TexTKAN: Parameter-Efficient Text-Based Depression Detection Using Temporal Kolmogorov–Arnold Networks

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***Abstract*—Depression remains a significant mental health issue worldwide. One approach being explored to address this is using deep learning to automate depression detection from social media texts. Besides accuracy improvement, a primary challenge in this research area is the vast number of parameters required for deep learning, particularly in text classification tasks involving multiple sentences. Moreover, the issue of over-parameterization arises, resulting in prolonged training times and an increased risk of overfitting. To address these limitations, this study proposes TexTKAN, a modified Temporal Kolmogorov–Arnold Network inspired by the parameter efficiency of Kolmogorov–Arnold Networks. Experimental results indicate that TexTKAN achieves an accuracy of 0.816 and an F1-score of 0.802 using GloVe embeddings, outperforming conventional recurrent architectures, including RNN, LSTM, GRU, and BiLSTM, while requiring fewer trainable parameters. These results highlight that TexTKAN provides an effective trade-off between predictive performance and model efficiency, making it well-suited for resource-constrained and real-world depression detection applications. The findings further suggest that KAN-based architectures offer a promising direction for efficient text classification beyond depression detection.**

***Index Terms*—depression detection, kolmogorov-arnold network, temporal model, text classification**

I. Introduction

One of the most urgent needs in healthcare is the early identification and treatment of mental health issues, as underscored by their inclusion in the Sustainable Development Goals. Mental health disorders are the foremost drivers of global disability and should be addressed as a central concern in public health policy and practice [1], [2]. Mental disorders comprise a variety of psychological health issues, such as dementia, bipolar disorder, anxiety, schizophrenia, and depression [3]. The World Health Organization (WHO) characterizes depression as a highly prevalent global disorder that substantially influences an individual's mood and emotional functioning [4]. A subtantial portion of the population experiences this mental health disorder, manifesting in diverse symptoms such as insomnia, loss of interest, and thoughts of death [5], [6].

Furthermore, mental health issues are often overlooked by individuals, remaining undiagnosed and untreated. This neglect often results in tragic incidents of self-harm and suicide [7]. Key factors contributing to the oversight of these critical human behavior issues include insufficient awareness and acceptance, the presence of social stigma, insensitivity, indifference, and the high costs and time-consuming nature of clinical diagnostic and treatment processes, such as extensive questionnaires and multiple interviews [3], [8].

In recent years, numerous studies in artificial intelligence have concentrated on developing methods for the automatic and early detection of depression, enabling timely intervention. Social media has emerged as a potential data source for early depression detection [4]. The stigma surrounding depression often discourages individuals from seeking professional help, leading them to express their feelings, thoughts, and emotions through social media instead [8]. Over the years, various approaches have been devised to address depression detection in social media, primarily focusing on extracting textual representations, predominantly utilizing deep learning-based text embedding [5]. Text data processing requires models that are capable of handling sequential data knowledge. Accordingly, deep learning architectures such as Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), and Long Short-Term Memory (LSTM) networks are among the most commonly adopted approaches [4], [7].

Despite their success, deep neural architectures for text-based depression detection suffer from two fundamental limitations. First, state-of-the-art models often require a large number of trainable parameters, resulting in high computational cost, increased memory consumption, and reduced feasibility for deployment in resource-constrained environments. Second, over-parameterization increases the risk of overfitting, particularly in mental health datasets that are relatively small, noisy, and imbalanced. These challenges motivate the exploration of alternative neural architectures that can achieve competitive performance with improved parameter efficiency and generalization.

Moreover, the issue of over-parameterization arises, resulting in prolonged training times and elevate the likelihood of overfitting. Overfitting refers to a condition in which a model captures noise and dataset-specific artifacts instead of underlying general patterns, thereby degrading its predictive performance on previously unseen data and restricting its practical applicability. Addressing these challenges necessitates the development of novel, efficient training approaches. Such approaches could involve techniques for reducing the number of parameters without compromising performance, streamlining the training process, or strategies to enhance the model's generalization capabilities. By overcoming these obstacles, it may be possible to create models that are both effective and viable for deployment in real-world scenarios.

Cutting edge technology called Kolmogorov-Arnold Networks (KAN) is reviving machine learning research [9]. Motivated by kolmogorov-arnold representation theorem, KAN provides an alternative to the Multi-Layer Perceptron (MLP), which serves as the foundation for numerous deep learning models. Unlike MLP, KAN use activation functions on node connections that can adapt and learn during training showcasing classification accuracy and interpretability [9]. The Temporal Kolmogorov Arnold Network (TKAN) model [10] is a modification of KAN that incorporates gating mechanisms from the LSTM [11] model. This adaptation enables TKAN to handle sequential data enhancing its performance in time series data forecasting by managing dependencies over time.

In this work, we propose TexTKAN, a modified Temporal Kolmogorov-Arnold Network specifically designed for depression detection from social media text. By adapting the Temporal KAN framework to sequential word representations, TexTKAN aims to capture temporal dependencies in text while significantly reducing model complexity. In summary, this work makes the following primary contributions:

- In previous research by [10], TKAN has been employed exclusively for time series data forecasting. In this study, we apply TKAN as a novel architecture for text classification in the context of depression detection. To the best of our knowledge, this study is the first to explore the concept of KANs for text classification, incorporating modifications to the TKAN model.
- We introduce architectural modifications to the Temporal KAN framework, including an embedding-aware input structure and a SoftMax-based output layer, enabling effective multiclass text classification.
- We empirically demonstrate that TexTKAN achieves competitive performance with substantially fewer trainable parameters compared to conventional recurrent neural architectures.

This paper is organized into five sections. Related research is reviewed in Section II. Section III presents the proposed model along with the experimental design used for evaluation. Section IV reports the experimental results and provides a thorough analysis and discussion. Finally, Section V concludes the study and identifies potential avenues for future investigation.

II. Related Work

Numerous studies have explored the automatic detection of depression using artificial intelligence, with a notable shift towards deep learning techniques over traditional machine learning algorithms. Various models have employed deep learning approaches to identify, predict, and categorize depression citeSLR. Recent advancements in AI research have led to significant improvements in accuracy. Researchers frequently utilize neural network-based deep learning methods, such as LSTM, BiLSTM, and RNN, as standalone models or in hybrid configurations to leverage their respective strengths [4].

Research by [12] evaluated the effectiveness of RNN and LSTM models in identifying depressive comments on Twitter. The LSTM model demonstrated superior performance compared to the simple RNN. Additionally, an ensemble approach incorporating multiple deep learning models, including BiLSTM, has been proposed to enhance the accuracy of detecting depressive states from social media posts. This method capitalizes on the strengths of various models to improve overall performance, particularly in real-world scenarios where data distribution may be imbalanced [13].

Research by [14] indicates that most research on depression detection through data from social media employ either text-based or person-descriptive feature extraction methodologies. The text-based approach emphasizes analyzing the linguistic properties of social media content, analyzing elements such as words, n-grams, parts of speech, and other linguistic features [14]. Common techniques for feature extraction and representation are applied to the textual content in social media datasets to generate input feature vectors. Neural embeddings have emerged as the preferred choice due to their superior performance compared to handcrafted features [7]. However, these gains are often accompanied by a substantial increase in parameter count and training complexity. More recently, transformer-based models such as BERT have demonstrated strong performance in depression detection tasks. Nevertheless, their deployment is constrained by high computational cost and memory requirements, which limit applicability in real-time or edge-based mental health monitoring systems.

In parallel, KANs represent an advanced neural architecture derived from the Kolmogorov–Arnold representation (KAR) theorem, distinguishing them from traditional neural networks that are based on the universal approximation theorem [9]. Unlike classical networks, which assign fixed activation functions to neurons, KANs employ learnable activation functions on the network edges. The Kolmogorov–Arnold theorem asserts that arbitrary multivariate functions can be reconstructed using a finite sum of continuous single-variable functions and additive operations.

KANs mark a significant breakthrough in neural network architecture by integrating the KAR theorem with B-splines, resulting in a dynamic and robust model. The KAR theorem offers a mechanism to decompose complex functions into simpler components, a principle KANs utilize by implementing learnable B-spline activation functions on each edge between neurons. Experiments by [9] demonstrate that KANs outperform MLPs in accuracy and interpretability. Notably, significantly smaller KANs can match or even surpass the performance of much larger MLPs in tasks such as data fitting and addressing partial differential equations (PDEs).

The presence of KANs has inspired researchers to apply them to various classification and prediction tasks to enhance deep learning performance, which traditionally relies on MLPs. For instance, [10] developed Recurrent KAN (RKAN) models to address sequential data problems. In subsequent research, [10] developed TKAN, integrating the strengths of LSTM and KAN. This innovative architecture tackles common RNN challenges, such as long-term dependency, by incorporating layers of RKAN, thereby improving the network's capability to process and retain both new and historical information effectively. TKANs exhibit outstanding performance in multi-step time series forecasting, delivering superior accuracy and efficiency. By addressing the limitations of traditional models in managing complex sequential patterns, the TKANs framework shows great promise for advancing fields that depend on accurate multi-step forecasting. This study bridges this gap by extending the Temporal KAN framework to text classification, positioning TexTKAN as a parameter-efficient alternative to recurrent neural networks for depression detection.

III. Material and Method

This section outlines the stages of depression detection utilizing the TKAN model, as depicted in Fig. 1 . The proposed model comprises two primary stages: text pre-processing and classification process incorporating a modified TKAN layer, which we have designated as Text Classification with Temporal Kolmogorov-Arnold Networks (TexTKAN).

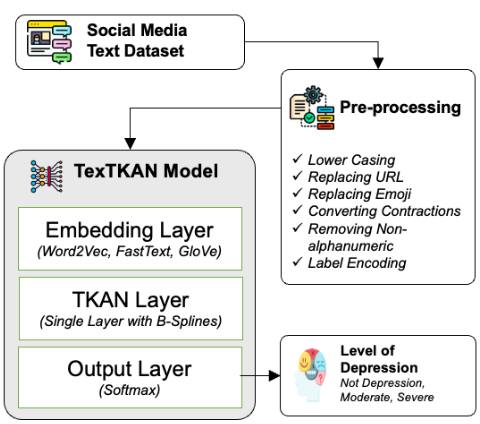

Fig. 1. The Proposed Model Architecture Block

A. Datasets and Pre-processing

This research utilizes datasets sourced from the social media platform Reddit. Specifically, the dataset employed is the depression dataset published for the DepSign-LT-EDI@ACL-2022 shared task [6], [15]. The dataset comprises two primary attributes: a collection of sentences posted by a Reddit user and labels indicating the user's level of depression. The dataset contains 16,632 entries, categorized as follows: 4,649 entries labeled as ”not depression,” 10,494 as ”moderate depression,” and 1,489 as ”severe depression”.

The initial step in detecting depression from social media text involves text pre-processing. This stage plays a critical role in refining raw textual data and converting it into a structured representation appropriate for machine learning models, thereby improving classification accuracy and robustness. As illustrated in Fig. 1, the pre-processing pipeline consists of the following key operations:

- *Lower Casing*: All textual content is transformed into lowercase to ensure uniform representation and prevent case-sensitive discrepancies.
- *Replacing URLs*: Since URLs are highly variable and typically do not convey meaningful semantic information for depression detection, they are substituted with a standardized token, `.url.`.
- *Replacing Emojis*: Emojis are converted into corresponding textual descriptions using regular expressions to preserve the emotional information embedded in them.
- *Removing Non-alphanumeric Characters*: All characters other than letters and digits, including punctuation marks, special symbols, and redundant whitespace, are eliminated.
- *Converting Contractions*: Contracted word forms (e.g., “don't”) are expanded into their full expressions (e.g., “do not”) to improve linguistic consistency.

These pre-processing steps are crucial for improving the quality and effectiveness of the subsequent text classification models.

B. TexTKAN: Temporal KAN for Text Classification Task

TexTKAN is our proposed model that leverages the KAN architecture [9] for text classification tasks. As depicted in Fig. 1, TexTKAN classifier model comprises three main layers: the embedding layer, the TKAN layer, and the output layer. The word embedding layer maps each word in the input sentence to a dense vector representation. The embedding matrix E is of size $V \times D$, where V is the size of the vocabulary, D represent the dimension of the word embeddings, and each row represents the embedding of a word wd in the vocabulary. Equation (1) show the input sentence X with length T representation in embedding layer of our TexTKAN model.

$$X = [wd_1, wd_2, \ldots, wd_T] \quad \text{with} \quad wd_i \in \{1, 2, \ldots, V\} \tag{1}$$

These indices are then used to look up their corresponding embedding vectors from the embedding matrix, transforming the input words into dense vectors, denoted as $X_{\text{embed}} = E[X] \in \mathbb{R}^{T \times D}$.

Following the embedding layer, the TKAN layer processes these dense vectors to capture temporal dependencies within the sequence of words. The TKAN layer refines the KAN architecture by integrating recurrent and gating mechanisms, akin to those in LSTM layers [10]. The Kolmogorov-Arnold representation theorem states that any multivariate continuous function can be expressed as a sum of individual univariate functions.

$$f(x_1, \ldots, x_n) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^{n} \phi_{q,p}(x_p) \right) \tag{2}$$

where $\phi_{q,p}$ are univariate functions mapping each input variable (x_p), with $\phi_{q,p} : [0,1] \to \mathbb{R}$ and $\phi_q : \mathbb{R} \to \mathbb{R}$. Additionally, a single KAN layer is defined as

$$\Phi = \{\phi_{q,p}\}, \quad p = 1, 2, \cdots, n_{\text{in}}, \quad q = 1, 2, \cdots, n_{\text{out}}, \tag{3}$$

where $\phi_{q,p}$ are parameterized functions of learnable parameters.

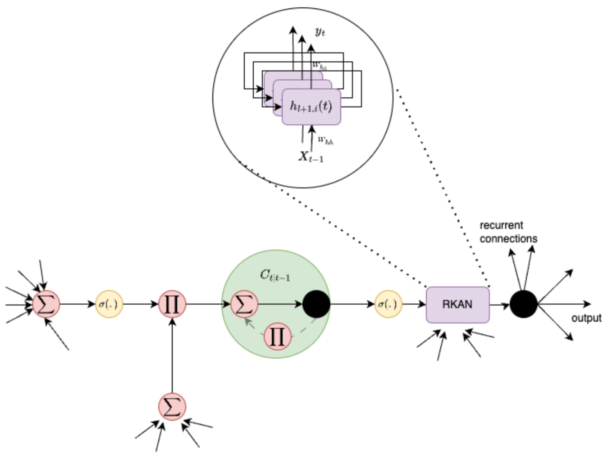

Fig. 2. A Single Layer TKAN Block [10]

The recurrent mechanism is crucial for TKAN layers to learn from sequences where the context and order of data are significant. Fig. 2 illustrates the mechanism of a single TKAN layer in processing input from the embedding layer. This mechanism modifies each transformation function $\phi_{l,j,i}$ in (2) to be time-dependent. We denote $h_{l,i}(t)$ as a memory function that captures the history of node i in the l-th layer:

$$x_{l+1,j}(t) = \sum_{i=1}^{n_l} \widetilde{x}_{l,j,i}(t) = \sum_{i=1}^{n_l} \phi_{l,j,i,t}(x_{l,i}(t), h_{l,i}(t)), \quad j = 1, \ldots, n_{l+1} \tag{4}$$

The "memory" step $h_{l,i}(t)$ is defined as a combination of past hidden states, such as:

$$h_{l,i}(t) = W_{hh} h_{l,i}(t-1) + W_{hz} x_{l,i}(t) \tag{5}$$

where W is a vector of weights that determine the importance of past values relative to the most recent input. In the RKAN layer, the network now embeds memory management at each layer:

$$\text{KAN}(x, t) = (\Phi_{L-1,t} \circ \Phi_{L-2,t} \circ \cdots \circ \Phi_{1,t} \circ \Phi_{0,t})(x, t) \tag{6}$$

To facilitate memory retention, the TKAN layer is designed by drawing inspiration from the gating mechanism of Long Short-Term Memory (LSTM) networks. This layer employs multiple internal vectors and gating units to control information propagation over time. Specifically, the forget gate, characterized by the activation vector f_t,

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \tag{7}$$

regulates which components of the previous cell state should be discarded. The input gate, defined by the activation vector i_t,

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \tag{8}$$

determines the extent to which new information is incorporated into the cell state.

The output gate, represented by the activation vector o_t,

$$o_t = \sigma(\text{KAN}(\vec{x}, t)), \tag{9}$$

controls the information exposed to the next layer based on the output of $\text{KAN}(\vec{x}, t)$ as defined in (6). The cell state c_t is updated according to

$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c}_t, \tag{10}$$

where the candidate memory state is given by

$$\widetilde{c}_t = \sigma(W_c x_t + U_c h_{t-1} + b_c).$$

All internal states are assumed to have a dimensionality of h. The hidden state h_t, which represents the output of the TKAN unit at time step t, is computed as

$$h_t = o_t \odot \tanh(c_t). \tag{11}$$

For multiclass depression level classification, the network is augmented with a final prediction layer composed of a fully connected layer followed by a SoftMax activation function. Upon processing the complete input sequence, the hidden state at the final time step, h_t, is utilized as the discriminative representation for classification.

C. Evaluation Setup

The evaluation of our proposed TexTKAN model's performance was carried out across three different testing scenarios. The first scenario involved testing to determine the impact of various word embedding methods on TexTKAN's performance. We employed several widely-used word embedding methods for text vector representation, including Word2Vec [16], FastText [17], and Global Vectors for Word Representation (GloVe) [18]. The TexTKan model utilizes pre-trained word embeddings to initialize the embedding layer with the pre-trained vectors. The configuration details for each embedding method are provided in Table I.

The second evaluation scenario involved a performance comparison between the TexTKAN model and various commonly used deep learning models for text classification, particularly in the context of depression detection. In the last scenario, we assessed the impact of the number of neurons in the TKAN layer on the accuracy and the number of trainable parameters in the detection model. This evaluation was conducted to demonstrate that our proposed model can achieve high accuracy with a relatively low number of trainable parameters.

TABLE I
WORD EMBEDDING METHOD CONFIGURATION FOR TEXTKAN

Embedding Method	**Pre-trained Model**	**Parameter Setup**
Word2Vec [16]	Gensim twitter word2vec model, word embeddings trained on 400 million microposts.	Embedding-dimension: 200 Vocabulary-size: 15,000 Input-length: 300
FastText [17]	The 'cc.en.300.bin' model is trained on the Common Crawl corpus, which is a massive dataset collected from a wide range of web sources.	
GloVe [18]	The Twitter word embeddings, referred to as 'glove.twitter.27B.zip', consisting of 2 billion tweets, which contain a total of 27 billion tokens.	

IV. RESULTS AND DISCUSSION

All experiments for training and evaluation of the TexTKAN model were carried out on an NVIDIA A100 GPU with 40 GB of memory. Table II reports the comparative performance of TexTKAN under different word embedding strategies. Using Word2Vec [16], the model achieves an F1 score of 0.782 and an accuracy of 0.794, reflecting a balanced yet moderate classification capability. The adoption of FastText [17] yields a slight performance gain, with the F1 score increasing to 0.788 and accuracy to 0.797. Among the evaluated embeddings, GloVe [18] demonstrates the strongest performance, attaining an F1 score of 0.802 and an accuracy of 0.816. This outcome indicates that GloVe embeddings provide more discriminative representations for the TexTKAN framework. GloVe leverages both local context (word co-occurrences within a context window) and global statistical information (word co-occurrence probabilities across the entire corpus). This dual approach allows GloVe to capture a more comprehensive representation of word relationships and meanings.

The subsequent testing results are detailed in Table III, which compares the performance of the TexTKAN model with various previously used deep learning models. In addition to the depression detection performance metrics, as shown in Table III, we also examined the number of trainable parameters generated by each model. To ensure fairness, the comparisons for all models were conducted using GloVe embeddings and the hyperparameter configurations specified in Table I.

TABLE II
PERFORMANCE COMPARISON OF EMBEDDING METHODS ON TEXTKAN MODEL

Method	**F1 Score**	**Accuracy**
Word2Vec [16]	0.782	0.794
FastText [17]	0.788	0.797
GloVe [18]	0.802	0.816

Table III shows that the TexTKAN model exhibits a well-balanced performance across all metrics, demonstrating its effectiveness and efficiency in depression detection compared to other deep learning models. The TexTKAN model demonstrates superior performance with the highest F1 score of 0.802 and accuracy of 0.816, indicating its enhanced ability to identify and classify instances of depression correctly. While LSTM and GRU models also exhibit strong performance, with F1 scores of 0.796 and 0.791, and accuracies of 0.808 and 0.807, respectively, TexTKAN still leads in these metrics. Regarding the number of trainable parameters, TexTKAN has 127,586 parameters, which is higher than RNN (42,499) but lower than LSTM (168,835) and BiLSTM (337,667). The proposed TexTKAN achieves its superior performance with a relatively moderate number of trainable parameters, highlighting its potential as a more reliable and efficient model for depression detection task compared to other popular deep learning approaches.

TABLE III
PERFORMANCE COMPARISON OF TEXTKAN WITH EXISTING DEEP LEARNING MODELS FOR DEPRESSION DETECTION

Model	**Trainable Parameter**	**F1 Score**	**Accuracy**
RNN	42,499	0.781	0.783
GRU	127,107	0.791	0.807
LSTM	168,835	0.796	0.808
BiLSTM	337,667	0.795	0.805
TexTKAN	127,586	0.802	0.816

Based on the results in Table III, additional experiments were conducted to analyze the scalability of TexTKAN with respect to trainable parameters. The proposed TexTKAN framework seeks to reduce parameter complexity while maintaining competitive detection accuracy. Fig. 3 illustrates how variations in the number of neurons affect the trainable parameter count and accuracy of TexTKAN, in comparison with the LSTM model, which achieved the second-highest performance in the previous evaluation.

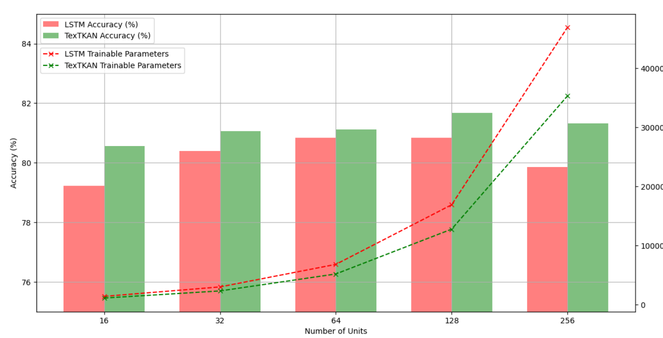

Fig. 3. A Comparison Between The Accuracy and Trainable Parameters of The LSTM and TexTKAN Models as the Number of Units Increases

As shown in Fig. 3, there is a notable difference in the increase of trainable parameters between the TexTKAN and LSTM models, with the gap widening as the number of units increases. TexTKAN has significantly fewer trainable parameters compared to LSTM for the same number of units. Despite having fewer trainable parameters, TexTKAN consistently achieves higher accuracy than LSTM across all unit counts. For the TexTKAN model, with 16 units, there are 11,106 trainable parameters, yielding an accuracy of 80.56%. As the units increase to 32, 64, and 128, the trainable parameters grow to 23,138, 51,810, and 127,586, respectively, with corresponding accuracy improvements to 81.06%, 81.11%, and 81.67%. With 256 units, the trainable parameters reach 352,866, and the accuracy remains high at 81.23%.

The experimental results demonstrate that TexTKAN consistently outperforms conventional recurrent architectures while maintaining a moderate number of trainable parameters. This improvement can be attributed to the adaptive activation functions in the KAN framework, which enable more expressive representations without increasing network depth or width. Unlike LSTM-based models that rely on fixed nonlinearities, TexTKAN dynamically learns transformation functions on network edges, allowing more efficient encoding of semantic and temporal patterns.

Importantly, the observed performance gains, although numerically modest, are achieved with a significantly reduced parameter footprint. In resource-constrained deployment scenarios, such as mobile mental health monitoring systems, this trade-off is particularly valuable. The results therefore highlight that TexTKAN's novelty lies not only in accuracy improvement, but in demonstrating that depression detection models can be redesigned to be both effective and computationally efficient.

V. Conclusion

This study proposed TexTKAN, a modified Temporal Kolmogorov–Arnold Network architecture tailored for text-based depression detection from social media data. The experimental findings indicate that TexTKAN delivers competitive and reliable performance across major evaluation metrics, notably F1-score and accuracy, demonstrating its effectiveness for depression detection. Using GloVe-based word embeddings, TexTKAN attained an accuracy of 0.816 and an F1-score of 0.802, outperforming conventional recurrent neural network architectures, including RNN, GRU, LSTM, and BiLSTM. Beyond predictive performance, TexTKAN exhibits a favorable trade-off between accuracy and model complexity. These findings indicate that KAN based architectures offer a promising alternative to traditional deep learning models for text classification, particularly in applications where computational efficiency and generalization are critical. Future work will investigate the explainability potential of KAN-based models to enhance interpretability in mental health applications. In addition, further performance improvements will be explored through architectural refinements and integration of TexTKAN with transformer-based language representations, aiming to combine parameter efficiency with richer contextual modeling.

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