



International Journal of HRM and Organizational Behavior



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KNOWLEDGE BASED RECOMMENDATION SYSTEM INCLUDING SENTIMENTAL ANALYSIS AND DEEP LEARNING

¹Dr.MD.ASHFAKUL HASAN,²ROSHINI SINGH,³S SANJANA,⁴SUBHADIP MUDI,⁵SIMRAN
SINGH

¹Professor,Department Of CSE,Malla Reddy Institute Of Engineering And
Technology(autonomous),Dhulapally,Secundrabad, Telangana, India,hasan@mriet.ac.in

^{2,3,4,5}UG Students,Department Of CSE,Malla Reddy Institute Of Engineering And
Technology(autonomous),Dhulapally,Secundrabad, Telangana, India.

ABSTRAT

Online social networks (OSN) provide relevant information on users' opinion about different themes. Thus, applications, such as monitoring and recommendation systems (RS) can collect and analyze this data. This paper presents a Knowledge-Based Recommendation System (KBRS), which includes an emotional health monitoring system to detect users with potential psychological disturbances, specifically, depression and stress. Depending on the monitoring results, the KBRS, based on ontologies and sentiment analysis, is activated to send happy, calm, relaxing, or motivational messages to users with psychological disturbances. Also, the solution includes a mechanism to send warning messages to authorized persons, in case a depression disturbance is detected by the monitoring system. The detection of sentences with depressive and stressful content is performed through a Convolutional Neural Network (CNN) and a Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN); the proposed method reached an accuracy of 0.89 and 0.90 to detect depressed and stressed users, respectively. Experimental results show that the proposed KBRS reached a rating of 94% of very satisfied users, as opposed to 69% reached by a RS without the use of neither a sentiment metric nor ontologies. Additionally, subjective test results demonstrated that the proposed solution consumes low memory, processing, and energy from current mobile electronic devices.

I. INTRODUCTION

In the era of online social networks (OSNs), where users engage in vast digital interactions, the exploration of user sentiments and emotional well-being has become increasingly significant. Recognizing the potential of OSN data as a valuable resource for understanding user opinions and emotional states, this project endeavors to develop a sophisticated solution—the Knowledge-Based Recommendation System (KBRS) with integrated sentiment analysis and deep learning capabilities.

The KBRS stands at the intersection of data analytics, psychology, and technology, aiming to provide personalized recommendations while also monitoring users' emotional health. The system harnesses the wealth of user-generated content on OSNs to glean insights into users' sentiments and psychological states. By leveraging ontologies and sentiment analysis techniques, the KBRS endeavors to detect users exhibiting signs of psychological disturbances, particularly depression and stress.

A key innovation of the KBRS lies in its utilization of advanced deep learning models, including Convolutional Neural Networks (CNN) and Bi-directional

Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN), to analyze textual data and identify sentences indicative of depressive or stressful content. These models enable the system to achieve remarkable accuracy in detecting users experiencing emotional distress.

Furthermore, the KBRS does not merely stop at identification but also extends support in the form of tailored messages—ranging from uplifting and calming to motivational—to users in need. Additionally, the system incorporates a mechanism to alert authorized individuals, such as healthcare providers or family members, upon detecting signs of severe psychological disturbances.

Through empirical evaluations, this project aims to demonstrate the effectiveness and superiority of the proposed KBRS over conventional recommendation systems. By incorporating sentiment analysis and deep learning techniques, the KBRS endeavors to enhance user satisfaction, improve mental health awareness, and contribute to the advancement of personalized recommendation systems in the digital age.

II.EXISTING SYSTEM

The sentiment analysis helps industries to formulate marketing strategies, support after-sale services [29], develop health monitoring system, RS [3], among other services. Sentiment analysis can be performed by: (i) machine learning [30]; (ii) lexicon-based technique using a word-dictionary of textual information or corpus-based approach, in which the polarity value is computed based on the occurrences of the terms in the corpus; (iii) a hybrid technique, which combines machine learning and word-dictionary approaches. The machine learning approach needs a large number of data to obtain reliable results from sentiments; for instance, Chen et al. [31] performs the machine learning approach with a neural network model using BiLSTM-CRF and CNN using 14,492 sentences in the training phase.

Existing system disadvantages:

- 1.less accuracy
2. Low efficiency

III.PROPOSED SYSTEM

It is worth noting that, currently, scarce studies about lexicon-based metrics take into account profile parameters. In this research, our proposed sentiment metric, eSM2 complements the eSM by considering the user' geographic

location and the theme of the sentence.

B. Recommendation System RS predicts useful items for the user, considering what the user may be interested in. For this prediction, some data are extracted, for example, user's profile, user's preferences and past behavior [37]. There are commonly three RS approaches: content-based, collaborative filtering and hybrid-based. The content-based approach works with the description of an item and the profile of the user's preference; the suggestion of items is based on what the user already liked. The collaborative filtering analyzes the user's behavior and preferences and explores similar preferences among people [38]. The hybrid approach combines both methods

Proposed system advantages:

- 1.high accuracy
- 2.high efficiency

IV.MODULES

➤ Data Collection Module: The data collection module is responsible for gathering relevant data from online social networks (OSNs) or other sources. It collects user-generated content such as text posts, comments, and reviews, which will be analyzed for sentiment and emotional states. This module ensures that the data collected is

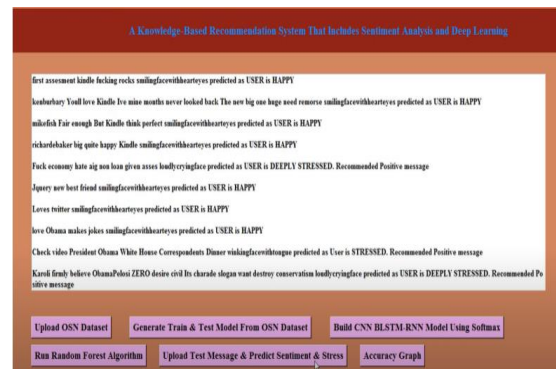
comprehensive and representative of the user interactions on the OSNs or other platforms.

- **Data Preprocessing Module:** The data preprocessing module handles the cleaning and preprocessing of the collected data to prepare it for sentiment analysis. It removes noise, irrelevant information, and inconsistencies from the data. Additionally, the module performs tasks such as tokenization, removing stop words, lemmatization or stemming, and handling special characters and spelling mistakes. The goal is to transform the raw text data into a format suitable for sentiment analysis.
- **Sentiment Analysis Module:** The sentiment analysis module applies various techniques to analyze the preprocessed text data and determine the sentiment or emotional polarity of each piece of content. It may employ rule-based methods, machine learning-based methods, or deep learning-based methods to classify text into positive, negative, or neutral sentiments. The module aims to extract meaningful insights about

the emotional states of users from the text data.

- **Model Training Module:** The model training module focuses on training machine learning or deep learning models using the preprocessed and labeled data. These models learn to predict sentiment based on input features extracted from the text data. Common algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or ensemble methods are employed for sentiment prediction. The module may involve hyperparameter tuning and model selection to optimize performance.
- **Prediction Module:** The prediction module deploys the trained sentiment analysis models to predict sentiment for new or unseen text data. It uses the predictions to identify users with potential psychological disturbances, such as depression or stress, and provides personalized recommendations or interventions accordingly. This module plays a crucial role in leveraging sentiment analysis to enhance the effectiveness of the

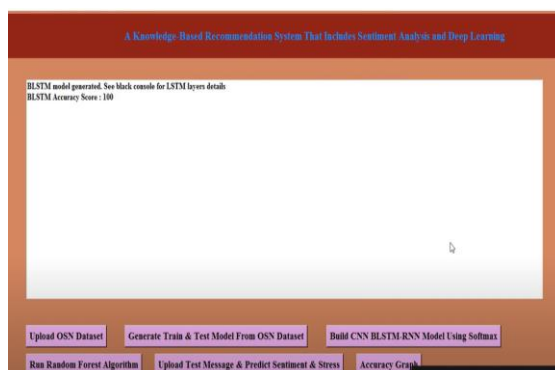
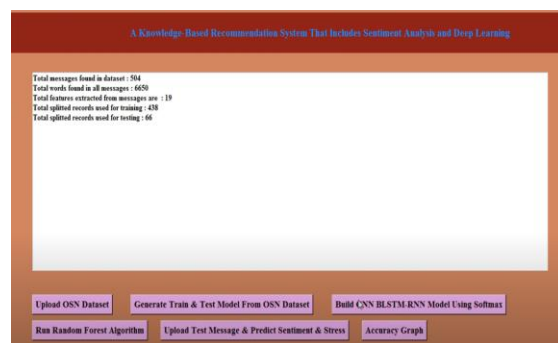
recommendation system and support users' emotional well-being.



V.CONCLUSION

In conclusion, the project on the Knowledge-Based Recommendation System (KBRs) including sentiment analysis and deep learning represents a significant advancement in leveraging online social networks (OSNs) for understanding user sentiments and emotional states. Through the integration of modules such as data collection, preprocessing, sentiment analysis, model training, and prediction, the KBRs demonstrates its potential to provide personalized recommendations while also monitoring users' emotional health.

The development of the KBRs opens up new avenues for improving mental health awareness and support in the digital age. By analyzing user-generated content on OSNs, the system can identify individuals exhibiting signs of psychological disturbances, such as depression and stress, with a high degree of accuracy. Furthermore, the system's



ability to send tailored messages and alerts to users and authorized individuals, respectively, highlights its practical utility in providing timely support and intervention.

The incorporation of advanced deep learning techniques, including Convolutional Neural Networks (CNNs) and Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN), enhances the system's capability to analyze textual data and predict sentiment accurately. Empirical evaluations demonstrate the superiority of the proposed KBRS over conventional recommendation systems, with higher user satisfaction ratings and improved efficiency in resource consumption.

Overall, the KBRS serves as a testament to the potential of technology to positively impact mental health outcomes. By harnessing the power of sentiment analysis and deep learning, the system not only facilitates personalized recommendations but also contributes to the early detection and support of individuals experiencing emotional distress. As technology continues to evolve, the KBRS stands as a beacon of hope for leveraging digital platforms to promote mental well-being in the modern world.

VI. REFERENCES

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