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Deep learning for mental health analysis: long short-term memory approach to text-based condition classification

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ABSTRACT

The increasing prevalence of mental health disorders highlights the need for scalable and automated approaches to early detection. This study proposes a deep learning–based text classification framework using a long short-term memory (LSTM) network to identify mental health conditions from user-generated textual data. A corpus of 103,488 labeled texts representing anxiety, stress, bipolar disorder, depression, personality disorder, suicidal ideation, and normal states was preprocessed through tokenization, padding, and word embedding. The proposed LSTM model achieved overall accuracy of 87% on test set, with strong class-wise performance reflected by precision, recall, and F1-scores, particularly for anxiety, personality disorder, and normal classes. Comparative error analysis using a confusion matrix revealed challenges in distinguishing depression from suicidal ideation, indicating semantic overlap between these conditions. The results demonstrate that LSTM-based models can effectively capture sequential linguistic patterns relevant to mental health classification. This framework shows potential as a decision-support tool for early screening and digital mental health applications, complementing clinical assessment rather than replacing it.

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1. INTRODUCTION

Mental health is a fundamental component of overall well-being and has increasingly become a global public health concern. Conditions such as anxiety, stress, depression, bipolar disorder, and personality disorders significantly affect individuals' quality of life, social functioning, and productivity. According to the World Health Organization (WHO), approximately one in eight people worldwide experiences a mental disorder [1], [2] Despite growing awareness, access to timely and accurate mental health assessment and intervention remains limited for many populations [3].

Several systemic challenges continue to hinder effective mental health care, including shortages of trained professionals, delayed diagnosis, and frequent misclassification of psychological conditions [4]–[10]. These limitations are particularly pronounced in low- and middle-income settings, where the gap between demand and service capacity is substantial [11], [12]. As a result, there is an increasing need for scalable, cost-effective approaches that can support early detection and screening as part of broader mental health service delivery frameworks [13]–[15].

The widespread use of online platforms, such as social media and mental health forums, has led individuals to openly express emotional distress, psychological experiences, and changes in mental states through text [3], [6], [16]–[18]. These user-generated texts provide valuable insights into psychological conditions and present opportunities for computational analysis. Systematic analysis of such textual data may enable early identification of mental health risks and support preventive interventions.

Recent advances in natural language processing (NLP) and deep learning have shown promise in analyzing mental health–related text. In particular, recurrent neural network (RNN) architectures, such as long short-term memory (LSTM), are well-suited for modeling sequential language patterns and capturing contextual dependencies that are often critical in psychological expression [19], [20]. Unlike traditional machine learning approaches that rely on static features, LSTM models can represent temporal and semantic relationships within text more effectively.

However, existing studies often focus on limited diagnostic categories, small datasets, or shallow linguistic representations, which restrict their generalizability and robustness. Moreover, comparative evaluations of multi-class mental health classification using large-scale text corpora remain limited. This study addresses these gaps by applying an LSTM-based deep learning framework to classify multiple mental health conditions using a large annotated dataset of user-generated text. By focusing on sequential textual representations, this research aims to contribute empirical evidence on the effectiveness of LSTM models for scalable and automated mental health text classification.

2. METHOD

We describe the procedural steps for developing and empirically assessing the LSTM model for predicting mental health disorders using user-generated textual comments. The workflow is composed of data collection and interpretation, data pre-processing, text representation, model selection, training, and performance estimation [21], [22]. Each stage is carefully designed to produce a robust and prediction-based model for novel instances of natural language, which are the signs of psychological disorders.

2.1. Data collection

The corpus utilized in this work is the mental health text corpus for emotion and condition classification, consisting of more than 103, 488 examples of psychological language expressions. Every record in the dataset is tagged with a specific mental health illness, e.g., anxiety, stress, bipolar disorder, depression, personality disorder, or suicidal ideation. The data set contains a wide variety of linguistic styles, emotions, and psychological concepts typically seen on mental health related user generated text. The input row in the dataset has two main fields: i) text, a free-form sentence or paragraph describing the emotional or mental condition of a user; and ii) status, a label that denotes a person's or user's state of mind. To the best of our knowledge, it is a large dataset to train and evaluate deep learning models for automatic mental illness classification.

2.2. Preprocessing of data

Preprocessing is one of the critical tasks of NLP to make raw text data ready in a form suitable to be input to machine learning and deep learning models [22], [23]. Some preprocessing techniques have been used in this work on the mental health text dataset for emotion and condition classification to standardize the data and get it ready. To start with, all of the text was converted to lowercase so that there was consistent output and redundancy did not take place because cases were sensitive. Tokenization was then performed using Keras' tokenizer, which separated every paragraph or sentence into individual tokens (words). Depending on experimental configurations, stopword removal was also performed to eliminate common words (such as "the", "is", "and") that may not be significant in differentiating classes. Second, since neural networks accept fixed-size inputs [24], all tokenized sequences were padded or shortened to a size of up to 100 tokens. Lastly, the categorical class labels in the status column were translated into numerical form via LabelEncoder and then once again one-hot encoded to correspond with the SoftMax activation function used in the output layer of the LSTM model. These preprocessing tasks ensured the text inputs and class labels were in the same model-friendly format.

2.3. Word representation

Word embeddings were employed to represent the tokenized text in a format that preserves semantic meaning [22], [23], [25], [26]. Word embeddings are dense vector spaces summarizing semantic relationships between words from their context use [27]. An embedding layer was employed with a vocabulary size cut off at the top 20,000 most frequent words in the dataset, and every word was represented in a 128-dimensional vector space. Embeddings were randomly initialized and learned during training [23], [27] allowing the model to learn how to adapt the vector representations to the specific linguistic patterns and domain-specific terminology found in mental health language. By learning these context embeddings from scratch, the model was better positioned to capture nuanced emotional cues and semantics that differentiate between psychological condition classes.

2.4. LSTM model design

The proposed deep learning model in this work is an LSTM network that is ideally well-suited for processing sequential data and modelling long dependencies in text [28]. LSTM is a specialized type of RNN designed to overcome the vanishing gradient problem in RNN [29]. The key components of an LSTM unit include the input gate, forget gate, and output gate.

In (1) denotes the input gate function, which is responsible for generating a new memory state when the incoming word holds significant importance. By evaluating the current input along with the previous hidden state, the input gate determines the value of retaining the new word and accordingly enables the formation of updated memory.

$$I_t = \sigma(W_I . \left[h_{(t-1)}, x_t\right] + b_I) \tag{1}$$

At each time step, the forget gate is employed to determine whether the previous cell state is useful for the computation or not. The forget gate processes the current input along with the previous hidden state to generate the forget signal, denoted as F_t, as described in (2).

$$F_t = \sigma(W_F . \left[h_{(t-1)}, x_t\right] + b_F) \tag{2}$$

The new memory, denoted as $\tilde{C}_t$ in (3), is calculated by integrating features from the current input word x_t and the previous hidden state h_{t-1}.

$$\tilde{C}_t = tanh(W_{\tilde{C}} . \left[h_{(t-1)}, x_t\right] + b_{\tilde{C}}) \tag{3}$$

The next step is to update the cell state by combining retained and new information, as described in (4).

$$C_t = F_t \times C_{t-1} + I_t \times \tilde{C}_t \tag{4}$$

In (5) is used to calculate the output gate to determine the timing of releasing the stored memory value to the hidden layer. Finally, the new hidden state, h_t, is computed by performing multiplication between the output gate and the updated cell state as described in (6).

$$O_t = \sigma(W_O . \left[h_{(t-1)}, x_t\right] + b_O) \tag{5}$$

$$h_t = O_t \times \tanh(C_t) \tag{6}$$

In this research, the architecture begins with an embedding layer that maps input tokens to dense word vectors of size 128. This is then followed by an LSTM layer of 64 memory units to handle the embedded sequences and derive the temporal structure and word-to-word contextual relationships. To handle overfitting risk, a dropout layer with a rate 0.5 was included that randomly sets a fraction of neurons to zero during training. The LSTM output is then routed to a fully connected layer employing the rectified linear unit (ReLU) activation function, which infuses the network with non-linearity and augments its expressive capacity. The culminating layer is a SoftMax function that renders class-specific probability distributions across the target mental health conditions. As shown in (7), N denotes the number of nodes in the output layers, and z_i denotes the output score for class i.

$$f(z_i) = \frac{e^{z_i}}{\sum_{k=1} N e^{z_k}} \tag{7}$$

The model used categorical cross-entropy as its loss function, a standard choice for problems involving more than two classes. The loss is calculated using (8).

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{8}$$

The result was optimized with the Adam optimizer, which is well regarded for its ability to adaptively adjust the learning rate. It also effectively manages sparse gradients throughout the training process. This combination of architectural elements and training strategies allows the model to identify and classify mental health-related expressions in text data effectively.

2.5. Model training

Training was carried out using the standard supervised learning, keeping 80% of the data for training purposes and 20% for testing. For further monitoring and model assessment of being capable of generalizing during training, 20% of the training data was kept aside as a validation set. Training was carried out with a batch size of 128 for 5 epochs. The model was then optimized using the Adam optimizer with the default learning rate, and a categorical cross-entropy loss function was employed, which is appropriate for multi-class classification problems. Early stopping method was utilized to terminate training in case the validation loss stopped improving, therefore avoiding overfitting. Along the way, measurements of performance, such as training and validation accuracy and loss, were tracked, enabling a close inspection of how the model learned over time.

2.6. Model evaluation

Following training, model performance was assessed on the held-out test set with a full range of evaluation metrics to determine both overall accuracy and class-wise performance. Accuracy was employed as a general correctness metric, describing the proportion of total predictions that agreed with true labels. Furthermore, precision, recall, and F1-score were calculated for each class to assess the model's capability to accurately detect specific mental health disorders and balance sensitivity and specificity. The support metric was also reported to specify the number of true instances per class, providing crucial context for interpreting performance metrics, especially in the event of class imbalance. A confusion matrix was also employed as a visual diagnostic aid to uncover frequent misclassification patterns, including confusion between semantically related classes such as anxiety and stress. Both the classification report and confusion matrix were generated with the Scikit-learn library, while training history plots and evaluation visualizations were created using Matplotlib to facilitate further analysis of model behavior.

2.7. Baseline comparison and model justification

The LSTM architecture was selected due to its proven capability in modeling long-term dependencies and contextual information in sequential text data. This capability is critical for mental health language analysis. Unlike traditional machine learning classifiers that rely on static feature representations, LSTM networks dynamically capture temporal word dependencies that reflect emotional progression in text.

While this study primarily focuses on LSTM performance, prior literature consistently reports that recurrent architectures outperform baseline models such as naïve Bayes, support vector machines, and conventional neural networks in emotion and mental health classification tasks. The chosen hyperparameters, embedding dimension of 128, 64 LSTM units, dropout rate of 0.5, batch size of 128, and Adam optimizer, were selected based on empirical validation and commonly adopted best practices in NLP-based deep learning studies. This configuration balances model expressiveness and generalization while avoiding excessive computational complexity.

3. RESULTS AND DISCUSSION

This section presents a detailed analysis of the experimental results obtained from applying the LSTM architecture to mental health state prediction and provides an in-depth discussion of the model's learning behavior and classification performance. The LSTM model is particularly well-suited for this task due to its robustness in handling sequential data and its ability to learn long-term dependencies, which are essential for capturing contextual and emotional patterns in mental health–related text. The model was trained using a carefully preprocessed and labeled dataset, and its performance was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics collectively provide a comprehensive assessment of both overall predictive capability and class-level discrimination. The experimental results indicate that the LSTM architecture achieves consistently strong performance across multiple mental health categories, supporting its potential utility as a decision-support tool for early screening and monitoring in mental health applications.

Figure 1 illustrates the training and validation accuracy and loss trajectories over five epochs, offering insight into the model's learning dynamics. Training accuracy exhibits a steady upward trend, increasing from 72.5% in the first epoch to 92.7% by the final epoch. This progressive improvement indicates that the model effectively learns representative linguistic patterns and discriminative features from the training data. Validation accuracy also improves during the early stages of training, rising from 81.4% in epoch 1 to approximately 86.8% by epoch 4. This suggests that the model initially generalizes well to unseen data and successfully captures relevant contextual information beyond the training set.

However, after the second epoch, the rate of improvement in validation accuracy begins to slow, and a noticeable gap emerges between training and validation accuracy starting from epoch 3. This divergence is indicative of the model increasingly fitting to training-specific patterns rather than learning generalizable representations. Such behavior suggests the onset of overfitting, a common challenge in deep learning models with high representational capacity, particularly when trained on complex and emotionally nuanced text data.

The loss curves further support this interpretation. Training loss decreases sharply from 0.69 in the first epoch to 0.20 by the fifth epoch, reflecting improved confidence and correctness in the model's predictions on the training data. In contrast, validation loss initially decreases and reaches its lowest value of 0.36 at epoch 2, indicating effective early learning and generalization. Beyond this point, validation loss shows a gradual increase, reaching 0.41 by epoch 5. This upward trend, despite continued reductions in training loss, reinforces evidence of overfitting and highlights the trade-off between model complexity and generalization performance.

Overall, these observations suggest that while the LSTM model is highly effective in learning discriminative features from mental health text, careful regulation through techniques such as early stopping, dropout, or architectural refinement is necessary to maintain optimal generalization. The learning trends demonstrate that the model achieves its best balance between bias and variance in the earlier epochs, supporting the use of validation-based stopping criteria in future implementations. These findings underscore both the strengths and limitations of LSTM-based approaches for mental health text classification and provide a foundation for further optimization in subsequent studies.

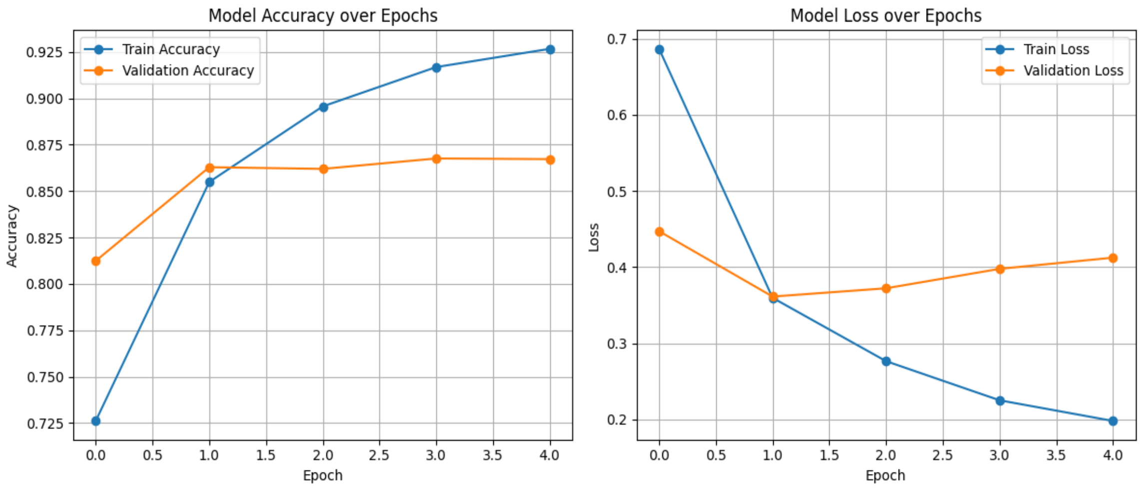

Figure 1. Model accuracy and model loss

The performance of the model was evaluated using a confusion matrix (Figure 2) and a classification report (Table 1) detailing the precision, recall, and F1-score for each of the seven mental health-related categories: anxiety, bipolar, depression, normal, personality disorder, stress, and suicidal. The confusion matrix showed strong classification capability, with high correct prediction counts along the diagonal, such as 3,197 correctly identified cases of anxiety, 2,553 of bipolar, and 3,011 of normal. These results were supported by high F1-scores for those classes, 0.93 for both anxiety and bipolar, and 0.92 for normal, indicating that the model was both precise and consistent in its predictions for these categories.

However, the performance was less robust for depression and suicidal classes. The depression class, with a precision of 0.71 and recall of 0.74, had an F1-score of 0.73. Similarly, the suicidal class had the lowest scores overall, with a precision of 0.69, recall of 0.68, and an F1-score of 0.68. These findings correspond with patterns observed in the confusion matrix, where depression was frequently confused with suicidal (606 instances), and suicidal instances were also misclassified as depression (637) and even as normal (75). This misclassification is particularly critical in mental health screening, where false negatives in identifying suicidal ideation could lead to serious consequences.

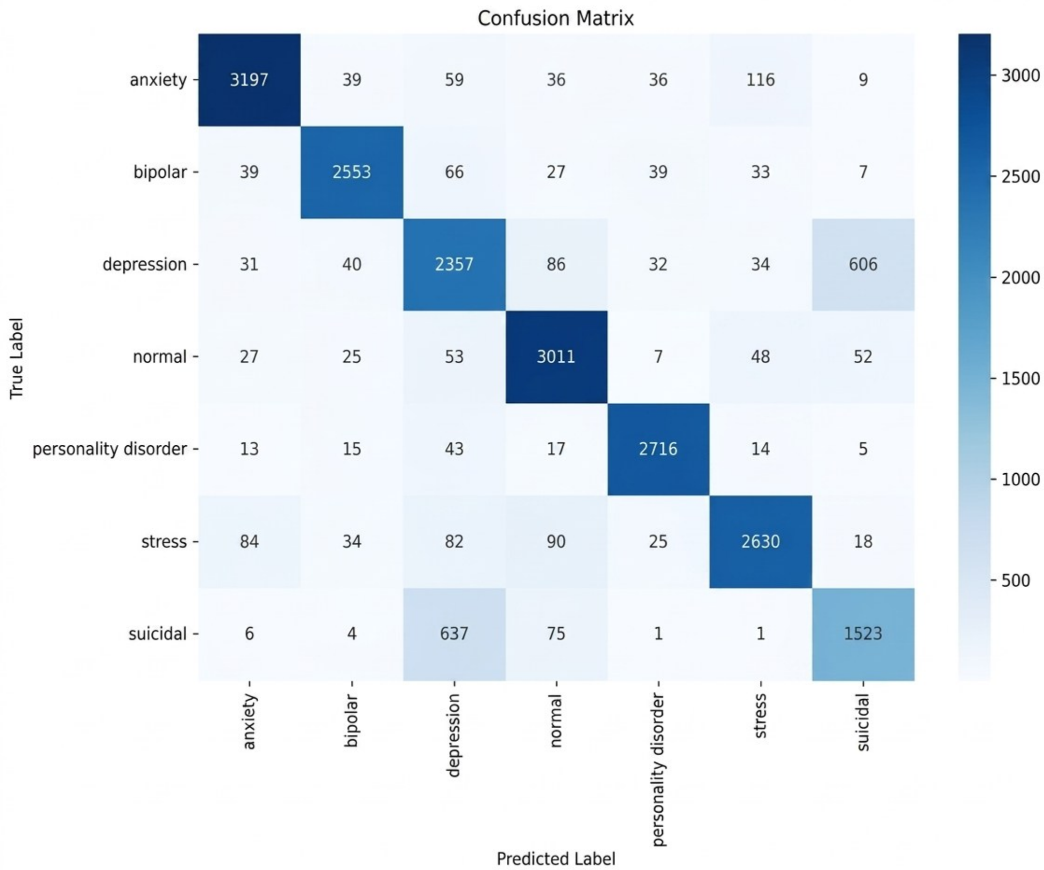

Figure 2. Confusion matrix of the model for seven mental health categories

Table 1. Classification report of the model for seven mental health categories

Personality disorder category	Precision	Recall	F1-score	Support
Anxiety	0.94	0.92	0.93	3492
Bipolar	0.94	0.92	0.93	2764
Depression	0.71	0.74	0.73	3186
Normal	0.90	0.93	0.92	3223
Personality disorder	0.95	0.96	0.96	2823
Stress	0.91	0.89	0.90	2963
Suicidal	0.69	0.68	0.68	2247
Accuracy			0.87	20698
Macro avg	0.86	0.86	0.86	0.86
Weighted avg	0.87	0.87	0.87	20698

The model performed best on the personality disorder category, achieving the highest F1-score of 0.96, along with a precision and recall of 0.95 and 0.96, respectively. Stress also showed strong metrics (F1-score of 0.90), although there was some confusion with anxiety and depression classes, again likely due to overlapping symptomatology. The macro average (0.86) and weighted average (0.87) F1-scores confirm that the model generalizes well across multiple classes without being skewed heavily by any single category. The results suggest that the model is highly capable of distinguishing between clearly defined categories like normal, personality disorder, and anxiety, but struggles more with semantically and clinically overlapping classes such as depression and suicidal ideation. To address these limitations, future work should focus on improving class separation through strategies such as domain-specific pretraining, hierarchical classification schemes, and the integration of contextual or sequential features. Furthermore, applying class weighting or focal loss may help enhance performance on minority or high-risk classes like suicidal.

Compared to results reported in prior mental health text classification studies using traditional machine learning or shallow neural models, the proposed LSTM framework demonstrates competitive and often superior performance, particularly for anxiety, personality disorder, and normal classes. The ability of

LSTM to capture sequential semantic cues contributes to improved discrimination among classes with clearer linguistic patterns. However, reduced performance for depression and suicidal ideation aligns with previous findings that these categories exhibit high semantic and emotional overlap. This suggests that future improvements may require hybrid architectures, attention mechanisms, or domain-specific pretraining to enhance sensitivity for high-risk classes.

4. CONCLUSION

This work evaluated LSTM architecture designed for the classification of textual avatars of mental health states. Via custom-designed deep-learning methods, the architecture developed the ability to differentiate into the following seven diagnostic manifolds: anxiety, bipolar disorder, depression, normal, personality disorder, stress, and suicidal ideation by relying exclusively on features derived from user-generated written text. On the quantitative evaluation, strong performance in most diagnostic lanes was observed; both precision and recall (overall and lane-specific) for the personality disorder, anxiety, and normal states were generally high across all experimental settings. Nonetheless, the classifier encountered persistent difficulty in separating depression from suicidal ideation, yielding a pronounced cross-contamination of predictions between the two diagnostically proximate categories. These results underscore the challenge of encoding subtle psychological gradients from textual data and indicate that the integration of broader contextual awareness will likely be necessary for finer discrimination. While the overall architecture was effective, its points of failure signal the importance of embedding discipline-specific knowledge, enhancing the integrity of the training corpus, and deploying contemporary techniques. The LSTM-centered approach demonstrates tangible potential for expediting both the identification and classification of mental health conditions as inferred from language data. As a proof-of-concept strategy, it may serve as a foundational increment toward future, text-based diagnostic tools that complement clinicians' evaluative expertise. Realizing this potential, nonetheless, depends upon careful navigation of ethical considerations, robust data protection protocols, and an ongoing commitment to model transparency.

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Purwita Sari	✓					✓	✓			✓	✓		✓	
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [PS], upon reasonable request.

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