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SENTIMENT ANALYSIS-FOCUSED KNOWLEDGE RECOMMENDATION SYSTEM USING DEEP LEARNING

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ABSTRACT

The opinions of people on many topics may be found in Online Social Networks (OSN). Applications that gather and evaluate this data include recommendation systems (RS) and monitoring systems. In order to identify users who may be experiencing mental health issues, such as stress or depression, this article introduces a Knowledge-Based Recommendation System (KBRS) that incorporates an emotional health monitoring system. The KBRS, which is triggered by monitoring results and is based on ontologies and sentiment analysis, may send individuals with psychological problems messages that are uplifting, calming, relaxing, or motivating.In addition, the system may notify authorized individuals via a warning message system in the event that it detects a depressive problem. The suggested method achieved an accuracy of 0.89 for detecting depressed users and 0.90 for stressed users by utilizing a Convolution Neural Network (CNN) and a Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN), respectively, to identify sentences with depressing and stressful content. In comparison to an RS that did not employ either a sentiment meter or Ontologies, the suggested KBRS achieved a rating of 94% of very pleased users, according to the experimental data. The suggested approach also uses little processing power, memory, and energy, according to subjective test findings.

1. INTRODUCTION

There has been a meteoric rise in the number of people using online social networks (OSNs), with predictions of 2.95 billion members by 2020 according to some research. One major factor contributing to OSN's large user base is the proliferation of Internet-enabled mobile devices. In today's world, OSN have evolved into a diverse and inclusive platform for expressing thoughts, emotions, and personal health routines.

Sentences containing words with negative connotations may suggest melancholy, tension, or discontent, for example, and the attitudes and emotions conveyed in these posts provide insights on several facets of users' behavior on OSN. On the other side, it stands to reason that someone who is feeling good about themselves probably has better emotional stability and self-confidence. Users exhibit a wide range of behaviors on OSN; nevertheless, signs of emotional instability, including sadness or stress episodes, may be revealed when the sentiment intensity value of uploaded phrases stays low or fluctuates wildly between high and low.

Very few research have looked at the possibility of using textual information gleaned from OSN data to identify physiological abnormalities. Xue et al. achieve an average accuracy of 80% when they apply several machine learning (ML) classifiers to conduct emotion categorization on micro-blogs focusing on psychiatric diseases. A 69% success rate was achieved by the suggested model for stress detection using data from Twitter activity. Studies on mood monitoring systems have also employed ML algorithms to analyze OSN signals, with an accuracy rate of 57%.

The primary objective of this study is to fill a gap in the current state of emotional health recommendation systems by introducing Nuadu, an RS that employs the Knowledge-Based Recommendation System (KBRS) methodology. This system will aggregate an ontology collection for health situations. An emotional health monitoring system and a sentiment analysis technique are also part of the planned KBRS. In order to detect possible users suffering from stress or depression, the monitoring system filters phrases from an OSN. In order to do this work, a CNN-based objective technique based on BLSTM-RNN is used to identify possible mental diseases. Subsequently, a KBRS is set up to convey positive, calming, soothing, or inspiring messages to these individuals.

2.LITERATURE SURVEY

It provides a comprehensive survey of deep learning-based recommendation systems, including those that use sentiment analysis. It covers various deep learning architectures and techniques that can be used for sentiment analysis and recommendation generation.

This proposes an improved collaborative filtering algorithm that uses deep learning to analyze user reviews and generate product recommendations. The algorithm considers both the product features and the sentiment of the reviews.

"A Hybrid Approach to Sentiment Analysis-based Recommendation System combines collaborative filtering and content-based filtering with sentiment analysis for generating personalized recommendations. The system uses a deep learning model to analyze the sentiment of the reviews and extract features for recommendation generation.

It prefers a deep learning-based sentiment analysis and recommendation system for e-commerce. The system uses a hybrid approach that combines collaborative filtering with sentiment analysis to generate personalized recommendations.

It provides a comprehensive survey of deep learning techniques for sentiment analysis, including those that can be used in recommendation systems. It covers various deep learning architectures and techniques for sentiment analysis, as well as their applications in recommendation systems.

Overall, this shows that deep learning-based sentiment analysis can be effectively used in recommendation systems to provide more personalized and relevant recommendations to users.

3. EXISTING SYSTEM

All Existing Application using traditional algorithms such as Random Forest or Support Vector Machine (SVM) to detect sentiments from user messages but those algorithms accuracy is not better. They are not maintaining user personal information such as their personal profile to send motivational messages in Ontologies. Proposed work maintain all user details such as personal or professional profile, sleeping hours and age etc.

Disadvantages of Existing System:

1. Less Accuracy

3.2 PROPOSED SYSTEM

Sentiment Analysis technique serves as a decision support system for the recommendation System.

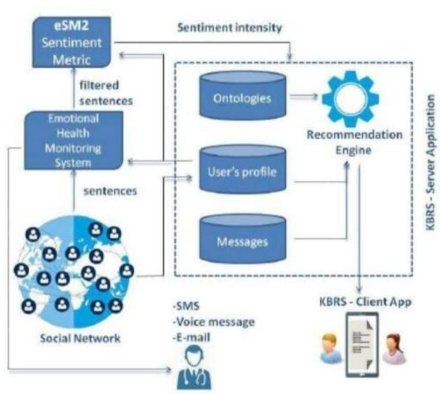
The goal of combining recommender system and sentiment analysis provides the most accurate results to the Users. Sentiment analysis uses different levels and types of techniques used for feature extraction and methods that are used for classification.

These techniques and methods provide the resultant user query with the negative or positive, sometimes positive or negative or neutral sentiment so that the recommended system can make Knowledge-based on the Sentiment Analysis procedure response.

Advantages of Proposed System:

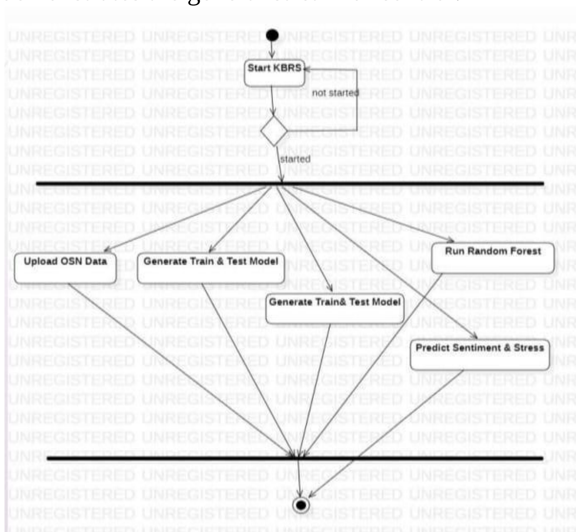
1. More Accuracy

4.SYSTEM ARCHITECTURE .



Activity Diagram

A graphical representation of the work process of stepwise exercises and activities with support for decision, emphasis and simultaneousness, used to depict the business and operational well-ordered stream of parts in a framework furthermore demonstrates the general stream of control.



5. SYSTEM IMPLEMENTATION

MODULES

1. UPLOAD OSN DATA
2. GENERATE TRAIN & TEST MODEL FROM OSN DATASET
3. BUILD CNN BLSTM-RNN MODEL USING SOSTMAX
4. RUN RANDOM FOREST ALGORITHM
5. UPLOAD TEST MESSAGE & PREDICT SENTIMENT & STRESS
6. ACCURACY GRAPH

5.1.1 Upload OSN dataset

Using this module, we will upload dataset to application.

5.1.2 Generate Train & Test Model From OSN Dataset

Using this module, we will read all messages from dataset and build a train and test model by extracting features from dataset.

5.1.3 Build CNN BLSTM-RNN Model Using SoftMax

Using this module, we will build deep learning BLSTM model on dataset and then using test Data we will calculate BLSTM prediction accuracy.

5.1.4 Run Random Forest Algorithm

For accuracy comparison between BLSTM and random forest we are running this algorithm also.

5.1.5 Upload Test Message & Predict Sentiment & Stress

Using this module, we will upload test messages and then application will detect stress by applying BLSTM model on test data.

5.1.6 Accuracy Graph

Using this will display accuracy comparison graph between BLSTM and random forest.

6.1 TYPES OF TESTING

■Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

■Integration testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

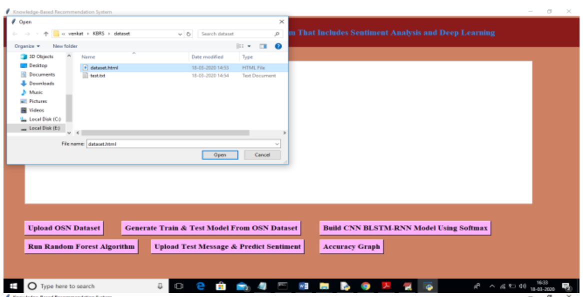
■Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

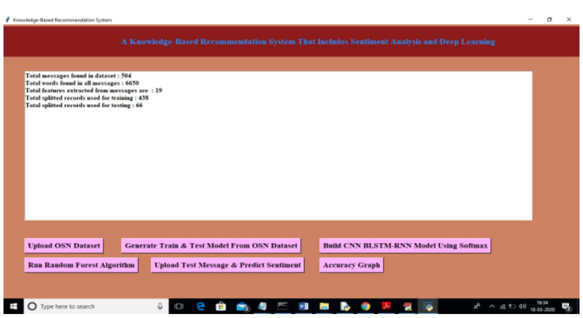
Functional testing is centered on the following items:

7.RESULTS

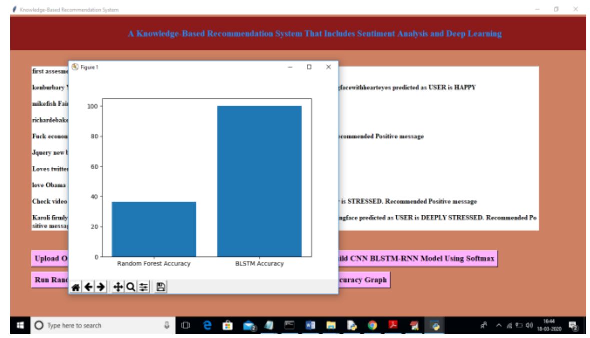
fig.7. 1 Home page



Now click on ‘Generate Train & Test Model From OSN Dataset’ button to read dataset and to extract features from dataset such as total messages and words etc.



In above screen we can see dataset contains total 504 messages and all messages contains 6650 words and application using 438 records for BLSMT training and 66 records to test BLSTM accuracy or prediction performance. Now click on ‘Build CNN BLSTM-RNN Model Using Softmax button to train dataset features with BLSTM model.



In above graph x-axis represents algorithm name and y-axis represents accuracy of those algorithms. From above graph we can conclude that BLSTM is much better than traditional Random Forest Algorithm.

8. CONCLUSION & FUTURE WORK

We modeled the eSM2 using user profile characteristics, geographical location, and sentence topic in mind to determine the sentiment intensity of a message, with the goal of improving the KBRS performance. Existing sentiment measurements do not take these two factors into account. Results from the perceptual evaluation of the RS showed that the eSM2 metrics performed better than the eSM, according to the performance assessment.

The need of including extra user profile characteristics to enhance the sentiment metric's efficacy was highlighted by this finding. The suggested KBRS also made use of the ontology idea. Keep in mind that additional sentiment measures may make use of the user-profile-based adjustment factor suggested in eSM2.

The use of OSN data to identify stress states is still in its infancy in the literature. The method for tracking OSN users' emotional well-being used convolutional neural networks (CNNs) for character-level representation and convolutional neural networks (BLSTM-RNNs) for disease entity identification. It achieved an accuracy of 0.89 for depression diagnosis and 0.90 for stress detection. The results achieved in related investigations are lower in comparison to these accuracy levels.

The suggested KBRS was pitted against an alternative KBRS that disregards sentiment metrics and ontologies in the performance evaluation tests. The results show that the suggested KBRS outperforms the RS without sentiment measure and ontology, with 94% of users being very pleased and 69% being satisfied with less. Users claim that recommendation systems (RSs) that fail to take ontology and sentiment metrics into account provide subpar suggestions based on less tailored material. Using ontology and, more specifically, a customized sentiment analysis rather than a generic one, yielded the best result for the KBRS. This study's most important finding is that, on average, the appropriated users' emotional states improved after receiving the advised messages.

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