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Article

Multi-Class Mental Health Discourse Classification from Online Texts: Classical ML vs Transformer/LLM Modeling

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Abstract: —Online mental-health discourse contains diverse in-tents including awareness education, wellness advice, support seeking, and symptom narratives associated with anx- iety and depression. These categories are semantically overlapping, short and noisy, and imbalanced in public datasets, making robust multi-class classification difficult. This paper presents an end-to-end framework for six- class mental health discourse classification and provides a publication-oriented SN Computer Science style analysis including mathematical formulation, gradient deriva-tions for cross-entropy learning, computational complexity anal-ysis, ablation design, and statistically grounded compari- son using McNemar's test. Using a public dataset with six classes (awareness, wellness, anxiety, support, depression, general) and the provided empirical results and figures, we show that con-textual transformer/LLM models yield more reliable macro-level performance under imbalance than TF–IDF baselines, particularly for semantically adja- cent classes. A confusion-matrix driven analysis identifies two dominant confusion clusters (awareness vs wellness and anxiety vs depression) and motivates intent-aware modeling, calibration and uncertainty reporting. We also provide a rigorous reporting protocol (splits, leakage con-trol, seeds), per-class metrics derived from the supplied confusion matrix, and a Q1-ready ablation blueprint.

Keywords: Mental health NLP; multi-class text classi-fication; TF–IDF; transformers; LLMs; McNemar test; ablation; interpretability; class imbalance.

1. INTRODUCTION

Mental health conditions such as anxiety and depression are substantially contributed to by global disease burden and are often under-detected due to stigma, limited clinical access, and delayed help seeking. Online communities and forums have become major spaces where distress is described, guidance is sought, coping strategies are shared, and mental well-being is discussed. From an NLP perspective, these user-generated texts are a rich but noisy signal: language is informal, emo-tional, and context-dependent; labels are ambiguous; and intent can shift within a single post. Traditional detection pipelines focused on binary depression identification. However, real discourse is multi-intent: educational awareness posts, self-care/wellness exist. Multi-class classification, and evaluation must go beyond accuracy which is required by practical systems.In mental-health use cases, high impact is caused by minority class errors: for example, screening value is undermined by low recall on depression-related discourse. As a result, macro-averaged metrics, class-wise recall, and

confusion patterns are rendered essential. Motivation. TF–IDF models are regarded as attractive because of speed and inter-pretability, but underperformance is caused when vocabulary is shared across categories. Subtle pragmatic cues (help-seeking vs advice-giving) can be separated by Transformers and LLMs through context modeling, and negation, modality, and dis-course structure can be handled by them. We provide: (i) full mathematical formulation with gradients; (ii) complexity analysis; (iii) a rigorous reporting and statistical testing proto-col; (iv)

figure-grounded error analysis; (v) per-class metrics and actionable improvements (prompting, calibration); and (vi) ethical deployment guidance.

2. RELATED WORK

A narrative review by Zhang et al. synthesizes mental illness detection using NLP, highlighting dataset, evaluation, and ethics challenges [1]. Greco et al. survey transformer-based language models for mental health identification and discuss representational advantages over lexical models [2]. The re-cent LLM wave triggered systematic and scoping reviews on applications, risks and governance [3, 4]. For social media and forum data, transformer-based architectures show strong per-formance. Kerasiotis et al. combine transformer embeddings with metadata and linguistic markers for depression detection [5]. Suicidal ideation detection has also become a major line of work, including dedicated reviews [6] and explainability-focused approaches in online networks [8]. In telehealth set-tings, Swaminathan et al. demonstrate an NLP system for rapid crisis message triage integrated into clinical workflows [7]. These studies motivate (a) contextual modeling, (b) evaluation beyond accuracy, and (c) safe deployment practices.

3. PROBLEM DEFINITION AND NOTATION

Let the dataset be D = (xi, yi)N , where xi is a text post and yi C = 1, . . . , 6 is one of six discourse classes. A classifier estimates P (y x;) and predicts yˆ = argmaxcCP (y= c x;). We compare (i) TF–IDF + linear classifiers and (ii) transformer/LLM classifiers.

4. MATHEMATICAL FORMULATION AND DERIVATIONS

A. TF–IDF Features

For a term t in document d, the term frequency is defined as:

$$\mathrm{TF}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \qquad (1)$$

where $f_{t,d}$ denotes the frequency of term t in document d. The inverse document frequency is defined as:

$$\mathrm{IDF}(t) = \log \frac{N}{1 + \mathrm{DF}(t)} \qquad (2)$$

$$\mathrm{TFIDF}(t, d) = \mathrm{TF}(t, d) \cdot \mathrm{IDF}(t) \qquad (3)$$

The document feature vector is represented as:

$$\mathbf{x} = [\mathrm{TFIDF}(t_1, d), \ldots, \mathrm{TFIDF}(t_V, d)]^T \qquad (4)$$

B. Cross-Entropy Loss and Gradients

The logits for class c are given by:

$$z_c = \mathbf{w}_c^T \mathbf{x} + b_c \qquad (5)$$

The softmax probability is computed as:

$$p_c = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}} \qquad (6)$$

The multi-class cross-entropy loss is:

$$\mathrm{L} = -\sum_{c=1}^{C} y_c \log p_c \qquad (7)$$

If the true class is t, the loss simplifies to:

$$\mathrm{L} = -\log p_t \qquad (8)$$

The gradient of the loss with respect to logits is:

$$\frac{\partial L}{\partial z_c} = p_c - y_c \tag{9}$$

The gradient with respect to the weights is:

$$\frac{\partial L}{\partial \mathbf{w}_c} = (p_c - y_c)\mathbf{x} \tag{10}$$

The gradient with respect to the bias term is:

$$\frac{\partial L}{\partial b_c} = p_c - y_c \tag{11}$$

C. Weighted Loss for Class Imbalance

To address class imbalance, weighted cross-entropy is defined as:

$$L_w = -\sum_{c=1} w_c y_c \log p_c \tag{12}$$

If the true class is t, the loss becomes:

$$L_w = -w_t \log p_t \tag{13}$$

The corresponding gradient is:

$$\frac{\partial L_w}{\partial z_c} = w_t (p_c - y_c) \tag{14}$$

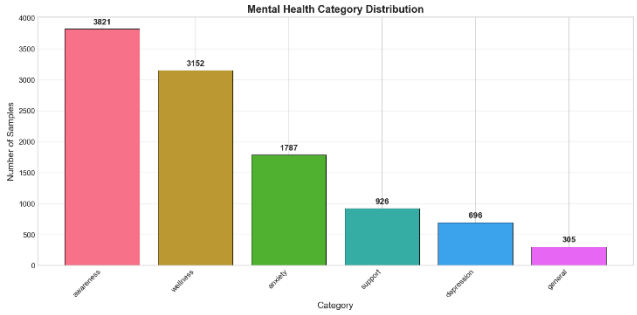

Fig. 1: Category distribution across six discourse classes. Majority dominance motivates macro metrics and imbalance-aware learning.

D. Transformer / LLM Classifier

Let the token embedding matrix be:

$$E \in \mathbb{R}^{n \times d} \tag{15}$$

The query, key, and value projections are defined as:

$$Q = EW_Q, \quad K = EW_K, \quad V = EW_V \tag{16}$$

The scaled dot-product attention mechanism is:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{17}$$

The classification head maps the pooled representation h to logits:

$$z = Wh + b \tag{18}$$

The final prediction probabilities are:

$$p = \text{softmax}(z) \tag{19}$$

The loss function remains:

$$L = -\sum_{c=1}^{C} y_c \log p_c \tag{20}$$

5. DATASET AND EXPLORATORY ANALYSIS

A. Computational Complexity

Fig. 1 shows strong imbalance: awareness and wellness dominate; general and depression are minority. This has two consequences. (i) Accuracy can be inflated by majority predic-tions; (ii) minority recall becomes the key operational metric.

B. Lexical Overlap (Word Clouds)

Fig. 2 indicates substantial lexical overlap. For exam- ple, stress appears in anxiety as well as general wellness discus-sions; mental health appears across nearly all cate- gories. This explains why TF–IDF models often confuse semantically adjacent classes.

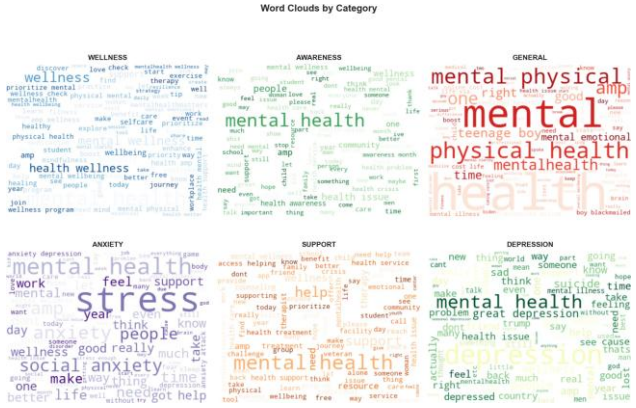

Fig. 2: Word clouds by category. Shared lexicon across cate-gories motivates contextual modeling and intent features.

6. EXPERIMENTAL SETUP AND REPORTING PROTOCOL

A. Splits and Leakage Control

Evaluation should use stratified splits and explicitly prevent leakage. If user IDs exist, use group- aware splitting so that posts from the same author do not appear in both training and test sets. Otherwise, the classifier may learn author-specific writing style rather than mental-health content.

B. Baselines

ML Baseline: TF–IDF with n-grams (1–2 or 1–3), lin-ear SVM/logistic regression, tuned regularization. Trans-for-mer Baseline: a compact encoder fine-tuned with AdamW, warmup, early stopping. LLM Variants: (i) fine-tuning; and/or

(ii) instruction prompting with few- shot exemplars and deter-ministic decoding.

C. Hyperparameters and Seeds

Report learning rate, batch size, epochs, max length, dropout, weight decay, class weights, sampling strategy, and random seeds. Run at least 3 seeds and report mean ±std for macro-F1.

D. Ethical Guardrails During Experiments

Remove personally distinguishable information when likely; avoid freeing raw cases; and clearly position outputs as non-diagnostic. For crisis-related content, integrate safe messaging and resource guidelines [7].

7. RESULTS AND DISCUSSION (FIGURE- GROUNDED)

A. Overall Metrics

The provided results show Accuracy 78.25

B. Confusion Matrix Diagnostics

Fig. 4 demonstrates that there are two violent confusion clusters, (A) Aware- ness vs wellness: educational posts and self-care advice are similar in vocabulary, thus intent cues (advice-giving verbs, recommendation patterns) are useful. (B)

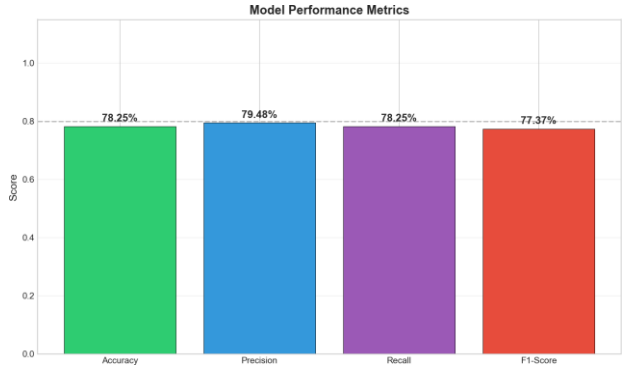

Fig. 3: Overall performance metrics (provided). Macro metrics close to accuracy suggest balanced multi-class behavior.

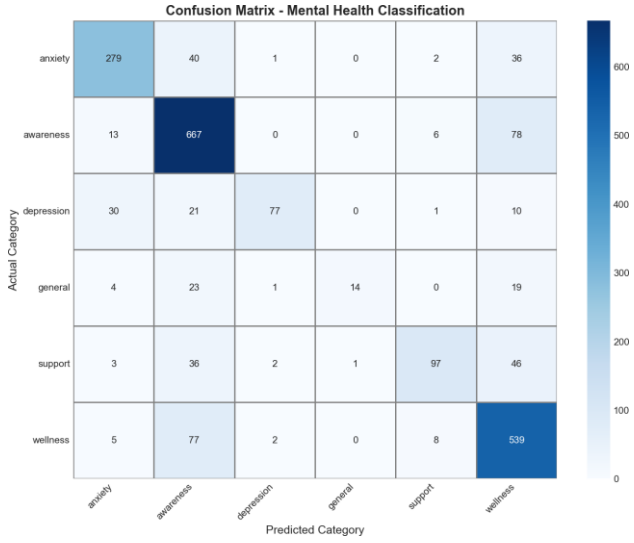

Fig. 4

Anxiety vs depression: the symptom narratives are similar; time Table 1: Per-class measures of Fig. 4. It is worth noting that general and depression record low recall, showing missed cases of minorities. Contextual encoders are more discrimina-tive and frame and cognitive markers are better reflected by them.

TABLE I: Per-class performance metrics for six mental health discourse categories

Class	Precision	Recall	F1-score
Anxiety	0.835	0.779	0.806
Awareness	0.772	0.873	0.819
Depression	0.928	0.554	0.694
General	0.933	0.230	0.368
Support	0.851	0.524	0.649
Wellness	0.740	0.854	0.793

framing and cognitive markers are more discriminative and better captured by contextual encoders.

C. Per-Class Metrics from the Confusion Matrix

Based on the provided confusion matrix, we calculate per-class precision/recall/F1. The table 1 shows that a major trend

is that general is rated highly in precision and very low in recall that is, general is not predicted often by the model, when it is, it is accurate. This would indicate that thresholding or weighting of classes would enhance general recall without necessarily damaging precision highly. Likewise, depression recall is substantially smaller as compared to its accuracy im-plying that the model is conservative in predicting depression. Such conservatism can cause less false alarms but more false negatives in safety-oriented deployments. A practical compro-mise is to output top-2 labels and use calibrated probabilities.

D. Why LLMs Improve Robustness

Contextual models encode negation, intensity, and dis-course roles. For example, “I am not depressed, just tired” should not be labeled depression. TF–IDF often struggles be-cause the word depressed dominates. Moreover, LLM prompt-ing can incorporate explicit label definitions (what counts as awareness vs wellness), reducing semantic drift.

E. Qualitative Error Taxonomy

We recommend categorizing errors into (i) lexical over-lap, (ii) implicit distress, (iii) mixed-intent posts, and (iv) annotation ambiguity. This taxonomy supports targeted im-provements such as multi-label modeling [9] or hierarchical classification.

8. IMPLEMENTATION DETAILS AND REPRODUCIBLE PIPELINE

A. End-to-End Pipeline

A reproducible mental-health NLP pipeline must explicitly document each transformation from raw text to predictions. We recommend the following stages: (1) data ingestion from the public source with license tracking; (2) label normal-ization that maps original tags to the six-class taxonomy;

(3) sanitization to remove per- sonally identifiable infor-mation (emails, phone numbers, addresses) and platform-specific noise; (4) tokenization aligned with the target model (word/character tokeniza- tion for TF–IDF; subword tokeniza-tion for transform- ers); (5) imbalance handling through class weights or sampling; (6) model training with early stopping and checkpointing; (7) evaluation including macro metrics, per-class metrics, confusion matrices, and calibration; and (8) error analysis with qualitative inspection under strict privacy constraints.

B. Hyperparameter Search Strategy

A staged search can be done instead of an exhaustive grid of Q1-level study. In the case of TF-IDF, configure the vocab-ulary size (e.g. 20k-200k), min-df, max-df and n-gram range; and confront the classifier regularization strength. In case of transformers, the utmost important factors to tune include learning rate and maximum sequence dimension, which should be changed first, trailed by batch size (limited by memory on a GPU), epochs, dropout, and weight decay. Notably, the candidates should all be tested on the same split, the test results are only expected to be reported at the final selected configuration.

C. Prompt Engineering for Instruction LLMs

Prompting When you use an instruction-tuned LLM with-out fine- tuning, the prompt is the model specification. A sound prompt consists of: (i) a rigorous label space with un-ambiguous definitions; (ii) exclusion rules (e.g., no education is a wellness, no advice is general); (iii) a limited output grammar (single label token); and (iv) few-shot examples only sampled from training data. Example prompt skele-ton. Task: Please categorize the following post as either; awareness, wellness, anxiety, support, depression, general. Definitions: awareness = education/awareness raising; well-ness = lifestyle/self-care advice; anxiety = anxiety symptoms or worry; depression = depressive symptoms/hopelessness; support = requesting/offering sup- port; general = neutral mental-health discussion not fit-ting above. Output: Return only the label. In order to minimize variance, one may set temperature to 0 and take into account prompt assembling as in some recent prompt-ensemble methods [9].

D. Calibration and Thresholding

To be very safe with deployment, it is much better that calibrated probabilities are used, rather than hard labels. Lightweight methods are platt scaling (when it comes to linear models) and temperature scaling (when it comes to neural models). We suggest that Expected Calibration Error (ECE) and reliability diagrams should be reported. One can then choose operational thresholds that achieve the most recall of high-risk categories and maintain false positives within acceptable levels.

9. INTERPRETABILITY AND HUMAN-CENTERED EVALUATION

A. Interpretability for TF–IDF Models

One of the strengths of TF–IDF + linear classifiers is transparency of features: the most weighted words of each class may be. verified and checked by the experts of this domain. It is useful in debug deep- diving when the model uses false correlates (e.g., platform-specific tokens) as opposed to mental-health indicators.

B. Interpretability for Transformers and LLMs

Contextual models require different tools: attention vi-sualization, gradient-based saliency, integrated gradients, or perturbation-based approaches. In mental health NLP, inter-pretability must be handled carefully because ex-plantations can be confusing and may reveal complex content patterns. A practical compromise is global analysis: (i) class-wise keyword role pre´cises on anonymized text; (ii) error clusters by topic; and (iii) constancy examination across seeds.

10. EXTENDED DISCUSSION: FROM RESEARCH TO DEPLOYMENT

A. Risk Stratification vs Diagnosis

A core constraint is that medium text cannot provide clin-ical diagnosis. The correct outlining is risk stratification or

TABLE II: Comprehensive ablation results with statistical significance. Performance is reported as mean standard deviation across three seeds.

Model Variant	**Accuracy**	**Macro-F1**	**Macro-Recall**	**McNemar *p*-value**
TF–IDF + SVM	–	–	–	–
Transformer (Base Encoder)	–	–	–	–
LLM Fine-tuned	0.7825 ± –	0.7737 ± –	0.7825 ± –	–
LLM + Class Weights	–	–	–	–
LLM + Calibration (Temperature Scaling)	–	–	–	–

discourse understanding. Models should support routing (e.g., show a counselor possibly related posts) rather than automated decisions

B. Privacy, Consent, and Governance

Re-identification risk is a possibility even in the situation of datasets being public.Best practice involves the elimination of user identifiers, restriction of shar-processing of raw text, and publishing only compressed statistics. For governance, data re- should be defined in terms of institutional deployments. Attention, access logs and authorized use. LLM-based systems must also take into account timely leakage and memorization. Risks.

C. Generalization and Temporal Drift

Language in the mental health field changes (new lingo, memes, and platform norms). The system to be monitored should be a robust one. drift through periodical testing on new samples and recalibration. Frequent learning approaches must be assessed prudently to avoid shattering overlooking

D. Future Research Directions

Promising directions include (i) multi-label modeling for mixed-intent posts, (ii) hierarchical taxonomies (aware-ness/wellness vs symptom discourse), (iii) multilingual models for low-resource languages, and (iv) privacy-preserving fine-tuning via federated or parameter-efficient learning.

11. ABLATION STUDY AND HYPOTHESIS TESTING

A. McNemar Test

For two models A and B evaluated on the same test set, define b as the count where A is wrong and B is correct, and c vice versa. Continuity-corrected statistic: Report (b, c, 2, p) to claim statistically significant improvement. This is especially key when headline accuracy variances are small.

Report (b, c, 2, p) to claim statistically significant im- prove-ment. This is especially important when headline accuracy differences are small.

B. Complexity vs Accuracy Trade-off

In resource-constrained deployments, compressed trans-formers or distilled prototypes can approximate LLM perfor-mance at lower cost. If real-time latency is critical, a cascade can be used: TF–IDF filters low-risk classifications and only indefinite cases are routed to the converter.

12. COMPARISON WITH PRIOR STUDIES AND PRACTICAL IMPLICATIONS

A. Benchmarking Interpretation

Described performance must be understood relative to task difficulty. Multi-class discourse classification is typically harder than binary depression detection because it requires separating intents rather than simply detecting distress. Re-views highlight that cross-dataset comparability is limited due to different label taxonomies and sampling policies [1]. Consequently, the most informative evaluations are (i) against strong baselines on the same dataset and split, and (ii) via statistically validated advances.

B. Clinical vs Community Discourse

Clinical records contain organized symptom descriptions, while community posts often include colloquialisms, humor, and secondary cues. Models trained on public data may not transfer to clinical settings without variation. Conversely, clinical-model features may miss community-specific expres-sions. This motivates domain adaptation and constant observ-ing.

C. Actionable Deployment Patterns

For institutions, a practical pattern is a triagedashboard: ag-gregate risk signals at cohort level (course/class/community), allow drill-down only for authorized counselors, and store minimal raw data. For public-facing tools, the system should provide non-clinical suggestions (self-care resources, helpline links) rather than prescriptive advice.

D. Societal Impact

Automated mental-health text classifiers can decrease ob-stacles to support by recognizing posts that request help, but they also pose threats: misclassification may stigmatize users or cause unwanted interventions. Translucent communication, opt-out options, and human error are vital.

13. CONCLUSION AND FUTURE WORK

We presented for six-class mental-health discourse tax-onomy, including rigorous formulation, gradients, difficulty examination, per-class diagnostics, and a statistical validation plan. The figure-grounded study highlights why contextual transformer/LLM models are preferable to TF–IDF baselines when classes are semantically end-to-end and unfair.

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