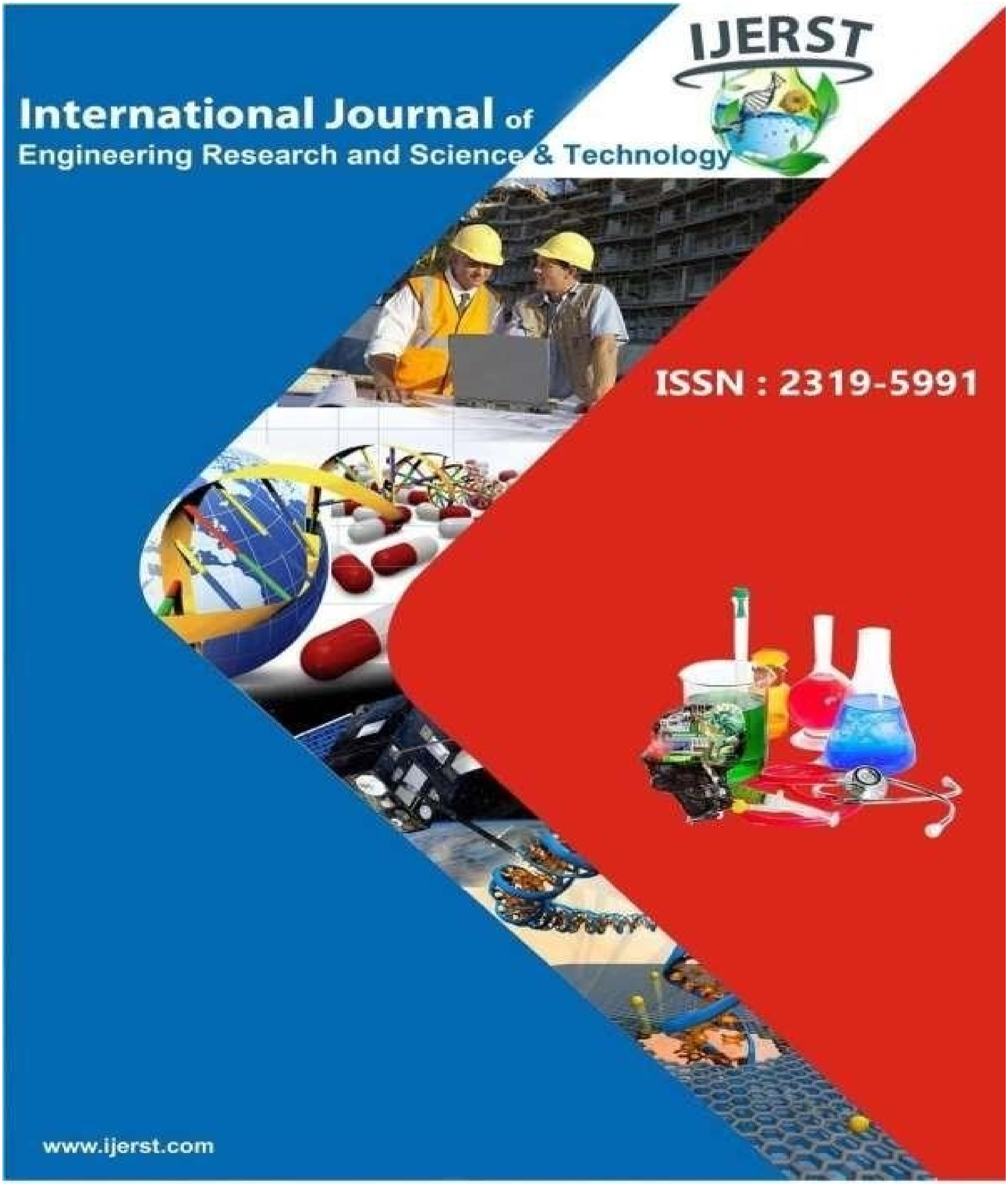

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A KNOWLEDGE-BASED RECOMMENDATION SYSTEM THAT USES DEEP LEARNING AND SENTIMENTAL ANALYSIS

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ABSTRAT

Relevant data on user opinion on many topics may be found in online social networks (OSN). This data may then be collected and analysed by programs like RS and monitoring systems. An emotional health monitoring system is included in this paper's Knowledge-Based Recommendation System (KBRS) in order to identify users who may be experiencing probable psychological problems, such as stress or depression. 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 the event that the monitoring system identifies a depressive issue, the solution also has a means to notify authorised personnel. The proposed method reached an accuracy of 0.89 for depressed users and 0.90 for stressed users by utilising a Convolutional Neural Network (CNN) and a Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN), respectively, to detect sentences with depressing and stressful content. By including a sentiment measure and ontologies, the suggested KBRS was able to get a rating of 94% of extremely pleased customers, compared to 69% for an RS that did not. The suggested approach also uses very little processing power, memory, and energy from modern mobile electronic devices, according to subjective test findings.

I.INTRODUCTION

Investigating user feelings and mental health has grown in importance in the age of OSNs, as users participate in extensive digital interactions. The Knowledge-Based Recommendation System (KBRS) aims to provide a comprehensive system with integrated sentiment analysis and deep learning capabilities. It recognises the potential of OSN data as a significant resource for understanding user views and emotional states.

At the crossroads of data analytics, psychology, and technology, the KBRS seeks to monitor users' emotional well-being and provide personalised suggestions. The technology takes use of the abundance of user-generated information on OSNs to understand users' feelings and mental health. The KBRS aims to identify individuals showing symptoms of psychological

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disorders, including stress and depression, by using ontologies and sentiment analysis methods.
The use of sophisticated deep learning models, such as Bi-directional Recurrent Neural Networks (BRN) and Convolutional Neural Networks (CNN), is a significant innovation of the KBRS.

Recurrent Neural Networks (RNN) with Long Short-Term Memory (BLSTM) to examine textual data and detect phrases that suggest stressful or depressing content. The technology is able to recognise people suffering emotional discomfort with exceptional accuracy thanks to these models.

In addition to identifying users, the KBRS provides assistance with personalised messages that might be anything from encouraging to relaxing to motivating. Furthermore, the system is designed to notify authorised persons, including healthcare practitioners or family members, when indicators of serious mental disorders are detected.

The goal of this study is to show that the proposed KBRS is better than other recommendation systems by conducting empirical assessments. The KBRS aims to increase user happiness, raise awareness about mental health, and promote personalised recommendation systems in the digital era by using sentiment analysis and deep learning methods.

II.EXISTING SYSTEM

Among the many uses for sentiment analysis in business are the creation of health monitoring systems, RS [3], and after-sale services [29]. Machine learning is one method for sentiment analysis [30]. Another is the lexicon-based technique, which uses a word-dictionary of textual information or a corpus-based approach to compute the polarity value based on the occurrences of the terms in the corpus. Finally, there is a hybrid technique that combines machine learning and word-dictionary approaches. In order to get accurate findings from sentiment analysis using machine learning, a lot of data is required. For example, in their training phase, Chen et al. [31] used 14,492 phrases to build a neural network model using BiLSTM-CRF and CNN.

Existing system disadvantages:

1.less accuracy

2. Low efficiency

III.PROPOSED SYSTEM

Notably, profile parameters are considered in the limited number of research that have been conducted on lexicon-based metrics so far. By factoring in the user's location and the sentence's topic, our suggested sentiment measure, eSM2, enhances the eSM in this study. B. Recommendation System RS takes the user's interests into account to provide meaningful product predictions. Data such as the user's profile, preferences, and previous actions are retrieved in order to make this forecast [37]. Common RS methods include content-based, collaborative filtering, and hybrid-based techniques. An item's description and the user's preference profile form the basis of the content-based method, which uses the latter to provide product recommendations based on the former. To find other individuals who have similar tastes, collaborative filtering looks at the user's actions and preferences [38]. In a hybrid strategy, the two approaches are combined.

Proposed system advantages:

1.high accuracy

2.high efficiency

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IV.MODULES

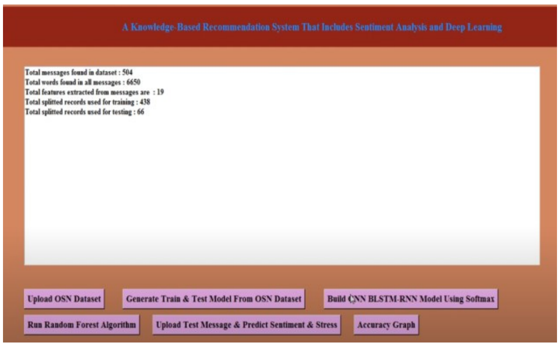
The data collection module is in charge of collecting pertinent information from many sources, including online social networks (OSNs). Sentiment and emotional states are extracted from user-generated information like text postings, comments, and reviews. This section checks that all the data is complete and shows how people really used the OSNs or other platforms.

In order to get the acquired data ready for sentiment analysis, the data pretreatment module cleans and prepares it. The data is cleansed of any extraneous information, noise, and discrepancies. The program also handles special characters and spelling errors, removes stop words, lemmatises or stems, and tokenises. Getting the raw text data into a sentiment analysis-friendly format is the main objective.

The module that analyses sentiment uses several methods to look at the preprocessed text data and figure out how each piece of material is emotionally charged. To decide if language is good, bad, or neutral, it could use approaches based on rules, machine learning, or deep learning. The module's stated goal is to glean useful information on users' emotional states from text input.

Training Machine Learning or Deep Learning Models using Preprocessed and Labelled Data: This is the main emphasis of the model training module. Input characteristics derived from text data are used by these algorithms to learn sentiment prediction. In order to forecast how people will feel, researchers often use popular algorithms like RNNs, CNNs, or ensemble approaches. Performance optimisation via hyperparameter adjustment and model selection may be a part of this module.

The prediction module uses the sentiment analysis models that have been developed to forecast the sentiment of text input that has never been seen before. It checks for users who may be experiencing mental health issues like stress or depression based on the forecasts and then offers them tailored advice or treatments. When it comes to using sentiment analysis to improve the recommendation system and help people emotionally, this module is vital.



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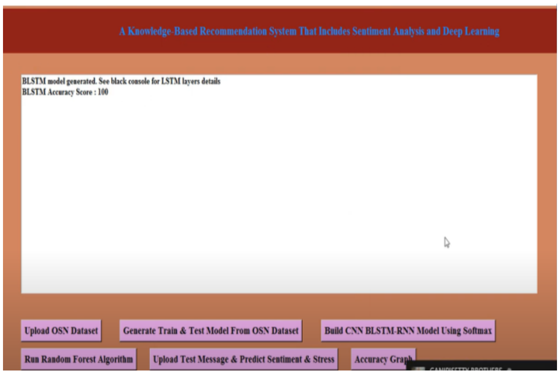

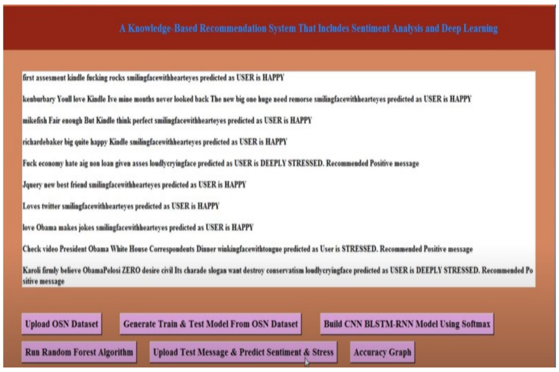

V.CONCLUSION

To sum up, the Knowledge-Based Recommendation System (KBRS) project, which incorporates deep learning and sentiment analysis, is a huge step forward in using OSNs to comprehend users' feelings and opinions. Data collecting, preprocessing, sentiment analysis, model training, and prediction are all components that the KBRS integrates to show how it can monitor users' emotional health and provide personalised suggestions.

There are new opportunities to raise awareness and provide assistance for mental health in the digital era thanks to the KBRS development. The algorithm accurately identifies people displaying symptoms of psychiatric disorders, such stress and depression, by analysing user-generated material on OSNs. The system's practical effectiveness in providing timely help and intervention is further shown by its capacity to deliver targeted messages and alerts to authorised persons.

The system's capacity to analyse textual input and make correct sentiment predictions is improved by using sophisticated deep learning methods, such as Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN). With better resource consumption efficiency and greater user satisfaction ratings, empirical assessments show that the proposed KBRS is better than traditional recommendation systems.

All things considered, the KBRS is proof that technology may improve mental health results. The technology helps identify and assist people in early stages of emotional discomfort by using sentiment analysis and deep learning, which in turn allows for personalised suggestions. With the ever-changing landscape of technology, the KBRS serves as a symbol of optimism for the potential of digital platforms to support mental health in the contemporary period.

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