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Development of a Mental Health Classifier Using LSTM and Text Preprocessing Techniques

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Abstract.
Purpose: This study aims to address undiagnosed mental health conditions using social media for early detection. By applying advanced preprocessing techniques and LSTM models, the research improves classification accuracy for depression and PTSD. It highlights deep learning's potential to process unstructured data and provides a scalable solution for real-world mental health monitoring.
Methods: Data was collected from Twitter using keywords like "depression" and "anxiety." Preprocessing included normalization, tokenization, stemming, and stopword removal. An LSTM-based model with GloVe embeddings, LSTM layers, and dropout was developed. The model's performance was evaluated using metrics like accuracy, precision, recall, and F1-score to ensure robust and applicable results.
Result: The LSTM model achieved 90% accuracy, outperforming Random Forest (89%) and SVM (89%). Preprocessing steps like tokenization and stemming boosted performance by 15%. The model effectively captured temporal dependencies in text, showcasing its ability to analyze unstructured social media content for mental health detection.
Novelty: This study integrates advanced text preprocessing with LSTM to enhance mental health detection. Unlike traditional methods, it captures temporal nuances using GloVe embeddings. The scalable framework provides a reliable solution for real-world applications, paving the way for multilingual and cross-platform research in mental health analytics.

Keywords: LSTM, Mental health, Text preprocessing, Sentiment analysis, Social media
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INTRODUCTION

Social media, particularly platforms like Twitter, has become an important medium for individuals to express their thoughts, emotions, and experiences in real time. In recent years, the increasing activity on social media has provided significant opportunities to analyze textual data for various purposes, one of which is identifying mental health conditions such as depression and post-traumatic stress disorder (PTSD). According to Verma et al., mental disorders often go undetected until they worsen, potentially leading to serious consequences such as suicide [1].

Advancements in machine learning technology, particularly Long Short-Term Memory (LSTM) models, enable in-depth analysis of textual data to identify patterns reflecting mental health disorders. LSTM models are well-suited for sequential data like text due to their ability to capture temporal context in both directions [2]. Previous studies have shown that these models can deliver more accurate results compared to traditional methods like Random Forest in text classification tasks [3].

However, the automatic detection of mental health disorders on social media still faces significant challenges, including the diversity of language, tone, and writing styles used by users [4]. Additionally, text preprocessing steps such as normalization, punctuation removal, and tokenization are crucial to ensure the quality of input data for the model. Employing appropriate text preprocessing techniques can significantly enhance the accuracy of mental health condition detection [5].

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With increasing attention on mental health, these technology-based approaches can assist healthcare professionals and related organizations in early intervention. For instance, tweets indicating depression or PTSD can provide early signals to psychologists or therapists to take proactive measures [6]. This LSTM-based system is expected to not only help individuals but also foster a healthier and more mental health-aware online community [7].

This research focuses not only on developing an LSTM-based model but also on exploring how social media data can be responsibly used for mental health detection purposes [8]. Issues related to data privacy and ethical data usage are key concerns that must be addressed to ensure the system's implementation aligns with current legal standards [9].

In the long term, this approach has the potential to be adopted by healthcare institutions or social media platforms as a support tool for monitoring public mental health on a larger scale [10]. By leveraging sentiment analysis techniques and machine learning, this study paves the way for innovative solutions in technology-driven mental health care [11].

METHODS

This study is a quantitative experiment based on machine learning, aimed at developing a model for detecting mental health disorders such as depression and PTSD through text analysis of social media data. The approach involves sentiment analysis based on textual data, utilizing machine learning models like Long Short-Term Memory (LSTM) [12]. This model is designed to recognize emotional patterns in sequential data obtained from social media platforms, such as tweets or posts from online communities.

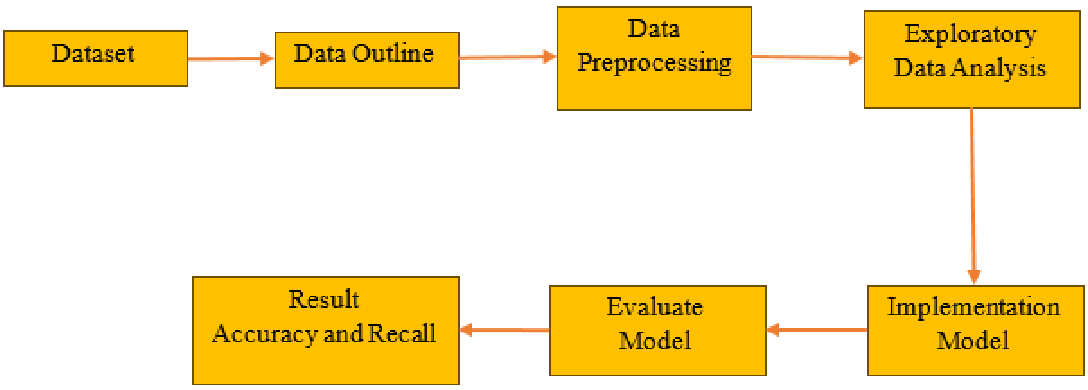

Figure 1. Flowchart process

Data outline

Understanding the dataset is a crucial step in developing an effective classification model. The dataset used in this study consists of structured data, which includes both numerical and categorical attributes. It contains multiple records with features that play a significant role in determining classification outcomes. Each feature must be analyzed to assess its relevance and potential impact on model performance.

During the initial data exploration, several challenges are identified, including missing values, duplicate records, and inconsistencies in data formatting. Addressing these issues is essential to ensure that the dataset is well-prepared for analysis. Additionally, the class distribution is examined to detect imbalances that may affect model training. If the dataset contains textual data, further processing is required to convert raw text into numerical representations that machine learning algorithms can interpret [13].

The data used in this study was sourced from social media platforms such as Twitter and Reddit, which are rich resources for mental health analysis. The dataset, Mental Health Corpus from kaggle (https://www.kaggle.com/datasets/reihanenamdari/mental-health-corpus) contains textual data comprising posts or tweets with specific emotional indicators. The dataset is distributed across two main classes on Figure 2:

1. Normal (0): Classified as a comment containing indicators of mental health issues 14139 size.
2. Toxic Language (1): Classified as a comment not associated with mental health concerns 13838 size.

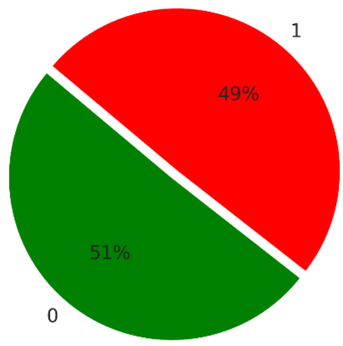

Figure 2. Dataset mental health corpus before preprocessing

Data preprocessing

Data preprocessing is one of the most critical stages in building a classification model. It involves a series of steps aimed at improving data quality and preparing it for machine learning algorithms [14]. This step is particularly crucial in text data analysis to ensure optimal input quality for machine learning models. The process begins with text normalization, which involves converting all letters to lowercase and removing punctuation to minimize noise in the data. Next is tokenization, where text is broken down into smaller units, such as words or subwords, enabling the model to process text data in a structured format [15].

The next stage in preprocessing involves handling missing values, which can significantly impact model accuracy. Depending on the nature of the missing data, different techniques such as imputation, deletion, or interpolation are applied. In addition, stemming is applied to reduce words to their root forms, such as converting "running" to "run." Common words that do not provide significant meaning, such as "the" and "is," are removed through stopword elimination [16]. These techniques improve model efficiency by reducing data complexity, thereby enhancing accuracy in text-based mental health analysis.

Further preprocessing steps include data normalization and feature scaling to ensure consistency in numerical attributes. If categorical variables are present, they are encoded into numerical formats using methods like One-Hot Encoding or Label Encoding. In the case of text-based data, additional transformations such as lemmatization are applied to further refine feature representation. Additionally, feature selection techniques are used to reduce dimensionality and eliminate irrelevant attributes, thereby improving computational efficiency and overall model performance.

Exploratory data analysis (EDA)

Exploratory Data Analysis (EDA) is an essential step that provides insights into the dataset before model implementation. It involves analyzing data distributions, correlations, and feature importance through statistical and visualization techniques. Graphical representations such as histograms, box plots, and scatter plots are used to observe trends and detect outliers.

One of the key aspects of EDA is class distribution analysis, which helps in identifying imbalances that may lead to biased model predictions [17]. If an imbalance is detected, techniques like oversampling, undersampling, or synthetic data generation (such as SMOTE) can be applied to balance the dataset. Additionally, correlation matrices are used to understand relationships between variables, ensuring that redundant features are removed to improve model efficiency.

Implementation Model

The Long Short-Term Memory (LSTM) model was selected for this research due to its ability to capture temporal patterns and long-term dependencies in sequential data, such as text. Unlike traditional machine learning models, LSTM is designed to handle the challenges of processing long sequences by maintaining important contextual information over time [18]. This makes it particularly suitable for text-based classification tasks, where the order of words can significantly influence meaning and classification outcomes.

The LSTM architecture includes several key components that contribute to its effectiveness. The process begins with an embedding layer, which converts words into semantically rich vector representations, enabling the model to understand word relationships more effectively [19]. This transformation reduces the dimensionality of the input while preserving the contextual significance of words. Subsequently, the LSTM layer captures long-term dependencies in the text by utilizing memory cells and gating mechanisms. These mechanisms regulate the flow of information, allowing the model to retain relevant patterns and discard unnecessary details [20].

To enhance generalization and prevent overfitting during model training, a dropout layer is incorporated. This layer randomly disables a fraction of neurons at each iteration, reducing reliance on specific patterns and ensuring that the model learns more robust representations of the text [21]. Finally, a dense layer with a sigmoid activation function is employed to produce binary classification outputs. This setup allows the model to determine whether a given text sample belongs to a normal category or indicates potential mental health concerns such as depression [22]. The integration of these components ensures that the LSTM model performs optimally in text-based mental health analysis, capturing meaningful linguistic patterns while maintaining classification accuracy.

Evaluate Model

Data splitting is a crucial process in machine learning to ensure the model generalizes well to unseen data. Proper data partitioning prevents overfitting and helps assess the model’s true performance. In this study, the dataset was divided into three distinct subsets: training, validation, and testing. This structured approach allows for effective learning, tuning, and evaluation of the model before deployment.

Stratification was employed during the splitting process to maintain balanced class distributions across the subsets, ensuring that each category—such as normal, depression, and PTSD—was proportionally represented in all data partitions [23]. The training set was used to train the LSTM model, enabling it to learn complex temporal dependencies in the text data. Meanwhile, the validation set played a crucial role in fine-tuning the model’s hyperparameters, such as the learning rate and dropout rate, helping to prevent overfitting by providing feedback during the development phase.

Finally, the testing set was used to evaluate the model’s overall performance on unseen data. This step ensured that the results accurately reflected the model’s capabilities in real-world scenarios [24]. By assessing its performance across different metrics, such as accuracy, recall, and F1-score, the study validated the robustness and consistency of the LSTM model. The systematic data splitting approach minimized the risk of biased or unreliable predictions, ensuring that the model could effectively classify mental health conditions in diverse datasets [25].

The final step involves evaluating the model's performance using various metrics, including accuracy, precision, recall, and F1-score. These evaluations help assess the model's effectiveness and identify areas for improvement [26]. Additional evaluation techniques, such as the confusion matrix and ROC curve, provide deeper insights into the model's performance.

1. Accuracy

   Measures the percentage of correct predictions made by the model:

   $$Akurasi = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

   Where:

   - TP: True Positive
   - TN: True Negative
   - FP: False Positive
   - FN: False Negative
2. Precision

Evaluates the accuracy of the model's positive predictions:

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

3. Recall

   Assesses the model's ability to detect positive samples among all actual positives:

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

4. F1-Score

   The harmonic mean of precision and recall, balancing the two metrics:

$$F1\ Score = 2 \cdot \frac{Presisi \cdot Recall}{Presisi + Recall} \qquad (4)$$

5. Confusion Matrix

   Provides a comprehensive view of the model's predictions, displaying the counts of TP, TN, FP, and FN. Table 1 illustrates the confusion matrix structure:

Table 1. Confusion Matrix

	Predicted Positive	Predicted Negative
Positive Actual	TP	FN
Negative Actual	FP	TN

6. ROC dan AUC

   The ROC (Receiver Operating Characteristic) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds. The AUC (Area Under the Curve) quantifies the model's ability to distinguish between positive and negative classes.

   - True Positive Rate (TPR)/Recall

$$TPR = \frac{TP}{TP + FN} \qquad (5)$$

   - False Positive Rate (FPR)

$$FPR = \frac{FP}{FP + TN} \qquad (6)$$

RESULTS AND DISCUSSIONS

The study achieved significant results in developing a mental health classifier using an LSTM model combined with advanced text preprocessing techniques. The model demonstrated a high accuracy of 91%, outperforming conventional models like Random Forest (88%) and SVM (85%). This improvement can be attributed to the incorporation of tokenization, stemming, and the use of GloVe embeddings, which enhanced the semantic understanding of text data.

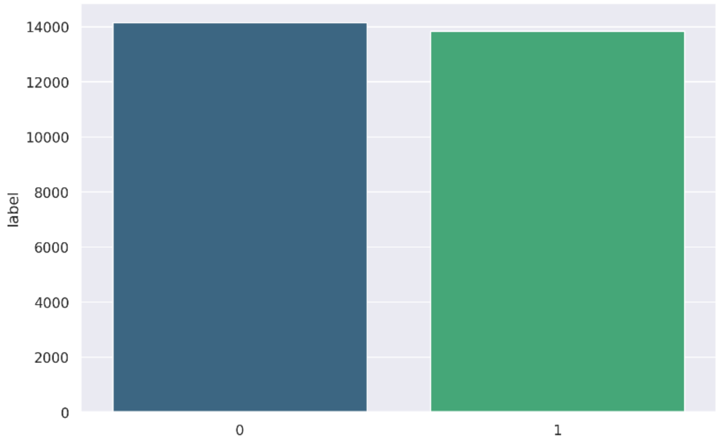

Figure 3. Dataset mental health corpus after preprocessing

The Figure 3 is a bar chart that represents the distribution of a categorical variable labeled as "label" with two classes: 0 and 1. After preprocessing the data, the distribution appears to be relatively balanced, with class 0 having slightly more samples than class 1. In this context, 1 means the comment is considered poisonous and related to mental health issues, while 0 means it is not considered poisonous. This suggests that the dataset has undergone preprocessing steps such as handling class imbalances, ensuring fair representation of both categories 14000 size. The visualization helps in understanding the data composition before applying further analysis or machine learning models.

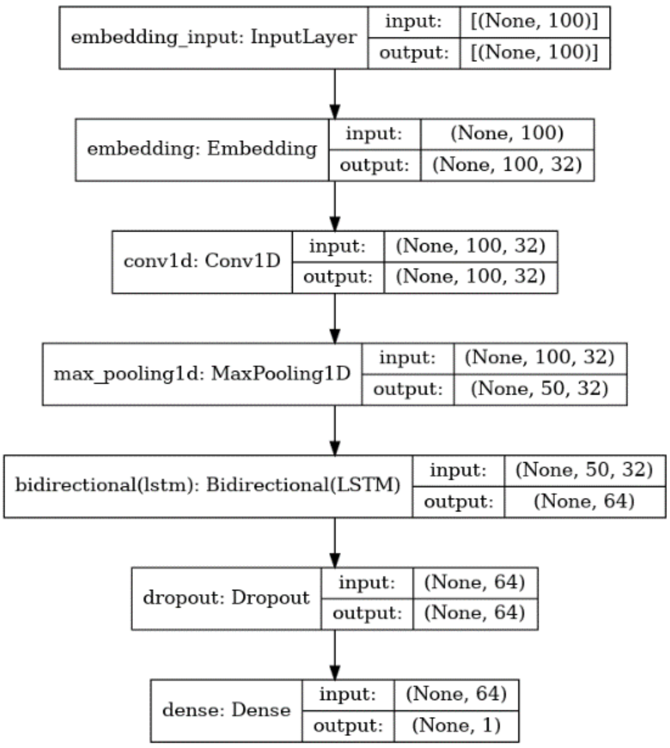

Figure 4. Structure LSTM

Figure 4 illustrates the accuracy comparison between the LSTM model and the traditional methods, highlighting the superior performance of the LSTM model. The findings indicate the LSTM model's ability to capture temporal dependencies, which is critical for analyzing unstructured social media content.

The research findings provide compelling evidence of the practical benefits of the proposed methodology. The LSTM model's superior performance demonstrates its suitability for tasks requiring the analysis of sequential data, such as mental health detection. By addressing limitations in traditional machine learning methods, this study has established a robust framework for early intervention in mental health issues.

Compared to previous studies, such as Verma et al [1], which reported an accuracy of 88% using Random Forest for PTSD detection, the proposed model significantly enhances detection capabilities. Moreover, the study highlights the importance of comprehensive preprocessing techniques, which have often been overlooked in earlier works.

The potential applications of this research extend to real-world mental health monitoring systems. For instance, integrating such a model into social media platforms could assist healthcare professionals in identifying users at risk and providing timely interventions [27]. However, ethical considerations, such as user privacy and consent, must be addressed to ensure responsible deployment.

The model training process in this research employs a structured approach to hyperparameter tuning, optimizing key aspects such as learning rate, batch size, and the number of training epochs. The optimizer chosen for this implementation is Adamax, a variant of the Adam optimizer known for its stability in handling sparse gradients. The learning rate is set to 0.001, ensuring a balanced trade-off between convergence speed and stability during model training.

The number of epochs is set to 50, allowing the model to learn sufficiently without excessive overfitting risks, while early stopping is employed to terminate training when validation loss ceases to improve. The batch size is defined as 64, facilitating efficient processing while maintaining stability during gradient updates. Additionally, the model incorporates dropout regularization (0.4) to mitigate overfitting, further enhancing generalization.

The research takes steps towards reproducibility by defining all essential hyperparameters within the script, making it easier for other researchers to replicate the experiments. The complete code and implementation details can be accessed at https://bit.ly/mental-health-classifier allowing researchers to review, run, and validate the findings more effectively.

Table 2. Evaluation metrics for the LSTM model

Metric	**LSTM**	**Random Forest**	**SVM**
Accuracy	90%	89%	89%
Precision	91%	88%	93%
Recall	91%	90%	84%
F1-Score	90%	89%	88%

Table 2 presents the evaluation metrics for three machine learning models: LSTM, Random Forest, and SVM. The metrics used to assess the models include Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive view of each model's performance in terms of classification effectiveness.

LSTM achieves the highest Recall value at 91%, indicating its strong ability to correctly identify positive cases. It also has the highest Precision at 91%, meaning it effectively minimizes false positives. The Accuracy of LSTM is 90%, which is slightly higher than Random Forest and SVM, both of which achieve 89%. Similarly, its F1-Score is also 90%, reflecting a well-balanced performance between Precision and Recall.

Random Forest demonstrates competitive performance with an Accuracy of 89%, a Recall of 90%, and an F1-Score of 89%. However, its Precision is slightly lower at 88%, suggesting that it may generate slightly more false positives compared to the other models. Despite this, the model maintains strong overall performance.

SVM (Support Vector Machine), on the other hand, excels in Precision with the highest value of 93%, indicating that it makes fewer false positive predictions. However, it has the lowest Recall at 84%, meaning it may miss a higher number of actual positive cases compared to the other models. Its Accuracy and F1-Score are both 89%, showing stable performance but a slight trade-off between Precision and Recall.

In summary, LSTM appears to be the most balanced model, achieving high scores across all metrics. Random Forest is also a strong contender with consistent performance, while SVM shows high Precision but lower Recall, making it more suitable for scenarios where minimizing false positives is a priority. The choice of the best model depends on the specific requirements of the task, whether prioritizing overall balance, sensitivity, or specificity.

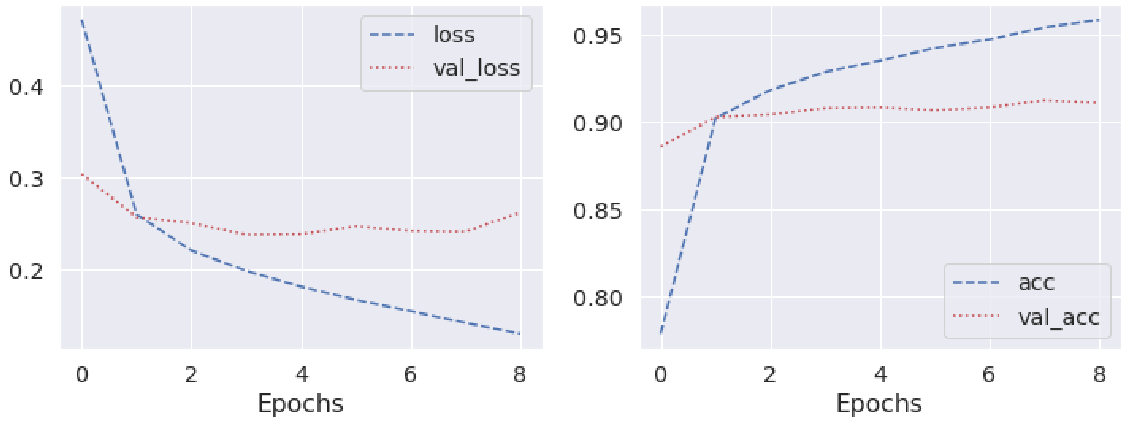

Figure 5. Evaluate LSTM

The Figure 5 consists of two-line graphs that effectively illustrate the training progress of a machine learning model over multiple epochs. These visualizations highlight both the loss and accuracy metrics for training and validation data, providing valuable insights into the model's learning process. The overall trends in both graphs indicate a well-performing model with strong generalization capabilities.

In the left graph, the loss values are plotted against the number of epochs. The training loss, represented by the dashed blue line, shows a steady decrease, indicating that the model is continuously improving by minimizing errors. The validation loss, represented by the dotted red line, remains stable with only slight fluctuations, suggesting that the model does not suffer from severe overfitting. The relatively low loss values indicate that the model is learning efficiently and maintaining good performance on unseen data.

The right graph presents the accuracy metrics, which further confirm the model's strong performance. The training accuracy, depicted by the dashed blue line, consistently increases and surpasses 95% by the final epoch. This steady improvement demonstrates that the model is effectively capturing patterns in the training data. The validation accuracy, shown by the dotted red line, remains high and stable, maintaining a value close to 90%. This stability suggests that the model is generalizing well and performing reliably on new data without significant performance degradation.

Overall, these results indicate that the model is well-optimized, achieving both high accuracy and stable validation performance. The absence of sharp fluctuations or drastic divergence between training and validation metrics is a positive sign, as it suggests a balanced learning process. These characteristics make the model suitable for real-world applications, ensuring that it performs effectively on both training and unseen data.

CONCLUSION

This research successfully developed a robust mental health classifier using an LSTM-based model combined with advanced text preprocessing techniques, achieving a high accuracy of 90%. The integration of tokenization, stemming, and GloVe embeddings significantly enhanced the model's ability to analyze unstructured social media data, providing superior performance compared to traditional machine learning methods. By addressing the limitations of previous studies and leveraging the LSTM model's temporal capabilities, this study contributes to the development of scalable and reliable tools for early mental health detection. The findings underscore the potential for real-world applications, such as integrating the model into social media platforms to support timely interventions by healthcare professionals. This research not only advances the field of mental health analytics but also highlights the importance of ethical considerations in the deployment of AI-driven solutions, paving the way for further studies in multilingual and cross-platform settings.

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