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Depression Detection in Social Media Data for Resource-Constrained Roman Urdu Using Machine Learning Methods

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ABSTRACT

Anxiety and depression are crucial issues related to human mental health globally and are especially prevalent among users of social networking and online platforms such as X and Reddit. Roman Urdu has become a dominant language for expressing and communicating personal feelings on these platforms, making it a valuable resource for detecting early signs of depression. This study focuses on the automatic detection of depression in Roman Urdu social media posts using machine learning methods. A human-annotated corpus of 6,000 posts was created, and four machine learning classifiers, namely Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN), were trained using natural language processing features such as TF-IDF. The accuracy, training time, and testing time of these models were compared. The results demonstrate that the Random Forest classifier outperforms the other models, achieving 93% accuracy with high efficiency. The study highlights the effectiveness of scalable machine learning-based early detection methods for underrepresented languages such as Roman Urdu.

1. Introduction

1.1 Study Background and Motivation

Depressive disorder, commonly known as depression, is a common mental health disorder. The World Health Organization (WHO) reports that this mental illness can lead to self-harm and can significantly interfere with an individual's ability to function in various situations [1]. Depression in adolescents is a major mental health disorder and mood condition that may continue into adulthood. Its disabling effects make depression one of the most common problems in society.

Almost 5% of the global population suffers from depressive disorder, and milder forms, including moderate depression and partial symptoms, have been experienced by 20% of people. It is most prevalent among middle-aged adults. Moreover, depression rates rose at an alarming rate worldwide from 2005 to 2022 [2].

Delayed intervention of mental health disorders can lead to psychological issues and the physical health problems associated with them. Early identification of the signs of depression, followed by proper evaluation and care, can significantly lessen the severity of the disorder, thus improving outcomes in the individual's overall health, quality of life, and functioning across various personal, social, and occupational domains [3]. Conventional methods for evaluating mental health have thus far been dependent on clinical measures using questionnaires to identify the psychological factors that give rise to depression disorder. Recently, however, studies have shown that evaluating the language patterns of individuals experiencing depression can yield important details about their mental state.[4]

The need for an automatic depression detection system [5] is significant for improving the diagnosis process. Such a system would enable psychologists to better understand their patients before treatment begins. With the rise of internet use, people now express their emotions, thoughts, and opinions online. Those facing psychological issues often turn to platforms like Twitter, Reddit, and Facebook to share their feelings.

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Text-based communication has become the primary medium for expressing emotions, as individuals dealing with depression often avoid revealing their identity or visuals, preferring text-based interactions.

For diagnosing depression, text has become a widely used source because it is easy to process and has low resource requirements [6]. Text messages require very low bandwidth and memory. Moreover, text messages are easy to forward. Thus, current research has started to focus on recognizing mental health disorders through text shared on social media networks. From this perspective, it is necessary to construct a depression detection system based on machine learning and artificial intelligence methods [7].

This research aims to develop robust and scalable methods for detecting early signs of depression by analyzing Roman Urdu social media content. The project involves creating a human-annotated Roman Urdu language dataset. This language lacks extensive linguistic resources. By applying natural language processing (NLP) techniques, such as TF-IDF, along with machine learning models such as SVM, RF, NB, and KNN, this study intends to classify emotional expressions in Roman Urdu. Additionally, the study evaluates of each model's suitability based on metrics such as training time, testing time, and accuracy.

1.2 Literature Review

One of the preliminary steps that can be taken to raise general awareness among society is the early identification of the mental well-being among social media platform users. Various researchers have proposed approaches and implemented systems that can provide early intervention for depression disorders. Several people prefer to share their thoughts via audio or video files due to the inherent features of these components in the recent digital era of smartphones and social media platforms. However, for general communication, many people still choose textual modalities to interact and express their feelings [8]. In this context, some of the recent works are detailed below.

The methodology proposed in [9] aligns with the focus of this research on leveraging social media data to detect depression, specifically in Roman Urdu content. The work by the authors in [10] addressed depression detection and analysis in social networks, considering Arabic and English languages. Five different machine learning algorithms were proposed in that study for binary classification and multi-classification.

The study in [11] collected data in the English language from Twitter social media, used the Word2Vec technique to convert textual data into a continuous vector representation, and developed a machine learning model. The proposed model combines five algorithms to enhance the overall performance. A Skip-gram architecture with a data ratio of 90:10 achieved the best results.

The work in [12] developed a depression detection system utilizing emotional artificial intelligence through online social profiles. Two supervised learning techniques, including LSTM and SVM, were implemented by the authors using the emotion dataset. SVM achieved the maximum accuracy of 81.79% while LSTM produced an accuracy of nearly 70%.

In addition to adaptive and gradient boosting, the authors used LR SVM, DT, RF, and multilayer perceptrons to propose an ensemble-based model. Various evaluation metrics indicated the improved performance for the suggested ensemble model in contrast to their individual classifiers' performance [13].

Apart from work on English-language Twitter data, different authors have also used advanced NLP techniques for depression detection using other social networking platforms like Reddit [14]. Facebook has also been employed to assess users' depression levels through their posts using models like SVM and Decision Trees [15].

In recent studies, authors have also addressed several other community languages. To generate a model for the analysis and detection of depression, the authors collected data from the Bengali community. Posts and comments about depression were included in the Bengali data. [16]. Experiments on gathered data have been conducted using different techniques of machine learning, such as SVM, DT, NB, RF, KNN, and LR [16].

The study in [17] formulated an approach using Hindi, English, and a mix of these two languages called Hinglish to classify the tweets as depressed or not depressed. The classification techniques were created using the TF∗IDF (term frequency-inverse document frequency) model. The formulated approach attained an accuracy of 96.15% and F1 score of 91.4% [17].

1.2.1 Research gap and contribution

• Most existing studies on depression detection via social media focus on English-language content.

• Limited studies have been conducted on low-resource languages like Roman Urdu, despite its widespread use in Pakistan and among South Asian communities.

• Previous research in depression detection has primarily relied on clinical questionnaires or English-based sentiment analysis techniques, which do not cater to Roman Urdu speakers.

1.2.2 Proposed solution

This study is one of the first to build a structured dataset for Roman Urdu depression detection, addressing this domain's lack of linguistic resources. While some studies, for depression detection, have applied machine learning algorithms in English and other languages, they do not evaluate multiple models on a structured Roman Urdu dataset. There is no comparative study analyzing the performance of different ML classifiers (SVM, Naive Bayes, Random Forest, KNN) on Roman Urdu text. In this work, a Human-Annotated Roman Urdu Depression Corpus was created and manually compiled, containing 6,000 labeled social media posts (from Twitter and Reddit) into depressed and non-depressed emotional markers. Numerous machine learning models have been applied for recognizing users presenting signs of depression.

2. Proposed Methodology

The methodology for the work is given in Fig. 1.

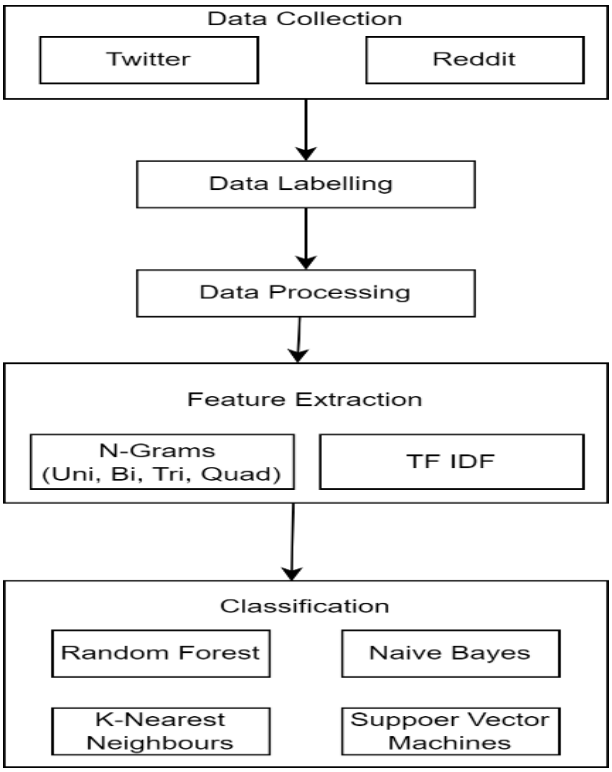

Fig. 1. Methodology

2.1 Data Collection

Two major social media networks were considered to collect data in Roman Urdu: (i) Twitter and (ii) Reddit. We classified the people's mental states using the six basic emotional markers of depression as defined by Carroll E. Izard [21]: Joy, Surprise, Sadness, Anger, Interest, and Disgust. A total of 3,000 reviews were gathered from the chosen social media platforms for each emotional marker, resulting in a dataset of 6,000 rows to maintain balance. Two approaches were considered to collect the data. According to [18], the data was gathered manually using various keywords from social media sites. Some important words related to various emotions include: “Uddas”, “dard”, “Ghum”, “takleef”, “khof”, “dar”, “moat”, “dukh”, “aansu”, and “nakam” are shown in Fig. 2., were used.

Fig. 2. Depressed Words

2.2 Analysis and Detection of Depression in Users

2.2.1 Analysis and detection of depressed users

To identify users showing signs of depression, a methodology proposed by [20] was incorporated, which avoided conventional mental health questionnaires. For data, social networks like Reddit and Twitter were used as venues where people often express their mental health conditions. Keywords and phrases like "pareshan hun" and "me udaas hon" were used to gather data on users potentially experiencing depression [21].

Table 1
Example Queries in Roman Urdu

Sr. No	Example Query in Roman Urdu
1	“pareshan hun”
2	“me udaas hon”
3	“marna chahta hun”
4	“Depression ho rha hy”
5	“Zindagi bht mushkil hy”
6	“Dil bht uddas hy”
7	“Zindagi bht mushkil hy”

For data collection, different queries were executed on Twitter and Reddit using various keywords. Some

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examples that indicate depressed users are given in Table 1.

2.2.2 Detection of non-depressed users

Various queries with different keywords were executed to obtain data for non-depressed users. Some of the examples from this category are given below:

• “Dard zindagi ka ek pal hota hai khushiyan hamesha aati hain”

• “Ansoo zindagi ka hisa hen”

• “Khushi k aansoo”

• “Marne k bad zindagi kesi hogi”

The frequency word graph is illustrated in Fig. 3. It shows a total of 6,000 reviews were extracted using these queries, after which the tweets underwent a rigorous manual verification process to ensure authenticity. The collected data were manually verified, to confirm whether the tweets accurately indicated a state of depression.

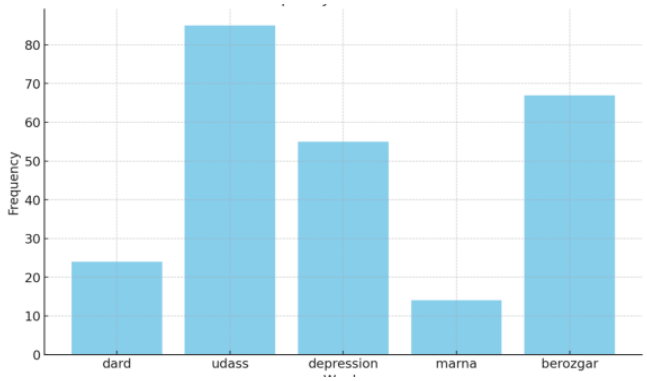

Fig. 3. Frequency Word Graph

2.3 Data Structure

Two Excel sheets were created to organize the data: one for depressed users and another for non-depressed users, as shown in Table 2

Table 2
Depressed and Non-Depressed Users

Emotions	Twitter	Reddit
Depression	2340	660
Non-Depression	2500	500

Each sheet contains the following columns:

Posts: The concatenated social media posts from each user, collected from various platforms.

Emotion: The identified emotional state (depressed or non-depressed), based on the content of the posts.

These sheets served as the foundation for the analysis of emotional states in Roman Urdu social media content, providing a clear separation between users exhibiting signs of depression and those who did not.

2.4 Approaches and Techniques

Several methods can be used to identify emotions in text. This section discusses some of these methods.

Bootstrapping Approach: To discover the semantic orientation of adjectives, this approach makes use of a set of seed opinion words. These seed words have opposite antonym orientations and the same synonyms [24].

Keyword-based approach: The keyword-based approach recognizes emotions by using synonyms and antonyms with a seed set of opinion words.

Dictionary-based or bag-of-words method: This method looks for indications of depression in a text by using the target, experiencer, and cause. "Ali (Experiencer) feels hopeless because he lost his job (Cause)," for instance. This structure shows that the person is experiencing the emotion of depression because of a particular cause [25].

In this research, a keyword-based approach was used to classify depression-related emotions in social media posts shown in Fig. 4, where specific words and phrases indicating sadness, hopelessness, or distress were identified and analyzed to detect potential signs of depression.

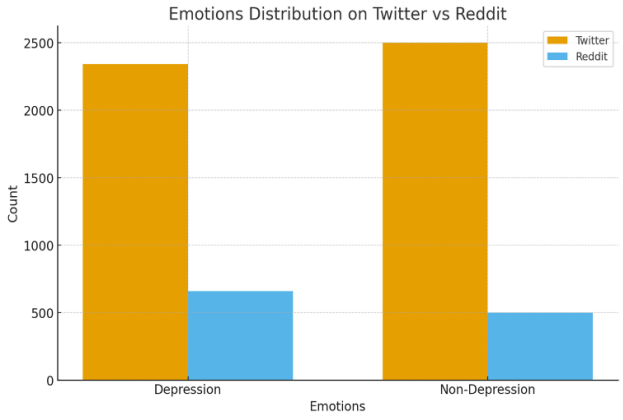

Fig. 4. Tweet Count for Each Dataset

2.5 Data Cleaning

Typically, the data is noisy, and some preprocessing is necessary to obtain a precise assessment of the suggested model. As a result, we processed our data according to the preprocessing recommendations outlined in [26]. Since this research focused on Roman Urdu, we performed tokenization, removing stop words, punctuation, special symbols, emoticons, words with fewer than three characters, and any data that was in any other language. It should be noted that preprocessing has already been done on the data in Table 2.

2.6 Data Splitting

The master dataset, which comprises preprocessed data, was divided into training and testing sets using an 80%-20% ratio. The data split is shown in Table 3

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Table 3
Number of Instances in Train and Test Sets

Training	4800	80%
Testing	1200	20%
Total	6000	100

2.7 Feature Extraction

The next step after preprocessing is the extraction of features. Many methods can be applied for feature extraction; however, we developed feature patterns based on n-grams, specifically Unigram (U), Bigram (B), Trigram (T), and Quadgram (Q), along with the Term Frequency-Inverse Document Frequency (TF-IDF). Their Cartesian product was also calculated, which is calculated as (U, B, T), (T, Q), (U, B, T), and (U, B, T, Q).

2.8 Algorithm

Different machine learning methods were used, such as SVM, RF, NB, and KNN to address the classification problem. These classifiers can reduce time and cost by predicting users' mental states. The master dataset is divided into 80% training data and 20% testing data after preprocessing. TF-IDF uses the n-gram techniques to extract features from the training dataset [28]. This step produces a sparse matrix, which is then sent to each of the chosen classifiers for the model's training. The same vectorizer transforms the testing dataset into the same feature dimensions as the training dataset [29].

Table 4
Hyperparameter Settings for Algorithms

Sr. No	Algorithm	Hyperparameters
1	Naive Bayes (NB)	Variant: Gaussian Alpha 1.0(default in Scikit-learn)
2	Support Vector Machine (SVM)	Kernel: Linear Regularization parameter C: 1.0 (default value)
3	Random Forest (RF)	N-estimators= 150 Max_features= “sqrt” (default value)
4	K-Nearest Neighbors (KNN)	n_neighbors and k=5 weights= uniform (default value)

The important hyperparameters and their values for all the implemented algorithms are given in Table 4.

2.9 Classification Metrics

Four evaluation metrics were used in this section to assess the classifiers' performance.

1. Accuracy: It represents the ratio of accurately labeled cases out of the total number of cases provided to the classifier, as given in Eq. (1).

$$Accuracy = \frac{TP+TN}{FP+FN} \quad \text{Eq. (1)}$$

2. Precision: Precision is computed as the proportion of posts correctly labeled as class cj among all posts assigned to class cj by the classifier, as given in Eq. (2).

$$Precision = \frac{TP}{TP+FP} \quad \textbf{Eq. (2)}$$

3. Recall: It indicates the ability of the model to correctly identify all the positive instances. The mathematical depiction of Recall is given in Eq. (3).

$$Recall = \frac{TP}{TP+FN} \quad \textbf{Eq. (3)}$$

4. F1-measure: It can be calculated using precision and recall, as shown in Eq. (4).

$$F1 - Score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad \textbf{Eq. (4)}$$

3. Results

To evaluate the performance of different models, numerous experiments were conducted using various features. In this work, we have trained four machine learning algorithms for depression detection. The obtained results are reported in Tables 5, 6, 7 and 8 for NB, KNN, SVM, and RF, respectively.

Table 5
Experimental Results for Naive Bayes

Feature pattern	Accuracy	Precision	Recall	F1 Score
Unigram	83.3%	86.1%	86.1%	86.2%
Unigram and bigram	90.1%	86.2%	86.3%	86.2%
Unigram and trigram	91.3%	86.4%	86.3%	86.4%

The evaluation results of four classifiers—Naive Bayes (NB), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF) using various n-gram feature patterns (unigram, unigram and bigram, and unigram and trigram) are discussed below.

• Naive Bayes performed best with unigram and trigram features, achieving 91% accuracy across all metrics.

Unigram and bigram features yielded 90%, while unigram alone reached 83%.

Table 6
Experimental Results for KNN

Feature pattern	Accuracy	Precision	Recall	F1 Score
Unigram	72.2%	77.1%	72%	65.1%
Unigram and bigram	76.4%	77.4%	72.3%	65.3%
Unigram and trigram	76.4%	77.4%	72.3%	65.4%

Table 7
Experimental Results for SVM

Feature pattern	Accuracy	Precision	Recall	F1 Score
Unigram	92%	87.8%	87.9%	87.7%
Unigram and bigram	93%	87.8%	87.9%	87.6%
Unigram and trigram	93%	87.8%	87.9%	87.7%

Table 8
Experimental Results for Random Forest

Feature pattern	Accuracy	Precision	Recall	F1 Score
Unigram	92%	87.8%	87.9%	87.8%
Unigram and bigram	93%	87.8%	87.9%	87.8%
Unigram and trigram	93%	87.8%	87.9%	87.8%

K-Nearest Neighbors achieved an accuracy as 72% with unigram features, elevating it to 76% with unigram and bigram features and 76% with unigram and trigram features, though its performance metrics remained consistent.

• Support Vector Machine achieved 93% accuracy with unigram and bigram, 92% with unigram, and 93% with trigrams, maintaining balanced performance across metrics.

• Random Forest consistently performed with 93% accuracy with unigram and bigram features and unigram and trigram features, whereas its performance slightly dropped to 92% with unigram features. Random Forest (RF) often outperforms Naive Bayes (NB), SVM, and KNN in practical applications because it is an ensemble method; it does not rely on one view of the data but combines the wisdom of many independent decision trees.

The combined performance of the implemented models with respect to the accuracy metric is illustrated in Fig. 5.

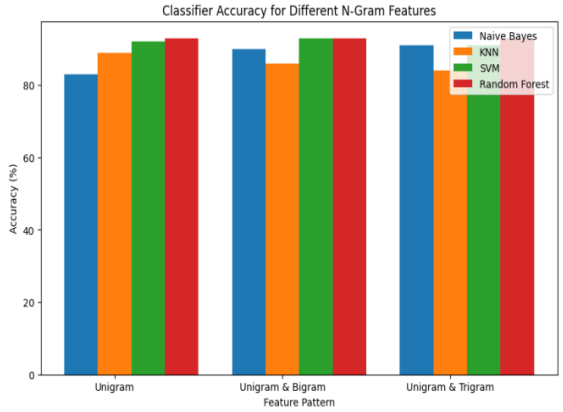

Fig. 5. Classifier Accuracy for Different N-Gram Features

Fig. 6 compares the performance of multiple classifiers. The ROC curve is used to evaluate the trade-off between the True Positive Rate (Sensitivity) and the False Positive Rate of different models.

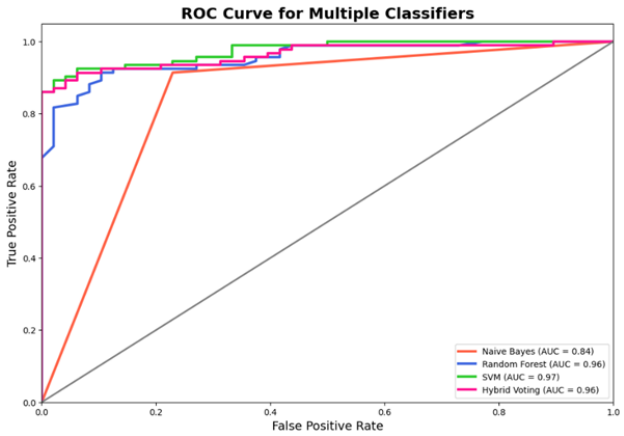

Fig. 6. ROC Curve for Different Classifiers

3.1 Confusion Matrix

The confusion matrix in Fig. 7 displays the model's classification results. It correctly identified 527 positive and 577 negative instances while misclassifying 73 positives as negatives and 23 negatives as positives. This breakdown helps assess the model's performance, including accuracy and error types.

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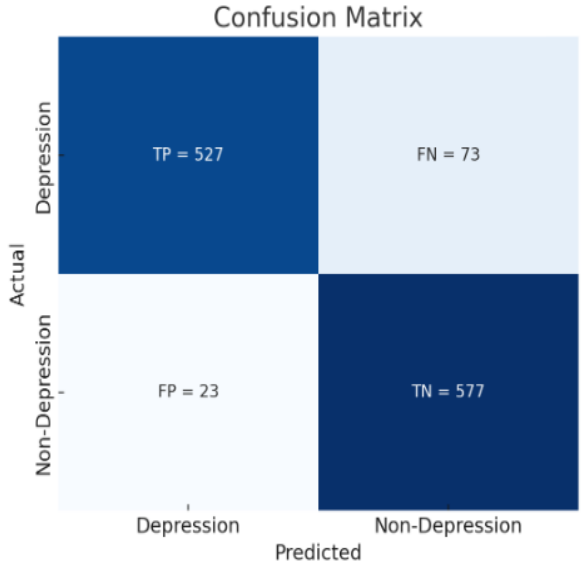

Fig. 7. Confusion Matrix

Fig. 8 shows how accuracy varies with different estimators and n-gram ranges. For n-gram = (1, 1), accuracy generally increases with more estimators, while for n-gram= (1, 2), accuracy peaks around 100 estimators before declining. This analysis helps determine the optimal settings for model accuracy.

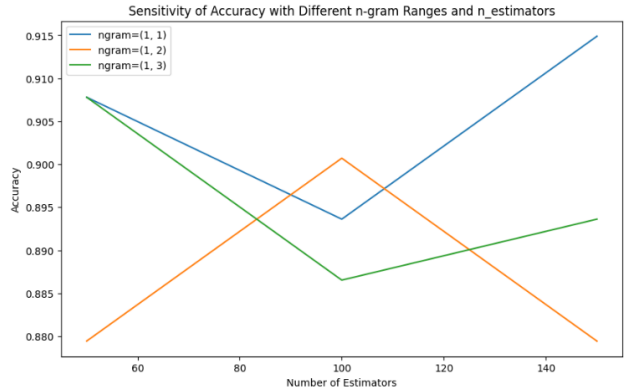

Fig. 8. Area Under Curve (AUC) Graph for All Classifiers

Conclusion

In conclusion, Random Forest and SVM outperformed Naive Bayes and KNN, achieving accuracies of 93% and 93%, respectively, with unigram and bigram features. In contrast, NB and KNN had lower accuracies of 76% and 81%, highlighting their limitations. The results emphasize the importance of n-gram patterns, which improved accuracy by 12%, demonstrating their role in optimizing text classification.

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