StressRoBERTa: Cross-Condition Transfer Learning from Depression, Anxiety, and PTSD to Stress Detection

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Abstract

The prevalence of chronic stress represents a major public health concern, yet automated detection of vulnerable individuals remains limited. Social media platforms like X (formerly Twitter) serve as important venues for people to share their experiences openly. This paper introduces StressRoBERTa, a cross-condition transfer learning approach for the automatic detection of self-reported chronic stress in English tweets. We investigate whether continual pretraining on clinically related conditions, such as depression, anxiety, and PTSD, which have a high comorbidity with chronic stress, improves stress detection compared to general language models. We continually pretrained RoBERTa on the Stress-SMHD corpus, a subset of Self-reported Mental Health Diagnoses focused on stress-related conditions, consisting of 108 million words from users with self-reported diagnoses of depression, anxiety, and PTSD. Then, we fine-tuned on the SMM4H 2022 Shared Task 8. StressRoBERTa achieves 82% F1, which outperforms the best shared task system (79% F1) by 3 percentage points. Our results demonstrate that focused cross-condition transfer learning from stress-related disorders provides stronger representations than general mental health training. To validate cross-condition generalization, we also fine-tuned the model on the Dreaddit. Our result of 81% F1 further demonstrates the transfer from clinical mental health contexts to situational stress discussions.

1 Introduction

Chronic stress is a persistent sense of pressure that continues for an extended period (VandenBos, 2007) and represents a significant public health concern. It is crucial to understand chronic stress because it can have serious negative effects on both physical and mental health. Many studies show that chronic stress can impair the immune system (Khansari et al., 1990) and may lead to other mental illnesses such as depression or suicidality (McEwen and Sapolsky, 2006). Detecting chronic stress is vital to prevent adverse health effects, implement effective stress management techniques, address underlying causes, improve overall quality of life, and reduce healthcare costs and lost productivity. Despite its clinical importance, automated detection of chronic stress from everyday language remains insufficient.

Building on Domain-adaptive pretraining strategies, this paper investigates whether continual pretraining on related mental health conditions improves the detection of a target condition. We evaluate our approach on the SMM4H 2022 Shared Task 8, which focuses on classifying self-reported chronic stress on X (Weissenbacher et al., 2022). This task presents several challenges. First, the dataset is highly imbalanced (37% positive, 63% negative). Second, X's 280-character limit requires models to extract stress signals from short text. Third, distinguishing genuine self-disclosure from mere mentions of stress requires understanding subtle linguistic cues. The shared task attracted multiple teams, with a median F1 of 75% and best performance of 79% F1 (Huang et al., 2022).

To address these challenges, this work introduces a **cross-condition transfer learning** approach. We continually pretrain RoBERTa, a transformer-based language model (Liu et al., 2019), on posts from users with depression, anxiety, and PTSD. These conditions are classified as stress-related disorders that have high clinical comorbidity with chronic stress (Association et al., 2013). Then, we fine-tune on stress detection. The central research question is whether continual pretraining on a focused set of clinically related conditions (depression, anxiety, PTSD) improves stress detection compared to both general language models and broad mental health models.

The Stress-SMHD corpus (Cohan et al., 2018) provides 108M words of training data across three

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stress-related conditions, which enables us to examine whether continual pretraining on a focused set of related conditions is sufficient for effective cross-condition transfer learning.

The contributions of this work are:

1. We achieve state-of-the-art performance on SMM4H 2022 Shared Task 8 for stress detection on X. StressRoBERTa attains 82% F1, which surpasses the best shared task system (79% F1) by 3 percentage points and the median (75% F1) by 7 percentage points.

2. We demonstrate that focused cross-condition continual pretraining on stress-related disorders improves stress detection. StressRoBERTa outperforms vanilla RoBERTa-base by +1% F1, while the general mental health model (MentalRoBERTa) shows no improvement over the same baseline.

3. We present *StressRoBERTa*[1], a domain-specific language model for stress detection that achieves 82% F1 on X and 81% F1 on Dreaddit, which demonstrates cross-condition generalization.

4. We validate that focused selection of stress-related disorders with user-level self-reported diagnosis data outperforms general mental health continual pretraining through clinical comorbidity analysis and methodological comparison.

2 Related Work

2.1 Continual Pretraining of Language Models for Mental Health

Continual pretraining of language models for specific domains has advanced biomedical and healthcare natural language processing (NLP). **BioBERT** (Lee et al., 2020) continually pretrains BERT on PubMed and PMC. **ClinicalBERT** (Alsentzer et al., 2019) adapts BERT to clinical notes. **MentalBERT** and **MentalRoBERTa** (Ji et al., 2022) target mental health text from social media and continually pretrain on mental health-related subreddits including r/depression, r/SuicideWatch, r/Anxiety, r/offmychest, r/bipolar, r/mentalillness, and r/mentalhealth. However, these models are continually pretrained on subreddit posts that are selected by topic rather than posts from users with self-reported diagnoses of clinically related conditions.

2.2 SMM4H Shared Task 8: Stress Detection on X

The SMM4H 2022 Shared Task 8 (Weissenbacher et al., 2022), which focused on identifying self-reported chronic stress in English tweets, uses the dataset from Yang et al. (2022). Multiple participating teams employed various approaches. Huang et al. (2022) fine-tuned BERT-based models with an averaging ensemble and achieved 79.2% F1 (4% above median). Zhuang and Zhang (2022) explored multiple pretrained encoders including BioBERT (Lee et al., 2020), PubMedBERT (Gu et al., 2021), DeBERTa (He et al., 2020), and BERTweet (Nguyen et al., 2020) with different loss functions and achieved 78.3% F1 with BERTweet as the best performer. Fu et al. (2022) fine-tuned RoBERTa with domain-adaptive pretraining and achieved 78.1% F1, and Kocaman et al. (2022) fine-tuned RoBERTa and achieved 76% F1. The median F1 across all submissions was 75%.

2.3 Clinical Motivation for Cross-Condition Transfer Learning

Cross-condition transfer learning for stress detection is motivated by established links between chronic stress and related mental health conditions. Research has demonstrated that chronic stress is a significant predictor of major depression and anxiety (Hammen et al., 2009; Hammen, 2005). These conditions share psychoneuroendocrinological pathways (Tafet and Bernardini, 2003), which suggests common biological and psychological mechanisms. Furthermore, PTSD is classified as a stress-related disorder (Shalev, 2009). This shared etiology suggests common psychological processes that may manifest in similar language patterns, with the potential to enable effective cross-condition transfer learning. Based on this clinical rationale, we propose **StressRoBERTa**, a language model continually pretrained on the Stress-SMHD corpus, which contains posts from users with self-reported diagnoses of depression, anxiety, and PTSD, all selected for their high clinical comorbidity with chronic stress.

To our knowledge, no shared task systems employed cross-condition transfer learning in which a model is continually pretrained on related conditions (depression, anxiety, PTSD) and then fine-

[1] `https://huggingface.co/Amalq/stress-roberta-base`

tuned on the stress detection task.

3 Method and Setup

3.1 Continual Pretraining Approach

Our training procedure follows domain-adaptive continual pretraining (Gururangan et al., 2020). We initialize StressRoBERTa from RoBERTa-base (Liu et al., 2019), which was pretrained on English Wikipedia, BooksCorpus, and CC-News, and continually pretrain on the Stress-SMHD corpus using the Transformers library (Wolf et al., 2020). This creates a cross-condition training scenario in which the model learns representations from depression, anxiety, and PTSD discussions before being fine-tuned for stress detection. Figure 1 shows the overall process. Table 1 presents the training configuration. We apply masked language modeling with 15% dynamic masking following the approach of Liu et al. (2019). The model achieves a final perplexity of 5.22 on the Stress-SMHD corpus.

Parameter	Value
Base model	RoBERTa-base
Learning rate	2×10^{-5}
Batch size	16
Number of epochs	5
Weight decay	0.01
Max sequence length	512
Final perplexity	5.22

Table 1: Continual pretraining hyperparameters

3.2 Continual Pretraining Corpus

Stress-SMHD corpus is a subset of the Self-Reported Mental Health Diagnoses (SMHD) (Cohan et al., 2018) containing Reddit posts from users with diagnoses of anxiety, PTSD, or depression. This ensures the continual pretraining data reflects language from individuals with these conditions. The corpus does not contain explicit stress labels; it consists of posts discussing experiences with depression, anxiety, and PTSD. This enables evaluation of whether representations learned from these related conditions transfer effectively to stress detection. Tables 2 and 3 summarize the corpus composition.

We preprocessed the Reddit posts while preserving authentic language patterns of users with mental health conditions. We removed deleted posts, decoded HTML entities, removed URLs, and replaced user mentions with a [USER] token for anonymization. We normalized whitespace, removed exact duplicates, and filtered non-English posts using langdetect (Kovács et al., 2022).

Corpus	Num of Words	Domain
English Wikipedia	2.5B	General
BooksCorpus	0.8B	General
CC-News	10B	General
Stress-SMHD	**108M**	**Psych.**

Table 2: Comparison of RoBERTa's original pretraining corpora and Stress-SMHD continual pretraining corpus

Condition	Posts	Tokens
Depression	1,272k	57.4M (53%)
Anxiety	795k	36.9M (34%)
PTSD	258k	13.7M (13%)
Total	**2,325k**	**108M (100%)**

Table 3: Distribution of Stress-SMHD corpus by condition

4 Evaluation

4.1 Datasets

4.1.1 SMM4H 2022 Shared Task 8: X Stress Detection

We evaluate on the SMM4H 2022 Shared Task 8 corpus (Weissenbacher et al., 2022), which focuses on identifying self-disclosures of chronic stress in English tweets. This binary classification task distinguishes tweets in which users explicitly report experiencing chronic stress from those that mention stress without self-disclosure. Table 4 reports the label distribution.

Split	P	N	#
Train	1,092 (37%)	1,844 (63%)	2,936
Valid	156 (37%)	264 (63%)	420
Test	NA	NA	839

Table 4: Distribution of SMM4H 2022 Shared Task 8 X stress detection dataset

4.1.2 Dreaddit: Reddit Stress Detection

To evaluate transfer from clinical mental health contexts to situational stress discussions, we also test on Dreaddit (Turcan and McKeown, 2019), a Reddit dataset for stress analysis that contains multi-domain posts labeled for binary stress classification. Posts are sourced from ten subreddits

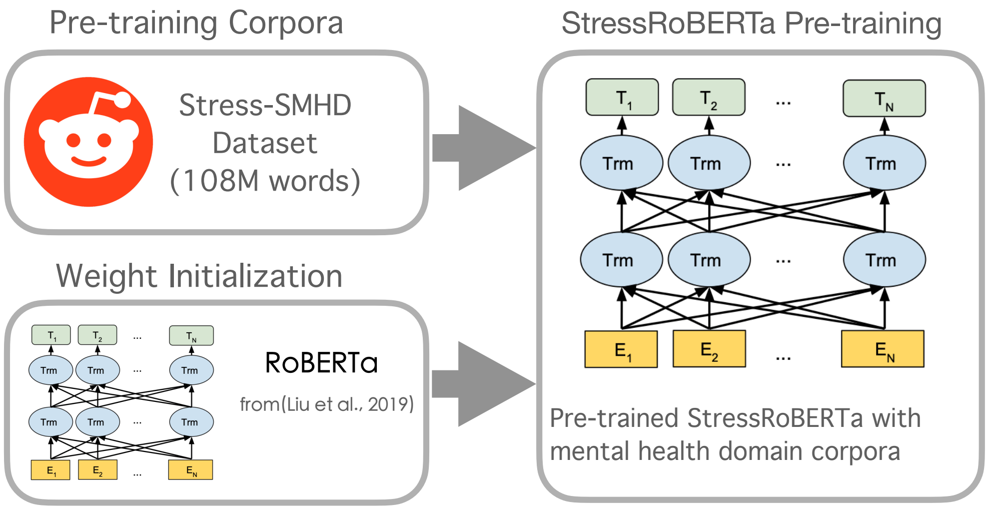

Figure 1: Detailed overview of StressRoBERTa cross-condition transfer learning pipeline

representing diverse stress contexts. The training split has 2,838 labeled segments, where approximately 1,464 (51.6%) are labeled as stress. The test split has 715 labeled segments, where approximately 375 (52.4%) are labeled as stress. Detailed information on this dataset can be found in Turcan and McKeown (2019).

4.2 Experimental Setup

We fine-tune RoBERTa-base (Liu et al., 2019) as our general baseline and StressRoBERTa as our cross-condition model. We also compare against domain-specific baselines, including ClinicalBERT (Alsentzer et al., 2019), BioBERT (Lee et al., 2020), MentalBERT, and MentalRoBERTa (Ji et al., 2022). All models are base-sized for fair comparison and share the configuration in Table 5.

Parameter	Value
Learning rate	2×10^{-5}
Train batch size	16
Validation batch size	16
Number of train epochs	6
Weight decay	0.01
Early stopping patience	3 epochs

Table 5: Fine-tuning hyperparameters

5 Results

5.1 Performance on SMM4H 2022 Shared Task 8

Table 6 reports F1 and recall for the positive (stress) class, comparing our approach with shared task participants and baseline models.

StressRoBERTa achieves 82% F1 on the X stress detection task, outperforming all shared task participants and baseline models. This represents a 3-percentage-point improvement over the best shared task system (Huang et al., 2022) (79% F1) and a 7-percentage-point gain over the shared task median (75% F1). The results demonstrate that cross-condition transfer learning from stress-related disorders provides effective representations for stress detection in short social media text.

5.1.1 Comparison to Shared Task Systems

Our approach differs from shared task systems in several key ways. First, shared task systems primarily used general pretrained language models (BERT, RoBERTa) or X-specific models (BERTweet) without domain-adaptive continual pretraining on mental health data. The best-performing system (Huang et al., 2022) used ensemble methods and pseudo-labeling post-processing rather than domain-specific continual pretraining. Second, no shared task systems employed cross-condition transfer learning from related mental health conditions.

StressRoBERTa's strong performance suggests that domain-adaptive continual pretraining on stress-related disorders captures linguistic patterns relevant to stress detection that general pretrained language models miss. The focused selection of depression, anxiety, and PTSD (conditions with high clinical comorbidity with stress) provides a stronger signal than either general language models or X-specific models trained on diverse content.

5.1.2 Comparison to Domain-Specific Baselines

StressRoBERTa also outperforms domain-specific baseline models. Clinical domain models (ClinicalBERT 75% F1, BioBERT 80% F1) show limited effectiveness, suggesting that clinical note language does not transfer well to social media stress detection. More relevant is the comparison to general mental health models. MentalBERT achieves 81% F1 and MentalRoBERTa achieves 81% F1, identical to vanilla RoBERTa-base (81% F1). This result shows that general mental health continual pretraining provides no improvement for stress detection, while focused cross-condition continual pretraining on stress-related disorders improves performance by +1% F1.

Both StressRoBERTa and MentalRoBERTa use the RoBERTa-base architecture with identical fine-tuning procedures, but differ in their continual pretraining corpora. MentalRoBERTa is continually pretrained on general mental health subreddits (see 2.1). StressRoBERTa is continually pretrained on posts from users with self-reported diagnoses of stress-related disorders (r/depression, r/Anxiety, r/PTSD), rather than on topic-selected subreddit posts. MentalRoBERTa's lack of improvement over vanilla RoBERTa-base suggests that diverse mental health content reduces transfer effectiveness, while StressRoBERTa's focused selection on stress-related disorders provides greater clinical and linguistic overlap, which enables effective cross-condition transfer learning.

5.2 Generalization Across Platforms and Contexts

To assess generalizability, we conduct two complementary evaluations. First, we test cross-platform transfer from Reddit to X using the SMM4H Task 8 dataset. Second, we test cross-context transfer from clinical/diagnostic subreddits (r/depression, r/Anxiety, r/PTSD) to situational stress discussions using Dreaddit, which comprises posts from diverse topical communities. Table 7 shows performance on both benchmarks.

StressRoBERTa achieves 81% F1 on Dreaddit, demonstrating that representations learned from clinical mental health discussions (depression, anxiety, PTSD) transfer effectively to situational stress contexts. The consistent performance across X (82% F1, cross-platform) and Dreaddit (81% F1, cross-context) validates that cross-condition continual pretraining captures transferable stress-related patterns rather than platform-specific or context-specific artifacts.

5.3 Analysis and Discussion

5.3.1 Why Does Cross-Condition Transfer Learning Improve Performance?

We examine two factors that explain StressRoBERTa's superior performance on the stress detection task.

Shared Symptomatology and Risk Factors The clinical overlap among depression, anxiety, PTSD, and stress provides a theoretical foundation for cross-condition transfer learning in text-based detection. First, these conditions exhibit high comorbidity rates; approximately 50% of individuals with major depression also meet criteria for an anxiety disorder (Hirschfeld, 2001), while individuals with PTSD show elevated rates of both major depressive disorder (Flory and Yehuda, 2015) and anxiety disorders (Brady et al., 2000; Spinhoven et al., 2014). Second, chronic stress serves as a common risk factor, increasing vulnerability to both depression (Hammen et al., 2009; Tafet and Smolovich, 2004) and anxiety disorders (Hussenoeder et al., 2022). This clinical overlap suggests that individuals discussing these conditions in social media may use similar linguistic patterns to express psychological distress, shared symptoms (e.g., sleep disturbance, concentration difficulties), and stress-related experiences. Consequently, models trained on depression, anxiety, or PTSD data should capture transferable linguistic features relevant to stress detection.

Focused Condition Selection Two methodological factors strengthen this cross-condition transfer. First, StressRoBERTa selects conditions with strong theoretical connections to stress. The Stress-SMHD corpus includes user-level data from individuals who self-reported depression, anxiety, or PTSD diagnoses, capturing all posts from these users. The inclusion of PTSD, a trauma-related disorder strongly associated with chronic stress exposure (Maeng and Milad, 2017), provides additional stress-relevant signal not present in MentalRoBERTa's broader selection. Second, this user-level aggregation ensures the training corpus reflects comprehensive language patterns from individuals with these conditions, rather than isolated posts that could come from anyone in these subreddits. This dual focus—selecting clinically related

Models	Recall	F1
SMM4H 2022 Shared Task 8 participants		
- Huang et al. (Huang et al., 2022) (Best system)	85%	79%
- Zhuang and Zhang (Zhuang and Zhang, 2022)	76%	78%
- Fu et al. (Fu et al., 2022)	82%	78%
- Kocaman et al. (Kocaman et al., 2022)	**87%**	76%
- Median of all submissions	76%	75%
General language models		
- BERT-base-uncased	75%	80%
- RoBERTa-base	83%	81%
Domain-specific language models		
- ClinicalBERT (Alsentzer et al., 2019)	64%	75%
- BioBERT-base (Lee et al., 2020)	77%	80%
- MentalBERT (Ji et al., 2022)	77%	81%
- MentalRoBERTa (Ji et al., 2022)	85%	81%
Our approach (cross-condition transfer learning)		
- StressRoBERTa	84%	**82%**

Table 6: Performance comparison on SMM4H 2022 Shared Task 8 for X stress detection. StressRoBERTa achieves 82% F1, outperforming the best shared task system (79% F1) and all baseline models.

Model	X	Dreaddit
BERT-base	80%	79%
RoBERTa-base	81%	81%
MentalRoBERTa	81%	81%
StressRoBERTa	**82%**	**81%**

Table 7: Performance (F1 scores) on X and Reddit. X evaluates cross-platform transfer; Dreaddit evaluates cross-context transfer.

conditions and using user-level data from individuals with self-reported diagnoses—enables more effective cross-condition transfer learning for stress detection.

Table 8 compares the training corpora for StressRoBERTa and MentalRoBERTa, highlighting the key differences in corpus selection strategy.

6 Conclusion

This work demonstrates that cross-condition transfer learning from stress-related disorders improves stress detection on social media. StressRoBERTa achieves state-of-the-art performance (82% F1) on SMM4H 2022 Shared Task 8 and surpasses the best shared task system by 3 percentage points.

Our key finding is that focused continual pretraining on clinically related conditions (depression, anxiety, PTSD) outperforms both general language models and broad mental health models. MentalRoBERTa shows no improvement over vanilla RoBERTa-base, while StressRoBERTa's focused selection yields a +1% F1 gain. This result validates that condition selection based on clinical relationships matters for effective transfer.

Clinical comorbidity and linguistic overlap between source and target conditions enable effective knowledge transfer. Empirical results across X (82% F1) and Dreaddit (81% F1) validate this approach. These findings have important implications for mental health NLP and show that domain-adaptive continual pretraining on carefully selected related conditions provides stronger representations than general language models or broad mental health models.

Limitations

StressRoBERTa demonstrates strong performance for English stress detection on social media but has several limitations. First, the model is continually pretrained and evaluated exclusively on English text from social media platforms (Reddit and X). Performance on other languages, different domains (e.g., clinical notes, formal writing), and longer documents remains unexplored. Second, the Stress-SMHD corpus comprises posts from users with self-reported diagnoses of three conditions (depression, anxiety, PTSD). Third, we did not systematically evaluate alternative condition combinations for cross-condition transfer. Fourth, continual pretraining requires substantial computa-

Model	Training Conditions	Data Level	Self-Reported?	Tokens
MentalRoBERTa	Depression, anxiety, suicide, bipolar, general mental health	Post	No	∼150M
StressRoBERTa	**Depression, anxiety, PTSD**	**User**	**Yes**	**108M**

Table 8: Comparison of continual pretraining corpora. StressRoBERTa uses user-level data from individuals with self-reported diagnoses of stress-related disorders, while MentalRoBERTa uses post-level data from mental health subreddits without diagnosis requirements.

tional resources, though we release the pretrained model to improve accessibility. Finally, as with any automated mental health detection system, StressRoBERTa should only be deployed with appropriate ethical safeguards and clinical oversight to prevent potential misuse.

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During the preparation of this work, we used AI assistants to correct grammar and improve the clarity of writing.

Ethics Statement

This work involves automated detection of mental health conditions from social media data, which raises several ethical considerations:

Privacy and Consent Our continual pretraining uses the Stress-SMHD corpus derived from Reddit, where users posted publicly. However, users may not have anticipated their posts being used for mental health research. We do not collect new data or attempt to identify individuals.

Clinical Validation Despite strong performance, classification errors remain. Any deployment must involve human clinical judgment and should not replace professional mental health assessment.

Responsible Release We release StressRoBERTa to advance mental health research, but urge users to consider these ethical implications and implement appropriate safeguards in any applications.

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