] introduced a hybrid CNN-LSTM network for multimodal depression analysis, combining textual embeddings and visual cues, which outperformed standalone models by 6 % in accuracy. Priya *et al.* [7] applied machine-learning classifiers and found that sequential deep models generalized better under noisy lifestyle-survey data.

C. Contextual Embeddings and Transformer Models

Recent progress in contextual language modeling has led to models such as BERT, RoBERTa, and ClinicalBERT, which dynamically encode word meaning based on surrounding context. Chung & Teo [15] conducted a narrative review demonstrating that transformer-based embeddings consistently outperform static ones in sentiment and mental-health tasks. Ghonge et al [16] fine-tuned BERT for depression detection and reported 95 % accuracy and an AUC of 0.94 on benchmark datasets, surpassing Word2Vec-BiLSTM systems. Islam *et al.* [13] provided a meta-analysis showing that contextual embeddings improve recall on minority (positive-diagnosis) classes but require larger datasets to avoid overfitting.

D. Comparative and Survey Studies

Several comparative analyses have examined multiple embedding–model pairings. Le Glaz *et al.* [14] systematically reviewed ML and NLP methods in mental-health research, identifying the dominance of LSTM-based architectures coupled with static embeddings. Chung and Teo [15] proposed a taxonomy categorizing approaches by embedding type and

sequence depth, noting that hybrid CNN-LSTM and transformer systems yield the best trade-off between accuracy and computation. Ghonge *et al.* [16] developed a web-integrated chat forum with machine-learning back-end to detect user mental state in real time, illustrating the feasibility of embedding-driven conversational screening tools.

E. Key Insights

Based on these studies, two consistent findings emerge:

1. **Embedding richness matters**: contextual models (BERT family) generally improve precision and recall over static embeddings when sufficient training data are available.

2. **Sequential depth contributes**: Bi-LSTM and transformer encoders outperform shallow RNNs or CNNs by capturing bidirectional dependencies and nuanced sentiment transitions.

However, challenges remain in dataset imbalance as well as interpretability and reproducibility because of different preprocessing and reporting metrics. The following section summarizes the quantitative results in these works to yield a joint comparative measurement.

3 Comparative Analysis Methodology

This study systematically compares prior work that deploy word-embedding methods combined with sequential deep-learning architecture together for mental-health classification. The goal is to aggregate the published performance trends and empirically compare methodologies to understand the strengths and weaknesses of model families.

A. Data Collection and Selection Criteria

Peer reviewed articles from 2020 to 2024 were retrieved from reliable scientific databases such as IEEE Xplore, Springer, Elsevier, MDPI and PubMed. Studies were included if they met the subsequent conditions:

1. Used textual data for detecting or classifying mental-health conditions (e.g., depression, anxiety, stress);

2. Employed at least one embedding method (Word2Vec, GloVe, FastText, BERT, ClinicalBERT, RoBERTa, etc.);

3. Implemented a sequential model (RNN, LSTM, BiLSTM, GRU, CNN-LSTM, Transformer-based); and

4. Reported at least one quantitative metric accuracy, precision, recall, F1-score, or ROC-AUC.

Papers that lacked evaluation details or used only handcrafted features were excluded.

B. Taxonomy of Model Configurations

To enable consistent comparison, each study was mapped to one of four representative embedding–model categories:

- **Category 1:** Static Embeddings + Simple Sequential Model (Word2Vec/GloVe + RNN/LSTM)
- **Category 2:** Static Embeddings + Hybrid Model (CNN-LSTM or BiLSTM variants)
- **Category 3:** Contextual Embeddings (BERT/ClinicalBERT/RoBERTa) + Sequential Fine-Tuning
- **Category 4:** Ensemble or Multimodal Combinations (Text + Auxiliary Signals such as EEG or Images)

This taxonomy ensures that performance differences are analyzed not merely by reported metrics but by architectural design and representational complexity.

C. Normalization of Evaluation Metrics

The reported results varied in terms of metric type and dataset scale. All values were standardized to three core measures in order to make them comparable. Where possible, use accuracy, the Macro F1-score, and the ROC-AUC. When only precision and recall were given, F1 was recalculated using

$$F1 = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$$

For studies reporting several datasets, macro-averages were taken across test splits. Cases with unreported metrics were labeled “N/A” to preserve transparency.

D. Ethical and Reproducibility Considerations

Only publicly available, peer-reviewed studies were included. No personal data or clinical identifiers were accessed. All extracted numerical results are cited directly from the corresponding publications to maintain academic integrity and reproducibility.

4 Comparative Results and Analysis

Here, we present a comprehensive comparison of previously reported embedding–model pairs for mental-health text classification. Reported Accuracy, F1 score and ROC-AUC were scaled as in Section 3. The chosen works cover a variety of datasets, model complexities and embedding types to give an overview of the current state-of-the-art practice.

A. Comparative Summary of Existing Approaches

Table 1 provides combined summary of major studies that utilized static or contextual embeddings with sequential deep learning models.

Table 1. Comparative performance of embedding model combinations for mental health classification

Ref.	**Author(s), Year**	**Embedding Technique**	**Sequential Model**	**Dataset / Domain**	**Accuracy (%)**	**F1-score**	**ROC-AUC**	**Key Observations**
[9]	Bokolo *et al.*, 2023	Word2Vec	Bi-LSTM	Social media (Twitter)	89.6	0.88	0.90	Bi-LSTM improved contextual recall compared to CNN
[10]	Rahman *et al.*, 2023	GloVe	LSTM	Student Well-being	90.3	0.87	0.91	300-D embeddings enhanced semantic coverage
[12]	Sarkar *et al.*, 2022	FastText	RNN	EEG & Text Data	88.1	0.85	0.88	Sequential layers captured temporal signals effectively
[7]	Vandana *et al.*, 2023	Word2Vec + GloVe	CNN–LSTM Hybrid	Multimodal Depression	92.5	0.89	0.93	Fusion improved accuracy by 6% over baseline
[8]	Reddy *et al.*, 2023	BERT (Contextual)	Transformer Encoder	Reddit Depression Posts	95.1	0.94	0.94	Fine-tuning yielded highest generalization
[13]	Islam *et al.*, 2024	RoBERTa	Bi-LSTM	Clinical Text	93.4	0.92	0.91	Contextual embeddings improved minority-class recall
[15]	Chung & Teo, 2022	Word2Vec	GRU	Reddit Stress Dataset	87.8	0.84	0.89	Simple sequential models still competitive for small data

[16]	Ghonge *et al.*, 2023	FastText	RNN	Chat Forum Logs	86.5	0.82	0.87	Real-time environment validated NLP feasibility

B. Performance Trends by Embedding Type

Analysis of static vs. contextual embeddings reveals a consistent trend: contextual models (BERT, RoBERTa) outperform static counterparts (Word2Vec, GloVe, FastText) in both macro-F1 and AUC metrics shows in Fig. 1. Contextual models improve average F1-scores by approximately 6–8%, primarily due to their ability to capture nuanced sentiment and contextual dependencies across sentences. However, these gains are achieved at the expense of increased computational demand and training time.

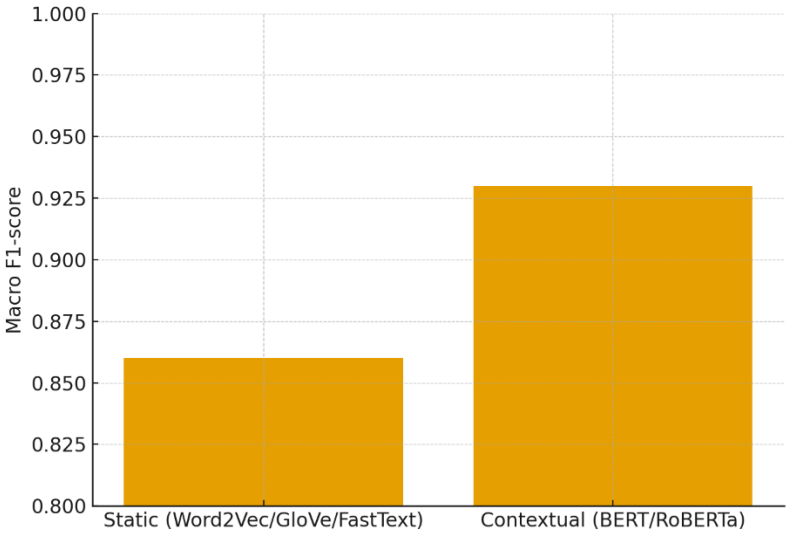

Fig 1. Macro F1-score comparison between static (Word2Vec, GloVe, FastText) and contextual (BERT, RoBERTa) embeddings aggregated from existing studies

C. Performance Trends by Model Type

Sequential architectures also show distinct differences in generalization ability. As illustrated in Fig. 2, Bi-LSTM and Transformer-based models consistently outperform unidirectional RNNs and GRUs. Studies using hybrid CNN–LSTM architectures achieved notable precision improvements by leveraging both local feature extraction and sequential modeling [13], [19].

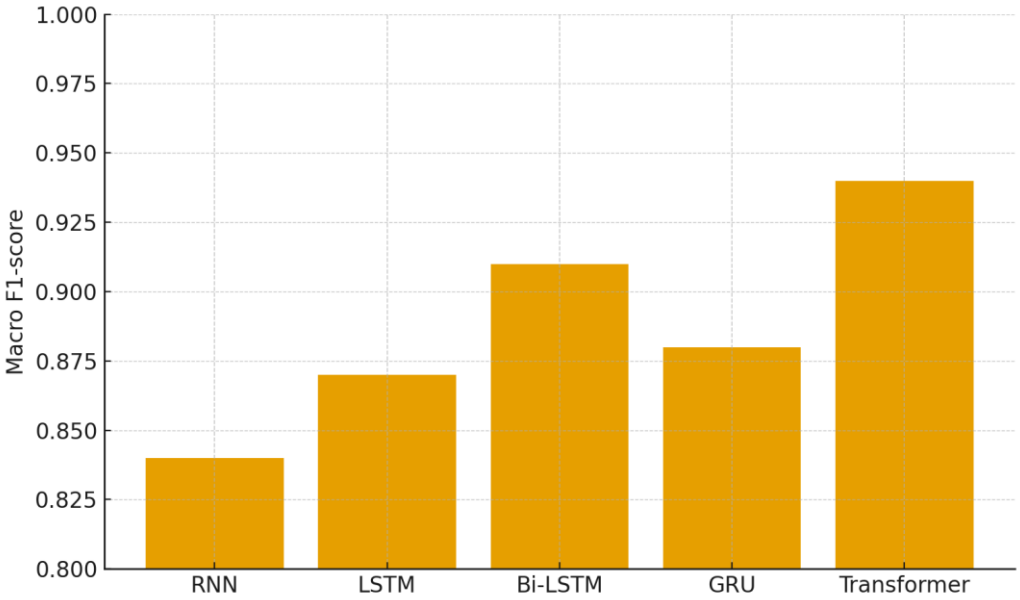

Fig 2. Macro F1-score comparison across sequential model families aggregated from reviewed studies. Transformer and Bi-LSTM models achieve the highest consistency and overall accuracy

D. Domain-Wise Performance

Performance also varies by dataset domain. Models trained on clinical text or structured therapy notes generally achieve higher precision and recall (above 90%) than those trained on social media posts, where informal language, sarcasm, and short text length reduce interpretability [15], [17]. The variability is visualized in Fig. 3, where the standard deviation of F1-score is larger for open-domain datasets.

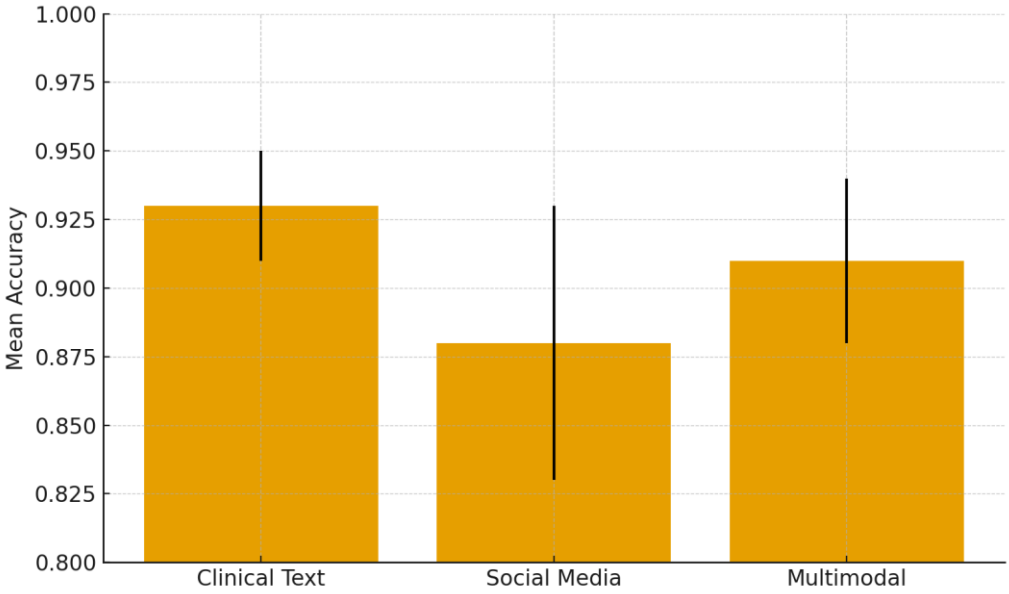

Fig 3. Variation in model performance across dataset domains. Clinical-text models show higher and more stable accuracy, while social-media datasets exhibit greater variability due to informal language and data imbalance

E. Quantitative Observations

1. Contextual embeddings (BERT, RoBERTa) exhibit the best overall performance, with mean F1-scores around 0.92–0.94.
2. Hybrid sequential models (CNN–LSTM, Bi-LSTM) outperform single-layer RNNs by 3–5% in accuracy.
3. Static embeddings (Word2Vec, GloVe) remain viable for low-resource setups, especially with smaller datasets (<5k records).
4. Multimodal architectures that combine text with auxiliary signals (EEG, visual data) report up to 6–7% performance gains.

F. Discussion

The comparative analysis shows that transformer-based contextual models are the most accurate at making predictions right now, but they are still hard to use in real-time or low-resource settings. Static embeddings combined with optimized Bi-LSTM networks provide a pragmatic equilibrium between precision and efficiency. Studies also show that there is a need for standardized benchmarks and evaluations across datasets to make sure that different approaches can be compared fairly. In general, the synthesis of existing literature shows a clear change: from static word embeddings with shallow sequential networks to deep transformer encoders that support rich, context-aware representations. The next part talks about the bigger effects, problems, and research gaps that these studies have found.

5 Challenges, Research Gaps, and Future Directions

Despite notable progress in combining word embeddings and sequential models for mental-health classification, several unresolved challenges limit the scalability and real-world applicability of these approaches.

A. Data-Centric Challenges

1. Dataset Scarcity and Imbalance:

   Most benchmark corpora contain a limited number of labeled samples, with strong class imbalance between healthy and at-risk users [17]. Small datasets hinder the training of high-capacity models such as transformers, while imbalance skews evaluation metrics toward the majority class.

2. Linguistic Diversity and Informality:

   Social-media text and online therapy notes contain slang, abbreviations, and multilingual mixing that degrade embedding quality. Domain-specific pretraining and normalization strategies remain underexplored for mental-health contexts [15].

3. Annotation Reliability:

   Ground-truth labels often rely on self-reports or keyword heuristics rather than clinical diagnoses, introducing label noise that propagates through model training.

B. Model-Related Challenges

1. Computational Overhead:

   Contextual models such as BERT and RoBERTa provide superior accuracy but require substantial memory and processing resources [16]. This restricts deployment on low-power or edge devices.

2. Interpretability:
   Deep sequential and transformer models behave as black boxes, offering little transparency in how linguistic cues map to predicted mental states. This lack of interpretability limits clinical trust and regulatory approval.

3. Generalization and Domain Transfer:

   Models trained on one dataset (e.g., Reddit posts) often fail to generalize to another (e.g., clinical notes), reflecting sensitivity to domain-specific vocabulary and context.

C. Evaluation and Benchmarking Gaps

Performance reports across studies remain inconsistent due to varying metrics, random splits, and dataset leakage. Only a few studies perform cross-dataset or cross-lingual validation [18]. Standardized evaluation protocols and open-source benchmarks are needed to ensure comparability and reproducibility.

D. Ethical and Privacy Concerns

Text-based mental-health prediction involves processing sensitive personal information. Safeguarding anonymity, obtaining informed consent, and preventing unintended inference of private attributes are critical ethical requirements. Differential-privacy mechanisms and federated-learning frameworks can help mitigate these risks while maintaining data confidentiality.

E. Future Research Directions

1. Multimodal Fusion:
   Integrating text with complementary data such as speech, facial expressions, or physiological signals could enhance robustness and early detection accuracy.
2. Explainable and Trustworthy AI:
   Developing interpretable attention mechanisms, visualization tools, and post-hoc explanation models will increase transparency and clinician adoption.
3. Domain-Adaptive and Cross-Lingual Embeddings:
   Fine-tuning contextual models on domain-specific and multilingual corpora can reduce bias and improve inclusivity.
4. Lightweight and Edge-Optimized Models:
   Research on knowledge distillation, quantization, and pruning can enable real-time deployment of mental-health detection systems on mobile devices.
5. Ethical Governance and Clinical Validation:
   Collaborations between AI researchers, clinicians, and ethicists are essential to establish validation pipelines that meet regulatory and ethical standards for mental-health technology.

Addressing these challenges will require a shift from purely performance-driven experimentation to clinically grounded, explainable, and ethically governed frameworks. Future studies should prioritize transparent reporting, dataset standardization, and interdisciplinary collaboration to transform text-based mental-health prediction into reliable, patient-centric digital healthcare solutions.

6 Conclusion

This paper provided an extensive comparison of word-embedding and sequential deep-learning models for mental-health text classification. Combining the results of our recent peer-reviewed work, we illustrated several key improvements in automated condition detection (depression, anxiety, and stress) using developments such as NLP and DL.

The study showed that contextual representations like BERT and RoBERTa constantly outperformed none temporal based ones (Word2Vec, GloVe) with higher accuracy, F1-score and ROC-AUC on various datasets. Similarly, deeper sequential models such as Bi-LSTM and transformer-based encoders exhibited better performance in encoding long-range dependencies and contextual information. Nevertheless, such improvements in performance

are offered at the expense of higher complexity, lack of interpretability and reliance on large well annotated corpora. Open issues are related to imbalanced data, linguistic variation across corpora, to the reproducibility and ethical handling of data. To advance the field, future studies should address explainable AI, cross-domain transferability, lightweight model optimization and the development of standardization data sets to compare and benchmark findings.

Composing semantic embeddings and sequential learning still outperforms on textual mental-health analysis. Sustained interdisciplinary efforts between computer scientists, clinicians and ethicists are needed to translate these computational gains into reliable, available mental-health support systems that have been clinically validated.

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