Automated Depression Detection in Text Data: Leveraging Lexical Features, Phonesthemes Embedding, and RoBERTa Transformer Model*

Elizabeth Martinez[1], Juan Cuadrado[1], Daniel Peña[1], Juan Carlos Martinez-Santos[1] and Edwin Puertas [1,*,†]

[1]*Universidad Tecnologica de Bolivar, School of Engineering, Cartagena de Indias 130010, Colombia.*

Abstract
Depression is a prevalent mental disorder characterized by persistent sadness, lack of interest, and diminished pleasure. Detecting depression is crucial for timely intervention and support. In this paper, we address the task of depression detection in text data, focusing on binary classification and regression. We present our approach, leveraging a dataset comprising labeled messages from Telegram groups related to mental disorders. We begin by exploring the existing literature on depression detection, highlighting the challenges faced and the methods employed. Our approach involves data pre-processing, lexical feature extraction, phonesthemes embedding, and using the RoBERTa transformer model. We achieved promising results in the training phase through rigorous experimentation and model refinement. However, we encountered challenges upon evaluating our approach in the MentalRiskEs evaluation. We identified areas for improvement, particularly in latency and speed of detection for real-time monitoring of depression-related risks. This research contributes to the ongoing efforts in automating depression detection and provides insights into the potential of text analysis techniques for mental health assessment. We remain committed to further enhancing our methodology and advancing the field to improve the well-being of individuals affected by depression.

Keywords
Mental Risk, Depression, Lexical Features, Phonesthemes Embedding, Transformers

1. Introduction

Depression, a prevalent mental disorder affecting millions worldwide, poses significant challenges regarding timely identification and support [1]. Traditional methods of depression detection, which rely on clinical assessments and self-reporting, are limited by subjectivity and resource constraints [2, 3]. As a result, there has been a growing interest in developing automated approaches that utilize natural language processing and machine learning techniques [4].

IberLEF 2023, September 2023, Jaén, Spain
*

*Corresponding author.
eayala@utb.edu.co (E. Martinez); jflechas@utb.edu.co (J. Cuadrado); dgnecco@utb.edu.co (D. Peña); jcmartinezs@utb.edu.co (J. C. Martinez-Santos); epuerta@utb.edu.co (E. P.)
0000-0001-6592-347X (E. Martinez); 0000-0002-8226-1372 (J. Cuadrado); 0009-0004-6244-1060 (D. Peña); 0000-0003-2755-0718 (J. C. Martinez-Santos); 0000-0002-0758-1851 (E. P.)

Considerable research has been conducted in depression detection, exploring various linguistic and contextual features, sentiment analysis, and machine learning algorithms [5, 6, 7]. However, accurately identifying depression from text remains a complex task due to the inherent subtleties and contextual nuances associated with expressions related to mental health [8]. Furthermore, the availability of annotated datasets for training and evaluation purposes is limited, which further complicates the development of effective detection models [9].

In this paper, we present our approach to depression detection using IberLEF 2023 Mental Risk dataset , section 3, obtained from Telegram groups focused on mental disorders [10]. Our methodology, section 4, consists of a pipeline that incorporates data pre-processing techniques, such as removing stop words and punctuation, followed by extracting lexical features to capture linguistic patterns [11] . To enhance the effectiveness of our approach, we also integrate phonesthemes embedding, which encodes phonetic information and leverage the powerful RoBERTa transformer named RoBERTuito model to capture contextual representations [12].

During the training phase, section 5, our model achieved promising results, demonstrating the accuracy of approximately 80% in binary classification Task 2a using SVM [13] and competitive performance when incorporating lexical features, phonesthemes, and the RoBERTa transformer [14]. However, in the evaluation conducted by IberLEF and the MentalRiskEs organization [10], section 6, our performance experienced a significant decline, indicating the need for further exploration and improvement in our methodology. To address this, section 7, we shifted our focus to analyzing individual messages separately, significantly improving binary classification Task 2a. Our accuracy increased from 60.4% to 78.2%. It represents a notable gain of 17.8 percentage points. Furthermore, in the regression Task 2b, our Root Mean Square Error (RMSE) decreased from 0.45 to 0.27 when incorporating lexical features, phonesthemes, and the RoBERTa transformer. It is a substantial reduction of 0.18 in the RMSE metric. Nevertheless, additional research and development are required to achieve optimal depression detection accuracy.

2. Related Work

In recent years, the automatic detection of depression using machine learning and natural language processing methods has gained significant attention. Researchers have explored various approaches to identify depression signals in text data, leveraging linguistic and contextual features. This section provides an overview of previous studies in this domain, highlighting the approaches, challenges, and results obtained.

De Choudhury et al. [15] conducted one of the pioneering studies in this area. They utilized data generated from interactions on Twitter to predict depression in users. The rise of social media has provided much data for developing machine learning models focused on mental health detection [16].

Burdisso et al. [17] proposed a text classification framework for the early and effective detection of depression in social media streams. Based on supervised learning techniques, their approach outperformed standard models while providing computational efficiency and explainability.

Chiong et al. [18] investigated text pre-processing methods and feature extraction techniques for depression detection using machine learning classifiers and social media texts. Their approach effectively detected depression even without specific keywords related to depression in the training datasets.

Amanat et al. [19] proposed a model based on recurrent neural networks (RNN) and long short-term memory (LSTM) for depression detection in textual data. Their approach achieved a precision of 99.0 % in the early identification of depression, surpassing frequency-based models.

Babu and Kanaga [20] conducted a review focused on sentiment analysis in social media for depression detection using artificial intelligence. Their work emphasized multiclass classification techniques and deep learning algorithms, highlighting the importance of obtaining more accurate results in depression detection from social media text data.

Mustafa et al. [21] employed word-based sentiment analysis and psychological attributes to detect depression in social media. Their study used machine learning techniques to classify users into three classes of depression: high, medium, and low. The results emphasized the significance of feature selection and combination in enhancing classifier performance and precision.

3. Data

A new dataset was made available for depression detection by the organizers of the Mental Risk Challenge, IberLEF 2023. This dataset consists of labeled messages obtained from public groups on the Telegram platform. The extraction and anonymization of conversations from these groups were performed by IberLEF 2023, ensuring the privacy of the involved users.

A team conducted a meticulous manual annotation process using the Prolific service by IberLEF 2023 for the dataset labeling. Ten annotators carefully examined the history of each user, determining the presence or absence of evidence indicating the targeted disorder. This approach facilitated regression analysis, allowing the evaluation of prediction tools based on alignment with the collective confidence of human judgments.

We divided the dataset into three subsets, each associated with a different mental disorder. Specifically, the depression corpus, comprising 335 users, was divided into trial, training, and testing sets of 10, 175, and 150 users, respectively.

4. Architecture

This section comprehensively describes the predictive model developed to address Task 2a and Task 2b in the Mental Risk Challenge of the IberLEF 2023 competition. Task 2a involves binary classification to detect depression in users based on their textual messages, while Task 2b focuses on estimating the probability of an individual suffering from depression.

To tackle these tasks effectively, our model follows a systematic approach of several stages. The first stage involves data reading and pre-processing. Multiple messages belonging to the same user are concatenated into a single string, ensuring the continuity of information.

4.1. Pre-Processing

The text data from the IberLEF 2023 competition underwent a cleaning process to ensure its quality and suitability for analysis. Specifically, we subjected the text data to a stop word

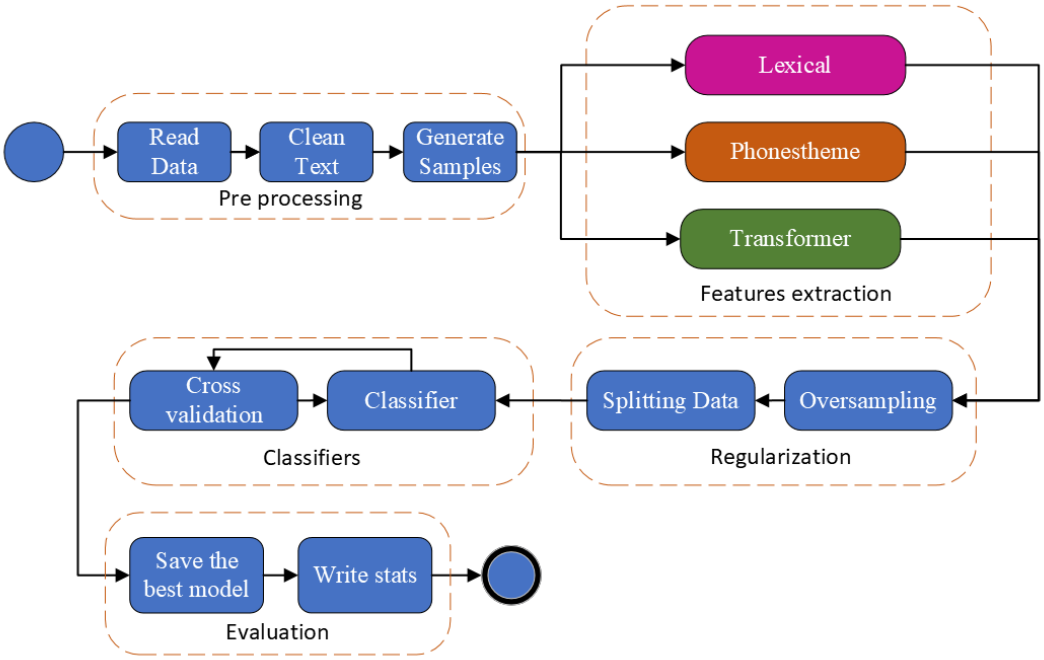

Figure 1: System Pipeline.

removal process.

Stop words are commonly used words in a language that do not carry significant meaning. We removed them to reduce noise and improve the accuracy of natural language processing tasks. Examples of stop words include articles, prepositions, and conjunctions.

By eliminating stop words from the text data, we aimed to enhance the clarity and focus of the dataset, allowing the model to capture better the relevant information related to mental health analysis.

4.2. Feature Extraction

In sentiment analysis, feature extraction is crucial in capturing relevant linguistic aspects within the text. This section focuses on incorporating various feature extraction techniques into our model.

4.2.1. Lexical Features

Lexical features play a significant role in enhancing sentiment analysis by capturing important linguistic characteristics within the text. Our model incorporates several lexical features, including:

1. Personal Pronouns: The inclusion of first-person, second-person, and third-person singular and plural pronouns provides valuable insights into self-referential and interpersonal perspectives, which can be indicative of potential depressive tendencies.

2. Adverbs: Adverbs of time, negation, place, manner, and quantity are employed as lexical features to provide contextual information, aiding in accurately interpreting temporal, spatial, and emotional aspects within the text.
3. Adjectives: We considered negative and positive adjectives lexical features to capture the emotional tone of the content and reflect pessimistic or optimistic sentiments.
4. Lexical Patterns: Specific lexical patterns, such as 'mention,' 'URL,' 'hashtag,' 'emoji,' and 'rt,' reveal communication style and patterns associated with potential depressive symptoms.

4.2.2. Phonetic Embedding

We utilized phonetic embedding as a feature extraction method to complement the sentiment analysis of the textual data. This approach focuses on capturing the phonetic representations of words, enabling the model to capture additional nuances of language. To achieve this, pre-trained Word2Vec models specifically trained on phonesthemes, the minor sound units in a language, are leveraged. It enables the generation of vector representations that effectively capture the phonetic structure of words.

4.2.3. Transformer RoBERTuito

The Transformer RoBERTuito is employed to capture contextual relationships within the text. This variant of the RoBERTa model utilizes deep learning techniques and extensive pre-training on large text corpora. By leveraging its capabilities, RoBERTuito provides contextualized embedding that encodes rich semantic and syntactic information. It enhances the model's understanding of sentiment-related concepts, idiomatic expressions, and subtle linguistic nuances, significantly improving the accuracy of sentiment analysis predictions.

4.2.4. Concatenated Features

We concatenated the feature vectors obtained from the lexical features, phonetic embedding, and Transformer RoBERTuito to consolidate the extracted features. This process results in a single comprehensive feature vector that leverages a diverse range of linguistic information for robust analysis and prediction. Combining the lexical features, phonetic embedding, and contextual embedding from RoBERTuito, our model captures a comprehensive set of linguistic cues and patterns, enabling a holistic understanding of the sentiment expressed in the text and providing valuable insights into mental health conditions.

Depending on the specific task, the consolidated feature vector serves as the input for subsequent stages of the predictive model, such as classification algorithms or regression models. These models utilize the extracted features to predict depression detection or estimate the probability of an individual suffering from depression.

4.3. Regularization

We performed data augmentation to increase the diversity and representation of the dataset. Specifically, we utilized the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE generated synthetic data points by interpolating between existing minority class samples. This process effectively addressed class imbalances, improving the representation of underrepresented instances.

Furthermore, class balancing techniques were applied to address potential class imbalance issues in the binary classification Task 2a as part of the regularization process. The aim was to rectify the uneven distribution of instances across different classes, enhancing the model's performance and mitigating biases that could arise from an imbalanced dataset.

It is important to note that the regression Task 2b, which focused on estimating the probability of depression, did not involve class balancing techniques as it had a different objective. Therefore, class balancing was not applicable in Task 2b.

The model was trained and optimized by combining data augmentation and regularization techniques to handle class imbalances and regression tasks effectively. This comprehensive approach enhanced the model's predictive capabilities for mental health analysis.

4.4. Classifiers

This subsection provides an overview of the classifiers utilized for binary classification Task 2a and regression Task 2b, focusing on their unique contributions and considerations. Scikit-learn classifiers were chosen with default parameters and varying characteristics to ensure accurate and reliable results in detecting depression severity. We will discuss the classifiers employed for binary classification and regression, highlighting their unique contributions and considerations.

4.4.1. Binary Classification Classifiers

In order to assess their performance and predictive capability, we implemented several classifiers for the binary classification Task 2a of detecting depression in text data. We utilized the following classifiers:

- Random Forest (RF)
- Decision Tree (DT)
- Naive Bayes (NB)
- Logistic Regression (LR)
- Support Vector Machine (SVM)
- k-Nearest Neighbors (kNN)

These classifiers were carefully selected based on their distinctive characteristics and demonstrated effectiveness in accurately classifying instances in detecting depression in text data.

4.4.2. Regression Classifiers

For Task 2b, we employed a regressor to estimate the severity of depression in text data and various regression classifiers. The classifiers utilized were as follows:

- Support Vector Machine (SVM)
- Ridge

- Linear Regression
- Lasso
- ElasticNet
- k-Nearest Neighbors (kNN)
- Decision Tree Regressor (DTR)

These classifiers were selected based on their suitability for regression tasks and their potential to provide precise estimations of depression severity in text data.

4.4.3. Cross-Validation

Cross-validation is a widely employed technique used to evaluate the performance of machine learning models. Its primary objective is to estimate how well a model will generalize to unseen data. This study employed cross-validation to reliably assess the classifiers and regressors used in detecting depression in text data.

Specifically, k-fold cross-validation was applied, dividing the dataset into k subsets (folds) of similar sizes. Then, we trained the model and evaluated k times, employing each k subsets as a test set once while we utilized the remaining k-1 subsets as the training set. This methodology guarantees the utilization of all instances in the dataset for training and testing.

4.5. Evaluation

In this stage, we rigorously compared the results obtained from different models, and the model with the best performance in each metric, or most metrics, is selected. Task 2a, which involves binary classification, and Task 2b, which focuses on regression, are evaluated using specific performance metrics.

We utilized the following metrics for Binary Classification Task 2a: Accuracy, Precision, Recall, and F1 score. These metrics are critical indicators for assessing the classifiers' ability to correctly classify instances and measure the balance between true positives, false positives, and false negatives. By analyzing these metrics, we can determine which classifier performs better in accurately detecting depression in text data.

Regarding Regression Task 2b, the evaluation encompasses the following metrics: Root Mean Square Error (RMSE), Pearson correlation coefficient, and Pearson's recall. RMSE measures the average difference between predicted and actual depression severity scores, while the Pearson correlation coefficient quantifies the linear relationship between predicted and actual scores. Additionally, Pearson recall evaluates the ability of regression classifiers to capture the recall of depression severity levels accurately.

By employing these comprehensive metrics, we ensure a thorough evaluation of the classifiers' performance in both binary classification and regression tasks. The selection of the best-performing model in each task is based on an objective analysis of the model's performance across these metrics, enabling us to make informed decisions and derive reliable conclusions.

5. Experiments Conducted and Training

In the conducted experiments, we followed a step-by-step approach to classify depression in text data. First, we evaluated the performance of classifiers using individual and parallel feature extractions of phonesthemes and lexical features. Then, we examined the performance of concatenated features, combining phonesthemes and lexical features. In the next step, we incorporated transformer-based feature extraction, phonesthemes, and lexical features. We repeated these steps for binary classification Task 2a and regression Task 2b. The experiments involved evaluating various classifiers and measuring their performance using different metrics. The results of these experiments provided insights into the effectiveness of different feature combinations and classifiers for depression classification and regression tasks.

5.1. Results of Training Process for Binary Classification Task 2a

The binary classification Task 2a involved evaluating multiple models for different feature combinations. The models assessed included Random Forest (RF) with DecisionTreeClassifier(200), Decision Tree (DT) with DecisionTreeClassifier(4), Gaussian Naive Bayes (NB), Logistic Regression (LR) with LogisticRegression(), Support Vector Machine (SVM) with SVC(), and K-Nearest Neighbors (kNN) with KNeighborsClassifier(). These models were tested and compared in terms of their performance for each feature combination.

Table 1 displays the performance of the evaluated models for different feature combinations. Notably, the SVM model consistently outperformed the other models. When considering the phonesthemes approach, the SVM model achieved an accuracy of 0.80. Similarly, for the Lexical approach, the SVM model demonstrated an accuracy of 0.78. Furthermore, the SVM model maintained a high accuracy of 0.80 when incorporating phonesthemes, Transformers, and Lexical features.

The superior performance of the SVM model across multiple feature combinations highlights its effectiveness for the task at hand. The high accuracy and precision make it the most suitable choice for the phonesthemes and Lexical approaches and the combined phonesthemes, Transformers, and Lexical approaches.

Table 1
Performance of Different Feature Combinations

Approach	Name	Model	Accuracy	Precision	Recall	F1
Phonesthemes	SVM	SVC()	0.80	0.81	0.80	0.80
Lexical	SVM	SVC()	0.78	0.79	0.78	0.78
Phonesthemes and Lexical	RF	DT(200)	0.68	0.69	0.69	0.68
Phonesthemes, Transformers, and Lexical	SVM	SVC()	0.80	0.81	0.80	0.80

5.2. Results of Training Process for Regression Task 2b

The regression Task 2b involved evaluating various regression models for different feature combinations. The models considered for evaluation were SVR (Support Vector Regressor), Ridge, LinearRegression (LR), Lasso, ElasticNet, KNeighborsRegressor, and DecisionTreeRegressor. These models were tested and compared using four distinct feature combinations: phonesthemes, Lexical, phonesthemes, and Lexical, and phonesthemes, Transformers, and Lexical.

As shown in Table 2, the results demonstrated that the Ridge regression model consistently outperformed the other models across all feature combinations. Specifically, when combining lexical, phonesthemes, and transformer features, the Ridge model achieved the best performance with an RMSE (Root Mean Squared Error) of 0.29, a Pearson correlation coefficient of 0.81, and a Pearson recall of 0.62.

These results concluded that the Ridge regression model was the most suitable choice for the regression task, particularly when considering the combination of lexical, phonesthemes, and transformer features.

Table 2
Regression Model Performance for Different Feature Combinations

Approach	Name	Model	RMSE	Pearson	Pearson recall
phonesthemes	Ridge	Ridge()	0.36	0.63	0.25
Lexical	LR	LR()	0.36	0.70	0.39
phonesthemes and Lexical	LR	LR()	0.67	0.66	0.32
phonesthemes, Transformers, and Lexical	Ridge	Ridge()	0.29	0.81	0.62

6. Results of UTB in MentalRiskEs Task Evaluation

In this section, the results obtained by the UTB team in the evaluation of the MentalRiskEs task are presented. The task was focused on the detection of mental disorders, with a specific emphasis on the early identification of depression in Spanish comments from Telegram users. Note that for each subtask, the exact same model was submitted by the UTB team for evaluation three times.

6.1. Task 2a: Depression Detection

The UTB team approached Task 2a using various classification models to detect if users suffer from depression. Table 3 showcases the classification-based evaluation results for Task 2a by the UTB team. The table includes the team's rank, run number, accuracy, macro-precision (Macro-P), macro-recall (Macro-R), and macro-F1 (Macro-F1) scores. These metrics measure the accuracy and overall performance of the team's models in detecting depression.

Furthermore, the team's performance in terms of latency and speed of detection for Task 2a is presented in Table 4. The table includes the team's rank, run number, ERDE5, ERDE30, latencyTP, speed, and latency-weighted F1 scores. These metrics assess the team's ability to detect mental disorder risks promptly.

The results indicate that the UTB team achieved competitive accuracy scores in depression detection. However, we could explore further improvements in terms of latency and speed of detection to enhance the real-time monitoring and identification of depression-related risks in Telegram comments.

Table 3
Classification-based evaluation in Task 2a - NLPUTB

Rank	Team	Run	Accuracy	Macro-P	Macro-R	Macro-F1
23, 24, 25	NLPUTB	0, 1, 2	0.604	0.619	0.579	0.554

Table 4
Latency-based evaluation in Task 2a - NLPUTB

Rank	Team	Run	ERDE5	ERDE30	latencyTP	speed	latency-weightedF1
28, 29, 30	NLPUTB	0, 1, 2	0.362	0.356	2.000	0.984	0.397

6.2. Task 2b: Regression-based Evaluation

In Task 2b, the UTB team focused on regression-based evaluation to estimate the level of affectation for users suffering from depression. Table 5 presents the team's RMSE (root mean square error) performance, which reflects the accuracy of their regression models. The table includes the team's rank, run number, and RMSE score.

On the other hand, Table 6 presents the results of the ranking-based evaluation for the same Task 2b in the NLPUTB project. The NLPUTB team also participated in three runs, identified as 0, 1, and 2. However, in this evaluation metric, a p@30 score of 0.000 was obtained by the NLPUTB team, indicating that correct rankings within the top 30 positions were not achieved.

The UTB team's results in the regression-based evaluation highlight their ability to accurately estimate the level of affectation for users with depression. These findings demonstrate the team's competence in quantitatively utilizing regression models to assess mental health conditions.

Overall, the UTB team showcased their proficiency in addressing classification and regression tasks within the MentalRiskEs evaluation. Their results demonstrate their efforts in accurately detecting mental disorders, estimating affectation levels, and considering the challenges posed by the online nature of the problem.

Table 5
Regression-based evaluation in Task 2b - NLPUTB

Rank	Team	Run	RMSE
10, 11, 12	NLPUTB	0, 1, 2	0.381

Table 6
Ranking-based evaluation in Task 2b - NLPUTB

Rank	Team	Run	p@30
17, 18, 19	NLPUTB	0, 1, 2	0.000

Table 7
Alternative Binary Classification Approach.

Approach	Model	RMSE	Pearson
New	Ridge()	0.44	0.18
Profiling	Ridge()	0.381	-

7. Error Analysis and Discussion

In this study, we initially developed an approach based on profiling for the binary classification and regression tasks of mental health analysis. The profiling approach involved concatenating messages and features to capture the overall behavioral patterns of individuals. While the initial evaluation showed promising results, our approach performed differently during the assessment conducted by Mental Risk, where various research groups with diverse methodologies participated. The evaluation incorporated additional metrics, such as p@k and latency, which we had yet to consider in our approach initially. Consequently, the performance of our approach significantly declined in all evaluation metrics.

Upon further investigation and analysis, we hypothesized that the limitations of our initial approach stemmed from its inability to capture the temporal dynamics of message content. The concatenation of numerous messages without considering their chronological order and the analysis of the entire dataset led to increased computational time, affecting the overall performance. To address these challenges, we designed and implemented a new approach that focused on considering the temporal aspect of message sequences.

The new approach involved analyzing messages individually while preserving their chronological order and incorporating temporal dependencies. By examining the messages in a time-based sequence, we aimed to more effectively capture the evolving patterns and nuances of individuals' mental states. Consequently, we observed notable improvements in several evaluation metrics.

Table 7 summarizes the new approach's performance compared to the regression task's profiling approach. The new approach, implemented using the Ridge regression model, achieved an RMSE of 0.44, indicating a significant reduction in prediction error compared to the profiling approach. However, it is essential to note that the Pearson correlation coefficient did not demonstrate substantial improvement, suggesting that the revised approach may still benefit from further refinement.

For the binary classification Task 2a, Table 8 presents the classification-based evaluation metrics. The new approach achieved an accuracy of 0.530, indicating an enhancement over the profiling approach. However, the macro-Precision, macro-Recall, and macro-F1 scores were slightly lower for the new approach, indicating that the revised methodology did not yield

Table 8
Classification-based evaluation new approach

Approach	Accuracy	Macro-P	Macro-R	Macro-F1
New	0.530	0.526	0.526	0.526
Profiling	0.604	0.619	0.579	0.554

significant improvements in the precision, recall, and F1 scores.

Table 9
Latency-based evaluation new approach

Approach	ERDE5	ERDE30	latencyTP	speed	latency-weightedF1
New	0.529	0.352	21.0	0.701	0.453
Profiling	0.362	0.356	2.000	0.984	0.397

Furthermore, Table 9 presents the latency-based evaluation metrics. While the new approach demonstrated improvements in ERDE5 and ERDE30, the latency-weighted F1 score was slightly lower than that of the profiling approach. It suggests that the revised approach may have introduced specific latency-related challenges or trade-offs.

The findings from our study underscore the complexity of mental health analysis tasks and the need for continuous exploration and refinement of approaches. Although the new approach improved several evaluation metrics, we should have observed the areas where we made the enhancements. Future research efforts will focus on addressing these limitations and optimizing the performance of our approach across all evaluation metrics. One potential avenue for improvement involves developing techniques to effectively capture the temporal dynamics of message sequences while considering computational efficiency.

8. Conclusion

In conclusion, our study aimed to address the challenge of depression detection in text data through binary classification Task 2a and regression Task 2b. Our approach involved a comprehensive pipeline integrating data pre-processing, lexical feature extraction, phonesthemes embedding, and the RoBERTa transformer model.

During the training phase, our binary classification model achieved a good accuracy of approximately 80%. However, when subjected to the evaluation of the MentalRiskEs task, our performance experienced a decline, with lower rankings in Task 2a (23rd, 24th, and 25th positions) and Task 2b (10th, 11th, and 12th positions). These results highlight the need for further exploration and improvement in our methodology.

To address the limitations identified during the evaluation, we explored alternative approaches. By analyzing individual messages separately, we observed an improvement in our depression detection performance. This shift increased accuracy, demonstrating the value of considering individual messages as independent units of analysis.

Furthermore, we examined the impact of our initial profiling approach and found no significant difference in the evaluation metrics compared to our submitted results. This realization emphasizes the ongoing need for discussion and exploration to enhance the binary detection and regression tasks of depression.

Moving forward, we will focus on refining our methodology to overcome the challenges encountered during evaluation. It includes balancing the benefits of profiling and the need for efficiency. Potential avenues for improvement include selective concatenation based on message relevance or incorporating additional contextual information.

Acknowledgments

The authors would like to acknowledge the support provided by the master's degree scholarship program in engineering at the Universidad Tecnologica de Bolivar (UTB) in Cartagena, Colombia.

References

[1] D. Wasserman, M. Iosue, A. Wuestefeld, V. Carli, Adaptation of evidence-based suicide prevention strategies during and after the covid-19 pandemic, World psychiatry 19 (2020) 294–306.

[2] H. Kim, S. Lee, S. Lee, S. Hong, H. Kang, N. Kim, et al., Depression prediction by using ecological momentary assessment, actiwatch data, and machine learning: observational study on older adults living alone, JMIR mHealth and uHealth 7 (2019) e14149.

[3] J. M. Bolton, D. Gunnell, G. Turecki, Suicide risk assessment and intervention in people with mental illness, Bmj 351 (2015).

[4] J. Hirschberg, C. D. Manning, Advances in natural language processing, Science 349 (2015) 261–266.

[5] E. Puertas, L. G. Moreno-Sandoval, F. M. Plaza-del Arco, J. A. Alvarado-Valencia, A. Pomares-Quimbaya, L. Alfonso, Bots and gender profiling on twitter using sociolinguistic features, CLEF (Working Notes) (2019) 1–8.

[6] L. G. Moreno-Sandoval, E. Puertas, F. Plaza-Del-Arco, A. Pomares-Quimbaya, J. Alvarado-Valencia, A. Ureña-López, Celebrity profiling on twitter using sociolinguistic features notebook for pan at clef 2019 (2019).

[7] E. Puertas, L. G. Moreno-Sandoval, J. Redondo, J. A. Alvarado-Valencia, A. Pomares-Quimbaya, Detection of sociolinguistic features in digital social networks for the detection of communities, Cognitive Computation 13 (2021) 518–537.

[8] M. Kabir, T. Ahmed, M. B. Hasan, M. T. R. Laskar, T. K. Joarder, H. Mahmud, K. Hasan, Deptweet: A typology for social media texts to detect depression severities, Computers in Human Behavior 139 (2023) 107503.

[9] M. Shoaib, B. Shah, S. Ei-Sappagh, A. Ali, A. Ullah, F. Alenezi, T. Gechev, T. Hussain, F. Ali, An advanced deep learning models-based plant disease detection: A review of recent research, Frontiers in Plant Science 14 (2023) 875.

[10] A. M. Mármol-Romero, A. Moreno-Muñoz, F. M. Plaza-del-Arco, M. D. Molina-González, M. T. Martín-Valdivia, L. A. Ureña-López, A. Montejo-Ráez, Overview of MentalriskES at

IberLEF 2023: Early Detection of Mental Disorders Risk in Spanish, Procesamiento del Lenguaje Natural 71 (2023).
[11] E. A. Puertas Del Castillo, et al., Análisis de elementos fonéticos y elementos emocionales para predecir la polaridad en fuentes de microblogging (2023).
[12] J. M. Pérez, D. A. Furman, L. A. Alemany, F. Luque, Robertuito: a pre-trained language model for social media text in spanish, arXiv preprint arXiv:2111.09453 (2021).
[13] S. Huang, N. Cai, P. P. Pacheco, S. Narrandes, Y. Wang, W. Xu, Applications of support vector machine (svm) learning in cancer genomics, Cancer genomics & proteomics 15 (2018) 41–51.
[14] E. Puertas, J. C. Martinez-Santos, Phonetic detection for hate speech spreaders on twitter (2021).
[15] M. De Choudhury, M. Gamon, S. Counts, E. Horvitz, Predicting depression via social media, in: Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media (ICWSM), 2013.
[16] N. H. Di Cara, V. Maggio, O. S. P. Davis, C. M. A. Haworth, Methodologies for monitoring mental health on twitter: Systematic review, J Med Internet Res 25 (2023) e42734. URL: https://doi.org/10.2196/42734. doi:10.2196/42734.
[17] S. G. Burdisso, M. Errecalde, M. Montes-y Gómez, A text classification framework for simple and effective early depression detection over social media streams, Expert Systems with Applications 133 (2019) 182–197.
[18] R. Chiong, G. S. Budhi, S. Dhakal, F. Chiong, A textual-based featuring approach for depression detection using machine learning classifiers and social media texts, Computers in Biology and Medicine 135 (2021) 104499. URL: https://www.sciencedirect.com/science/article/pii/S0010482521002936. doi:https://doi.org/10.1016/j.compbiomed.2021.104499.
[19] A. Amanat, M. Rizwan, A. R. Javed, M. Abdelhaq, R. Alsaqour, S. Pandya, M. Uddin, Deep learning for depression detection from textual data, Electronics 11 (2022). URL: https://www.mdpi.com/2079-9292/11/5/676. doi:10.3390/electronics11050676.
[20] N. V. Babu, E. G. M. Kanaga, Sentiment analysis in social media data for depression detection using artificial intelligence: a review, SN Computer Science 3 (2022) 1–20.
[21] R. U. Mustafa, N. Ashraf, F. S. Ahmed, J. Ferzund, B. Shahzad, A. Gelbukh, A multiclass depression detection in social media based on sentiment analysis, in: S. Latifi (Ed.), 17th International Conference on Information Technology–New Generations (ITNG 2020), Springer International Publishing, Cham, 2020, pp. 659–662.