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A Novel Screening Tool System for Depressive Disorders using Social Media and Artificial Neural Network

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Abstract: Depression is one of the most common mental health disorders with over 264 million people suffering from it. Improvement in screening depressive disorders can lead to earlier treatment. However, some of the depression screening tools today have constraints and could be difficult to administer due to a lack of cooperation between patient and professional. It is indicated in some studies that there is a correlation between frequent use of social media and increased depression. With this finding, the authors aimed to develop a novel screening tool system incorporated with an artificial neural network that analyzes the patient's tweets. A design of the screening tool software application was proposed, and an ANN model was developed using a dataset curated from Kaggle. The dataset was cleaned, and features were extracted using the TF-IDF approach. PCA was also used to lessen the number of features for faster training and testing time. Four algorithms were used in training - SVM, Logistic Regression, Perceptron, and KNN. Even though PCA lessens the time for training and testing, it didn't greatly affect the performance of each model. The SVM model achieved the best performance followed by the Perceptron model. Both the SVM model and the Perceptron model achieved the highest accuracy (98%), but the SVM model achieved better results on the other parameters. However, the SVM model is very slow which prompted the authors to choose the Perceptron model that has a faster speed.

Keywords: *depression, social media, Twitter, neural network, SVM, logistic regression, perceptron, knn*

1. Introduction

More than 264 million people around the world suffer from depression [1]. Depression is a common medical disorder that negatively affects how you feel, the manner you're thinking, and the way you act.

Sadness is a negative emotion that happens from time to time. However, people with depression suffer from more intense sadness or depressive symptoms that could last for two weeks or longer.

There are different types of depression and each has a different effect on people. Major depressive disorder (MDD) can cause intense symptoms that can interfere with everyday activities and this could last longer than two weeks. On the other hand, seasonal depression is related to certain seasons like winter or fall. Persistent depressive disorder (PDD) is less severe than MDD, but people could experience this for two years or longer. Other types of depression include bipolar depression, postpartum depression, premenstrual dysphoric disorder, psychotic depression, and many more [2].

Screening is a means to identify the depressive disorder in a patient so they could receive appropriate treatment. Proper screening can improve the detection of depression which leads to earlier treatment and better quality of life [3]. Unfortunately, some depression screening tools are costly, require more time to administer, and in the case of self-administered tools, cannot be used accurately [4].

Furthermore, another challenge faced in mental health care is the lack of cooperation between patients and professionals [5]. This leads to difficulty in screening and diagnosing the patient.

Billions of people around the world use social networking services (SNS) such as Twitter. Twitter is a famous social media site that enables users to post messages known as "tweets" [6]. Other researchers conducted studies to determine the relationship between social media and depression [7]. It is indicated in these studies that there is a correlation between frequent use of social media sites and increased depression [8] [9][10].

There are several studies regarding the detection of depression in social media using machine learning techniques. Many of these studies are more focused on the development and evaluation of AI/ML models. Artificial Neural Network (ANN) is a machine learning algorithm that is a tool designed like a human brain that can learn patterns and relationships based on the input data [11]. Gupta et al. [12] conducted a comprehensive review to identify the

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different machine learning methods used in various studies from the year 2013 to 2020 related to depression detection on social media platforms. They concluded that the most used algorithms are CNN, SVM, NLP, and supervised learning.

Mahdy et al. [13] demonstrated different techniques such as convolutional neural networks (CNNs) and Support Vector Machine (SVM). The result of this study indicated that SVM with Linguistic Inquiry and Word Count (LIWC) is the best model for depression classification with 91% accuracy.

In the study conducted by Wolohan et al. [14], the combination of Linear Support Vector Machines, LIWC, TF-IDF, and character n-grams was used. The overall performance shows that the model is robust and well suited for a role in a diagnostic or monitoring capacity. Meanwhile, Orabi et al. [15] compared CNN-based and RNN-based models to determine the best models and parameters across diverse sceneries for depression detection. The best performing RNN model achieved 91.425% accuracy.

On the other hand, other studies focused on the application of depression detection models. In the study conducted by Hassan et al. [16], they presented an automated conversational platform that could detect the suicidal intent of a person during a conversation. In this platform, they used the Dialogflow Machine Learning algorithm. Together with Google Home mini and Twilio API, they achieved an accuracy of 76% in identifying the user's mental state. Katchapakirin et al. [17] presented a tool for easy and early detection of depression in Thailand. They have utilized Facebook since this is the most popular social network platform in Thailand. Natural Language Processing (NLP) techniques were used to develop the depression detection algorithm. The results from the study indicate that Facebook posts could predict depression levels. Prakash et al. [18] combined different machine learning algorithms to work as an ensemble model for better performance. They used real-time tweets as data for their system. The tweets were classified and represented in the form of a table as well as a pie-chart. Meanwhile, Uddin et al. [19] used Long Short-Term Memory (LSTM) Deep Recurrent Network for depression analysis on social media for Bangla Language. The result showed high accuracy for a 5 layered LSTM.

The aforementioned studies served as a proof-of-concept that demonstrates the feasibility of using machine learning techniques to detect depression using social media. Numerous applications of AI/ML models were also presented, however, none of these were designed as a screening tool system that could provide insights into the patient's symptoms, triggers, and type of depression.

This study presents a novel approach to screening depressive disorders that will be accomplished by designing a screening tool system that makes use of an artificial neural network (ANN) model and social media.

Artificial intelligence advances the mental health care field by providing solutions that lead to faster and more accurate health outcomes and better patient experiences. This study will contribute towards leveraging artificial intelligence in this field by helping solve some of the challenges in mental health care in terms of accuracy and convenience.

The scope of this study covers the design of the screening tool software application and the development of ANN models. These ANN models were evaluated to select the best ANN model for the system.

The rest of the paper is organized as follows: Section 2 presents the methodology used to achieve the final output of the study. Section 3 proposes the design of the screening tool while Section 4 presents the development of ANN models. Results and conclusions are discussed in Sections 5 and 6, respectively.

2. Methodology

2.1. Project Methodology

A hybrid model (Fig. 1) was used as a guide to accomplish the final output of this study.

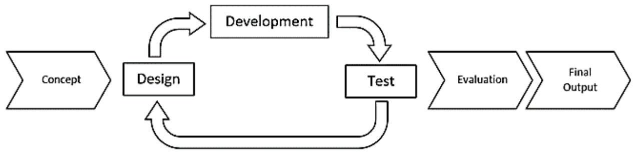

Fig. 1. Hybrid Methodology Model

The concept phase, evaluation phase, and final output follow a waterfall method while the design, development, and test phase follow the agile method.

- Concept phase
  This phase covers the identification of project requirements such as dataset, tools, and ANN techniques and models to be utilized.
- Design, development, and test phase
  These phases cover the system designs, flowcharts, and development of the ANN model. Since these phases are under the agile method, these were iterated until the best results were achieved.
- Evaluation phase
  This phase covers the evaluation of trained ANN models from the previous phases. The best ANN model to be utilized by the proposed screening tool system was determined in this phase.

2.2. Proposed Training Flow

The model training flow (Fig. 2) served as a guide on the training process of the ANN models that will be evaluated at the end of the development phase.

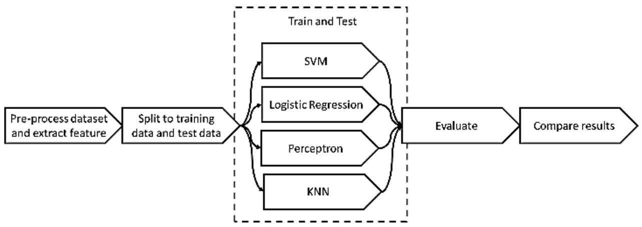

Fig. 2. Model Training Flow

Pre-processing dataset and feature extraction were performed before training to achieve better results. This process will be discussed further in the next section. The dataset was then split into training and testing sets.

The training dataset was used to train four artificial neural network algorithms:

- Support Vector Machine (SVM)
- Logistic Regression
- Perceptron
- K-Nearest Neighbor (KNN)

After training, the models were evaluated using the testing dataset. Lastly, the results were compared to determine the best ANN model for the screening tool system.

3. Design of Screening Tool

3.1. High-Level System Design

The screening tool system (Fig. 3) will be used by putting in the patient's Twitter username and the specified period. The tool will give outputs (graph and table) that will help the mental health professional gain insight into the patient's mental health. The mental health professional is the one that will analyze and make the final evaluation of the patient's mental state based on the report given by the tool.

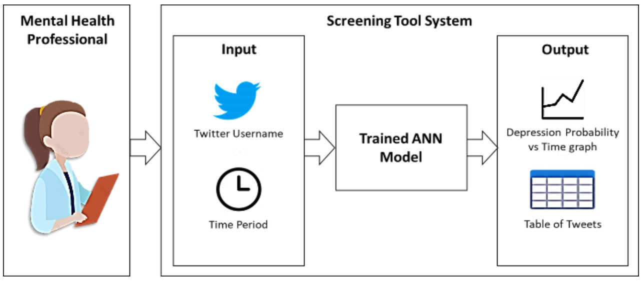

Fig. 3. High-Level Screening Tool System Design

The Depression Probability vs Time graph can help determine how frequent sadness or intense emotion occurs on the patient which could also indicate their type of depression. Furthermore, this system will also help determine depression disorder symptoms and triggers by displaying a table of tweets with a high probability of depression.

3.2. System Flowchart

The flowchart of the screening tool system (Fig. 4) elaborates the way how the system will work once it is implemented.

Twitter username, start date, and end date will be the inputs of the system. With these, the system will collect the tweets of the users based on the specified period. Each tweet will undergo preprocessing and feature extraction before being classified by the trained model. The system will then output the Depression Probability vs Time graph and table.

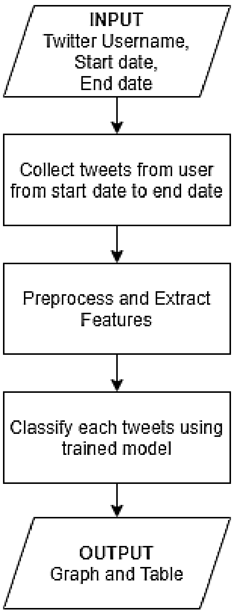

Fig. 4. Screening Tool System Flowchart

3.3. GUI Design

Graphical user interface (Fig. 5) is an important part of the screening tool system. This will serve as a way for mental health professionals to interact with the system. The GUI includes text boxes for inputs and graphs and table widgets for outputs.

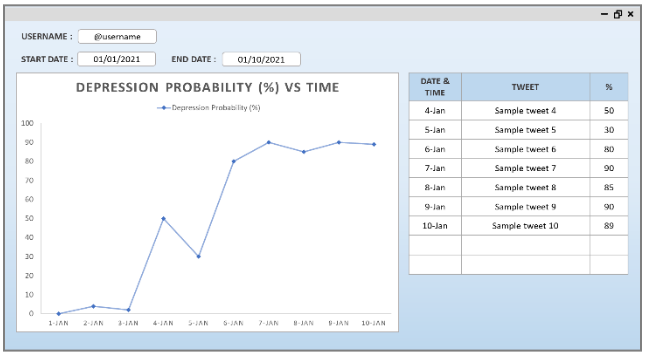

Fig. 5. Proposed Graphical User Interface

4. Development of ANN Model

4.1. Dataset

The dataset was curated from Kaggle [20] and contains a list of tweets with their corresponding label. One (1) is the label that corresponds to depressed tweets. On the other hand, zero (0) is the label of tweets that don't indicate depression. The summary of the dataset is presented in Table 1.

Table 1. Summary of Dataset

Label	Number of tweets
No depression (0)	7983
With depression (1)	2306
Total	10289

4.2. Tools

- Programming Language
  Python programming language was used in the development of ANN models. Python provides a wide range of libraries that can be used in AI development. It is also flexible and easy to use for beginners.
- Environment
  Google Colab served as the environment for the development of this project. It allowed the authors to execute python code in the cloud and utilize its free GPU.
- Libraries
  NLTK was the main library used for preprocessing. This library provides modules for natural language processing. On the other hand, Scikit-learn was the main library used for feature extraction and model training and testing. Other libraries were also utilized such as NumPy, pandas, etc.

4.3. Pre-processing and Feature Extraction

Fig. 6 presents the flow of pro-processing and feature extraction. Raw tweets from the data set were cleaned by removing links, Twitter handles and misspelled words. Clean tweets were then tokenized to easily remove stop words and add POS tags. The tokenized tweets with pos tags were lemmatized and then concatenated again to form the refined clean tweets.

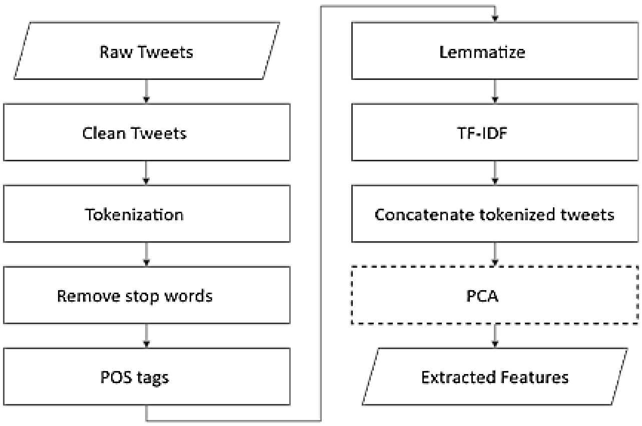

Fig. 6. Pre-processing and Feature Extraction Flowchart

Term frequency-inverse document frequency (TF-IDF) was used for feature extraction. This technique evaluated the relevance of each word in the whole dataset. If the relevance of a word increases, the weight of a word also increases, otherwise, it decreases.

After feature extraction, there were a total of 17,356 extracted features. This set of features was reduced using principal component analysis (PCA) which also sped up model training and testing. There was a total of 10,000 features after using PCA. Both sets of features with PCA and without PCA were split into 67% training set and 33% testing set (Table 2) which is one of the most common split percentages [21].

Table 2. Summary of Features

Number of Features		Number of Tweets	
With no PCA	17,356	Training set	6,893
		Testing set	3,396
With PCA	10,000	Training set	6,893
		Testing set	3,396

4.4. Model Training

For training the models, both pieces of the training set with and without PCA were fed to the four algorithms – SVM, Logistic Regression, Perceptron, and KNN. Scikit-learn modules were utilized to implement these machine learning algorithms. The performance of each trained model was evaluated using the testing set.

5. Results & Discussions

5.1. Performance

The confusion matrix of each model (Fig. 7) and without PCA (Fig. 8) were obtained. Each square of the confusion matrices corresponds to the following:

- True Negatives (TN): The top-left square which is the number of correctly classified tweets with no indication of depression.
- False Negatives (FN): The top-right square is the number of incorrectly classified tweets with no indication of depression.
- False Positives (FP): The bottom-left square is the number of incorrectly classified tweets with an indication of depression.
- True Positives (TP): The bottom-right square is the number of correctly classified tweets with an indication of depression.

The TN, FN, FP, and TP were used to compute for the precision, recall, f1-score, and accuracy of each model. The results for both set of features with PCA and without PCA are presented in Tables 3 to 6. Moreover, the time elapsed during the training and testing of each model is presented in Table 7.

Table 3. SVM Model Performance

SVM Model						
Label	**With PCA**			**Without PCA**		
	pre*	**rec***	**fs***	**pre***	**rec***	**fs***
0**	0.98	1.00	0.99	0.98	1.00	0.99
1**	1.00	0.93	0.96	1.00	0.93	0.96
acc	0.98			0.98		

* pre – precision, rec – recall, fs – f1-score, acc – accuracy
** Label 0 – no depression, Label 1 – with depression

Table 4. Logistic Regression Model Performance

Logistic Regression Model						
Label	**With PCA**			**Without PCA**		
	pre*	**rec***	**fs***	**pre***	**rec***	**fs***
0**	0.96	1.00	0.98	0.96	1.00	0.98
1**	1.00	0.85	0.92	1.00	0.85	0.92
acc	0.97			0.97		

* pre – precision, rec – recall, fs – f1-score, acc – accuracy
** Label 0 – no depression, Label 1 – with depression

Table 5. Perceptron Model Performance

Perceptron Model						
Label	**With PCA**			**Without PCA**		
	pre*	**rec***	**fs***	**pre***	**rec***	**fs***
0**	0.99	0.98	0.98	0.98	1.00	0.99
1**	0.93	0.96	0.95	0.98	0.94	0.96
acc	0.98			0.98		

* pre – precision, rec – recall, fs – f1-score, acc – accuracy
** Label 0 – no depression, Label 1 – with depression

Table 6. KNN Model Performance

KNN Model						
Label	**With PCA**			**Without PCA**		
	pre*	**rec***	**fs***	**pre***	**rec***	**fs***
0**	0.91	0.96	0.93	0.91	0.93	0.92
1**	0.82	0.69	0.75	0.74	0.69	0.71
acc	0.90			0.88		

* pre – precision, rec – recall, fs – f1-score, acc – accuracy
** Label 0 – no depression, Label 1 – with depression

Table 7. Time Elapsed with and without PCA

Model	***Training Time (s)***		***Testing Time (s)***	
	w/ PCA	***w/o PCA***	***w/ PCA***	***w/o PCA***
SVM	1289.553	2223.740	115.268	199.027
Logistic Regression	5.995	8.497	0.075	0.125
Perceptron	1.924	1.468	0.062	0.108
KNN	9.152	14.281	435.125	737.382

5.2. Evaluation

For the SVM model and Logistic Regression model, the results are the same with and without PCA. The perceptron model achieved better results without PCA. Meanwhile KNN model achieved better results with PCA.

Furthermore, using PCA reduced the training time and testing time which could lead to a faster classification process in an actual implementation. Due to these results, the authors proceeded to evaluate the models with PCA.

The precision, recall, and f1-score of the label zero (0) of the four models were compared (Fig. 9). The perceptron model achieved the highest precision followed by the SVM model. SVM model and Logistic Regression model achieved the highest recall. Lastly, the SVM model achieved the highest f1-score followed by the Logistic Regression model and Perceptron model. For label zero (0), the SVM model achieved the best performance followed by the Perceptron model and Logistic Regression model

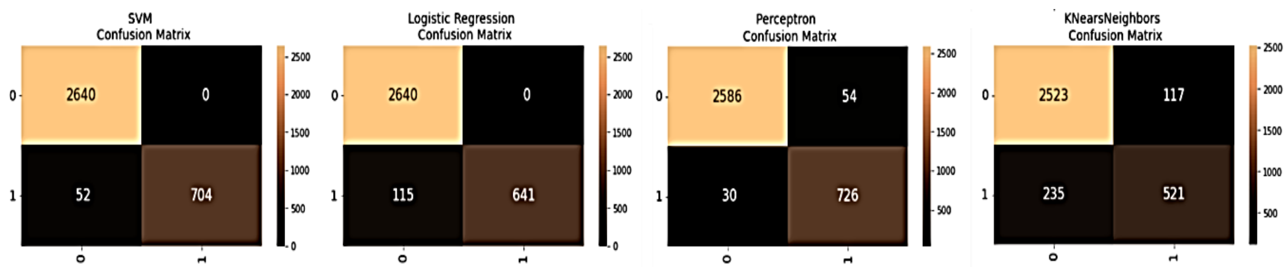

Fig. 7. Confusion Matrices with PCA

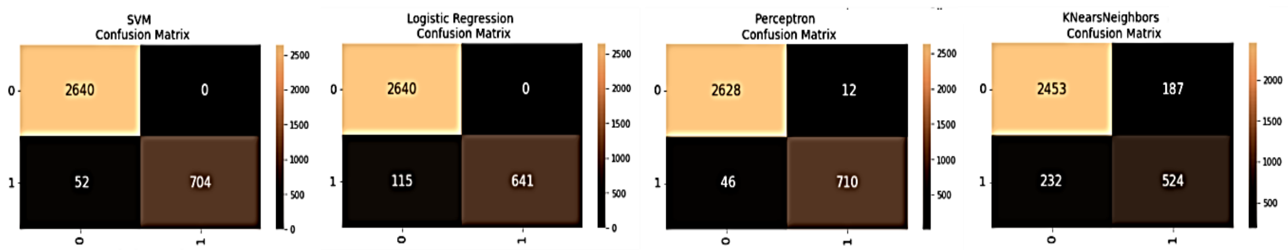

Fig. 8. Confusion Matrices without PCA

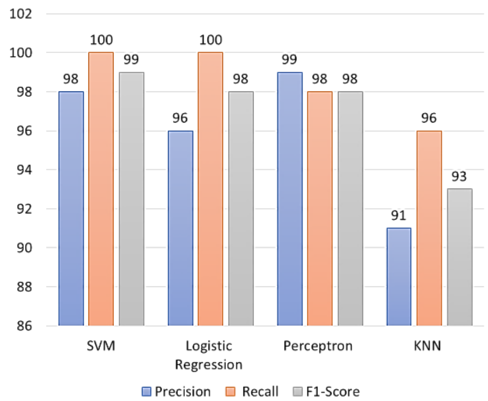

Fig. 9. Comparison of performance for Label 0

The precision, recall, and f1-score of the label one (1) of the four models were compared (Fig. 10). SVM model and Logistic Regression model achieved the highest precision. The perceptron model achieved the highest recall followed by the SVM model. Lastly, the SVM model achieved the highest f1-score followed by the Perceptron model. For label one (1), the SVM model also achieved the best performance followed by the Perceptron model.

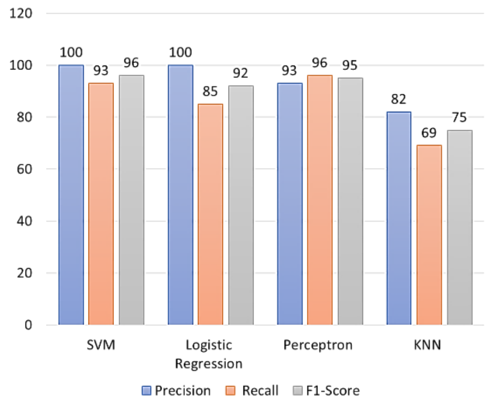

Fig. 10. Comparison of performance for Label 1

The accuracy of the four models was compared (Fig. 11). SVM model and Perceptron model achieved the highest accuracy. Overall, the SVM model achieved the best performance followed by the Perceptron model.

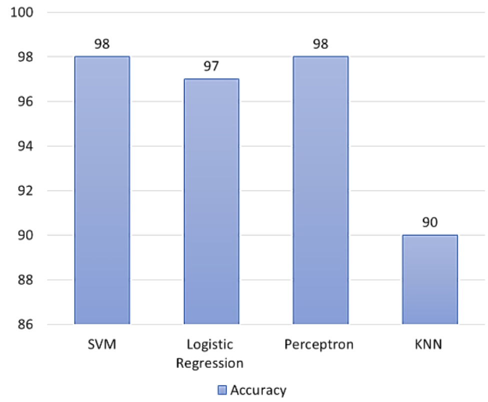

Fig. 11. Comparison of accuracy

Based on performance alone, the SVM model is the best candidate for the model to be used in the screening tool system. However, it has the slowest speed during training and the second slowest speed during testing which is a great drawback (Table 7). Moreover, there is a huge gap between the time elapsed of the SVM model and the faster models which can't be neglected. With that in mind, the authors selected the Perceptron model as the best model for the screening tool system.

5.3. Limitations and Future Works

This study only aimed to present a system design and GUI design of the screening tool system. In future work, the design will be implemented and will be evaluated by mental health professionals. It is also recommended to refine the model by using a larger dataset. Furthermore, since the models used in this study are limited to an shallow artificial neural network, deep learning can also be explored in future work.

6. Conclusion

With the advancement of technology, it is evident that the mental health care field will adopt advanced tools especially those incorporated with AI. This study accomplished its aim to help solve some of the challenges in screening depressive disorders by presenting a novel screening tool system that utilizes social media and ANN. The ANN model was developed by training four ANN algorithms (SVM, Logistic Regression, Perceptron, and KNN) and selecting the best model by evaluating each trained model.

PCA was used to reduce the training and testing time of these four models. Both sets of features with and without PCA were trained to conclude that PCA didn’t have a great negative impact on the performance of the models. In the end, the authors proceeded to use PCA.

The SVM model achieved the best performance followed by the Perceptron model. Both achieved 98% accuracy, but the SVM model achieved better results for recall and f1-score in label zero (0), and precision and f1-score in label one (1). However, its training time and testing time was very slow which could lead to a slower system in an actual implementation. This prompted the authors to choose the Perceptron model since its performance is on par with the SVM model but with a much faster speed.

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