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Incorporating sentiment analysis and deep learning into a knowledge-based recommendation system

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Abstract—***Using online social networks (OSNs), you may get a sense of what people think about a wide range of topics. As a result, applications like monitoring and recommendation systems (RS) may gather and evaluate this information. An emotional health monitoring system is included in the Knowledge-Based Recommendation System (KBRS) described in this study, which may help identify users who may be suffering from depression or stress. According to the monitoring data, the sentiment analysis-based KBRS is triggered to deliver messages that are calming, relaxing, or energising to users who are experiencing mental health issues. In addition, if the monitoring system detects a depressive disturbance, the solution contains a way to notify authorised individuals. A Convolutional Neural Network (CNN) and a Bi-directional Long Short-Term Memory (BLSTM) - Recurrent Neural Networks (RNN) were used to detect depressed and stressed users, respectively, with an accuracy of 0.89 and 0.90, respectively. The experimental findings demonstrate that the suggested KBRS achieved a rating of 94% of extremely pleased users, compared to an RS without the usage of sentiment metrics or ontologies, which achieved a rating of 69%. It has also been shown that the suggested method utilises little memory, processing and energy from existing mobile electronic devices via subjective test findings.***

Index Terms—Deep learning, sentiment analysis, recommendation systems, social media networks, and personalization and modification of knowledge

INTRODUCTION

According to some estimates, there will be 2.95 billion active OSN users by the year 2020 [1], a significant increase in the number of people using these services. The rise in the number of Internet-connected mobile devices, such as smartphones and tablets, is largely to blame for OSN's large user base. Today, OSN are a rich and ubiquitous method of expressing one's thoughts and emotions, and they reflect the poor habits or healthy behaviours of each user. In recent years, numerous applications in the health care informatics business have employed the analysis of messages posted on OSN. For instance, phrases containing words with negative connotations may convey unhappiness, tension, or dissatiisfaction [4], depending on their context. On the other hand, a person's self-confidence and emotional stability can be improved if they are in a positive mood state [5]. If the sentiment intensity value of uploaded words remains low, or if it regularly swings from high to low and vice versa, these facts may suggest some emotional problem, such as depression or stress events [6]. They found that when people were depressed, they wrote shorter sentences than when they weren't depressed [7, 8]. Additionally, these people speak in the first person and have trouble sleeping. Because of this, their actions may be seen in the OSN phrases. As a result of monitoring and analysing particular terms in the sentences, it is possible to identify individuals who are at high risk of committing suicide and to provide an appropriate intervention. In all locations and cultures of the globe, depression is one of the most common mental health conditions [10]. Unfortunately, the prevalence of depression is still underrecognized. Sensors are used in most research on health systems [11–13] to identify mental illnesses. Based on the results of [14], an electroencephalogram-trained classifier is able to accurately identify stress with an average accuracy of 80.45 percent. There are three categories of stress: baseline, moderate stress, and severe stress, and a classification model based on heart rate variability data is proposed by the authors in [15]. Using textual in formation from OSN data to diagnose physiological issues is a rare occurrence. Machine learning (ML) classifiers are used by Xue et al. [16] to classify emotions from micro-blogs, with an average accuracy of 80%. [17] found that the suggested model for stress detection based on Twitter activity has a 69 percent accuracy rate. Using OSN data, researchers investigate the causes of postpartum depression in [18]. Studies on mood monitoring systems utilising OSN signals [19] also employ ML

algorithms, with an accuracy of 57%. A combination of Long Short-Term Memory (LSTM), a Convolutional Neural Network (CNN), and a Conditional Random Field (CRF) is used by Ma and Hovy [20] to assess phrases' meaning at the character level (CRF). Combining CRFs with Recurrent Neural Networks (RNNs) yields the greatest performance on NER datasets, according to Lample et al. [21]. For labelling jobs, an upgraded variant of the LSTM called a bi-directional LSTM (BLSTM) is frequently utilised. One field in which deep learning has been investigated is personality analysis, as well as OSN age group classifications, sentiment analysis, and others. Psychopathology research have yet to take use of this method. Here, we'll see how well deep learning algorithms do in detecting sad, stressed, and non-depressed or non-stressed consumers. RS applications may be utilised to improve a person's emotional well-being and lift their spirits when they are experiencing low moods [26]. Ontology-based RS is being utilised in the medical field [27] to show accurate outcomes from treatment strategies for disorders. As a result, the primary objective of this research is to offer an RSM that makes use of a method called Knowledge-Based Recommendation System (KBRS), which aggregates an ontology collection for health situations called Nuadu [28]. Sentiment analysis and emotional health monitoring are also included in the planned KBRS. The monitoring system examines the content of an OSN to look for signs that a user may be depressed or stressed. Use of an objective approach to diagnose psychiatric problems, together with a CNN, is employed to achieve this purpose. It's later triggered to deliver positive, encouraging messages to these people. As a result, the strength of these signals might vary based on whether or not the statements posted on an OSN are positive or negative. Additionally, other information such as a user's personal data and his or her geographic location are included into this measure, making it more accurate. It also delivers warning messages to users who have been pre-registered in the system when depression is detected. Subjective findings showed that the KBRS was well-liked by participants, who felt it helped them feel better emotionally. To compare with the proposed KBRS, tests were also conducted using a regular RS sans the Nuadu ontology and the eSM2. Another subjective test showed the programme operating on the user's mobile electronic device to be simple and efficient. Based on the classification of phrases with sad or stressed content, this study provides a unique technique for monitoring and detecting prospective users with emotional problems. A CNN is utilised to represent characters at the character level and a BLSTM-RNN is used to recognise disorder entities. eSM2 and the Nuadu ontology, which is a health ontology, have been included into an enhanced version of the RS. • An improved gauge for sentiment. Incorporating the user's personal information, the location, and the topic of the phrase improves the sentiment metric's effectiveness, according to research and validation. Easy to use, minimal memory, processing, and energy consumption application loaded on a mobile device. Here's how the rest of the document is organised: Third, the suggested RS is described in Section III, which includes the proposed method for assessing mood using the eSM2 sentiment metric and machine learning for detecting depression and stress using the CNN, BLSTM-RNN model and the eSM2 sentiment metric. Experiment findings are discussed in Section IV of the paper. Section V summarises the debates, and Section VI summarises the findings and suggests directions for further research.

II. RELATED WORK

A. Affective and Sentimental Interpretation Using sentiment analysis, businesses may build marketing plans, support after-sale services, and establish a health monitoring system, RS [3]. Machine learning can be used to perform sentiment analysis [30], as can lexicon-based techniques that use a word dictionary of textual information or corpus-based approaches that calculate the polarity value from the occurrences of terms in the corpus; and (iii) a hybrid technique that combines machine learning and word-dictionary approaches. Using a neural network model trained on 14,492 phrases using BiLSTM-CRF and CNN, Chen et al. [31] used a huge amount of data in their machine learning technique to get solid findings from feelings. Emotional terms are used in the lexicon-based method; word dictionaries such as WordNet, Sentimeter-Br2, and eSM [3] are examples. This method is used in this study to analyse sentiment. Words in the Sentimeter-Br2 lexicon are classified according to their emotional charge (positive or negative), taking into account n-grams, verb tenses, and adverbs. Using the Sentimeter-Br2, the sentiment intensity of an S-sentence

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iscalculated by (1):

$$Sentimeter\_Br2(S) = \frac{SU + SB + ST}{k + p + q + r}$$

S-sentence Sentimeter-Br2(S): the global emotion intensity of the S-sentence; k is connected to how the verb in the past participle of the sentence is tensed; k = 1, and k = 0 for sentences in any other tense or if there is no verb in the phrase; Words that lack emotion (stopwords) are not included in this calculation since they are not part of unigrams; instead, they are part of bigrams; and finally, they are part of trigrams. ST is the trigram's sentiment score; SB is its bigram's sentiment score; and SU is its unigram's emotion score. In addition to Sentimeter-Br2, the eSM takes into account the user's age, gender, and educational level from their profile. An S-sentiment sentence's intensity may be determined using eSM (2). Subjective test findings, in which participants submitted sentences on social media, were used to draw this conclusion. Then, the same individual who submitted the phrases and the eSM connection assessed these sentences. The correlation between sentiment intensity and user profile variables may be shown in the eSM formulation.

$$eSM(S) = Sentimeter\_Br2(S) * C * exp(a_1 * A_1 ... + a_n * A_n + g_1 * M + g_2 * F + e_1 * G + e_2 * nG) \quad (2)$$

There are four ranges of age: A1, A2, A3, and A4 are the weight factors for each range; g1 and g2 are binary factors related to the gender; M and F, respectively, are the weight factors for man and woman; e1 and e2 are binary factors related to educational level (higher education or not); G and nG are the weight factors of education. Observing several variations in the writing style, the authors of [34] demonstrate that teens act differently in blogs. A sentiment measure based on the user's location and the topic of the phrase collected on an OSN is developed in our research. It is possible to classify people's emotions as good, negative, or neutral using techniques like sentiment analysis. The affective analysis is not confined to three sentiment polarities since it examines the diverse feelings, such as melancholy and rage, even if they share the same sentiment polarity (negative). Sentiment and emotional meaning may be conveyed via the use of emoticons, symbols for expressing emotions, and utterances like "LOL" (laughing out loud). An individual's emotional state may be assessed via the application of affective analysis. There are a number of questions that need to be answered in the sentiment and affective analysis, such as whether or not the user profile influences the sentiment metric's performance, which characteristics must be considered, and how to perform the association between the user's profile and the sentiment metric. For example, the strength of a metric's mood may be affected by gender [36]. To be fair, there aren't many studies looking at lexicon-based measures that account for profile factors just yet. In this study, we provide eSM2, a sentiment measure that incorporates the geographic location of the user as well as the sentence's topic to complete the eSM.

Recommendation System

RS anticipates what the user will find valuable based on his or her previous interests. Predictions are made using information from the user's profile, preferences, and previous actions, among other things [37]. Content-based RS, collaborative RS, and hybrid RS are the three most popular RS techniques. The content-based method uses the item's description and the user's preference profile to propose things based on what the user has previously shown an interest in. Users' behaviour and preferences are studied to find out what other people are interested in [38]. For example, the hybrid approach is a combination of the two techniques. For example, a user may search for a term in a search engine, but that word may have been searched a long time ago, therefore the search results may not reflect current information. In RS [40], the concept of

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sentiment analysis was first introduced as a way to provide users with more relevant and up-to-date material. The semantic approach relies on an ontology, which is a collection of knowledge, to fill in the gaps in the user's knowledge. [41] One of the numerous advantages of using a KBRS is that it may be used to alleviate the cold-start issue. In contrast to the method previously proposed, this research presents an approach that integrates a sentiment-based measure. In order to compare performance, tests were carried out utilising both the standard RS and the suggested KBRS model.

Emotional Health Monitoring System

Continuous monitoring of emotional disorder issues, such as depression and stress disorders, is necessary. Traditional methods such as rating scales and questionnaires are often used to measure mood because of the disorder's unpredictable behaviour [42]. PSYCHE [43], a portable sensing device-based sentiment analysis tool, is another example of a method to address human body signals. Voice signals are also used for emotional evaluation, along with other signs, such as sleep quality, galvanic skin reaction and activity. Depressive illnesses may be detected by language style, according to psychiatric research [45]–[47]. Using the lexicon technique, Nguyen et al. [48] identify the most frequently used terms in a sample of depressed users. There is a link between anger and stress disorders, according to [6], [49]. A health monitoring system does not use these studies to analyse textual and linguistic aspects. Textual analysis has the benefit of not requiring specialised equipment, making it a more affordable option. It is possible to gauge a person's mental health by observing his or her mood. Psychiatrists and therapists have endorsed the use of these programmes, which track self-reported mood, and allow users to monitor their own mental health. Wang et al. [51] built a model based on sentiment analysis in micro-blogs to achieve an accuracy of roughly 80% in the diagnosis of depression. There is no implementation of RS in Wang et al. [51] and [52] study since they solely concentrate on depression monitoring. As previously mentioned, OSNs contain a massive amount of data that may be utilised to monitor the mental health of its users. One of the biggest challenges in creating an OSN is making it possible to monitor the user's mental state when they're at home, at work, or at school/university. Emotional disorder identification is a major difficulty for researchers in the field of related tasks. It is the goal of our study to address this issue.

D. Machine Learning and Deep Learning Approach

The ML may be used for classification, statistical analysis, feature selection, and data normalisation [53, 54]. Affective analysis and the challenge of mood detection are both classified by ML. A supervised or unsupervised procedure may be carried out using this method. It is common practise to use word2vec [54] to extract words before sending them to an ML algorithm. Words may be modelled as vectors and distributed representations can be computed using the skip-gram and Continuous Bag-of-Words (CBOW) models. Predicting a word's context using the CBOW model is one thing, but determining the context with the skip-gram is quite another. A sentiment-driven and standard embedding linked with various pooling methods is presented in Vo and Zhang's [55] study to extract the sentiment of Twitter comments. The 'Ekman' model of emotion [57] divides human emotions into six categories: rage, disgust, fear, joy, sorrow, and surprise. ML is widely used to classify these emotions [56]. One or more emotion classes in the negative statement indicates that the speaker is stressed or depressed. In the field of emotion categorization, the SVM technique has been frequently employed because of its outstanding generalisation features. In the domain of depression detection, SVM is utilised with a variety of feature selection strategies [59]. SVM is trained using the SMO algorithm, which was shown to be the

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most accurate in predicting depression in elderly people [60]. Sentiment analysis on OSN may also be done using Random Forest and Na ve Bayes algorithms, which have an accuracy of approximately 0.8 [16]. Semantic and emotional characteristics have been extracted using deep learning methods [25]. Recent experiments utilising deep convolutional neural networks [61], [62] showed significant improvements in NLP performance. Word embedding into a CNN was utilised by Collobert et al. [61] to handle NLP challenges such as POS tagging and semantic labelling. [63] The Vietnamese language solution employs a deep learning approach made of the combination of BLSTM, CNN, and CRF model, which achieves an F1-score of 88.59%.. In the context of labelling tasks, BLSTM considers both the past and the future. Here, CNNs represent characters at the character level and feed RNN-based BLSTMs to represent entities at the entity level. On top of the first BLSTM-RNN, another BLSTM-RNN performs the relation between entities. Researchers are attempting to increase the accuracy of user-submitted depression and stress disorder-related language.

III. METHODOLOGY

In this part, we'll go through the steps we'll take to implement our KBRS solution. Subjective assessments were used to assist define the model for the proposed KBRS in this study. The KBRS is broken down into its component parts in the following sections.

Subjective Tests

The eSM2 metric characteristics were determined by conducting a series of subjective assessments in a laboratory setting. The testing allowed to determine the preferences of the users and to analyse the KBRS resources utilised by the electronic gadget. When everything else fails, a remote technique was utilised to ensure that everything worked as expected. A group of people were chosen to act as assessors, and they were asked to answer questions about their emotional condition and compose Facebook phrases. They were diagnosed with acute stress and mild to severe depression based on their medical history. They were taken from an OSN with both positive and negative nouns, adjectives and verbs eliminated. CNN, BLSTM-RNN, and other machine learning algorithms were used to classify sentences based on their content of depressed, stressful, and non-depressive and non-stressful sentences. Note that the assessors were advised to write sentences on the OSN if they were inspired to do so, replicating a real-life scenario where they might publish postings in their regular routine. This is critical to emphasise. For the sentiment measure, we conducted face-to-face and remote subjective testing with the assessors. An experiment was carried out to determine whether characteristics of the user's profile affected the sentiment intensity value of a statement using face-to-face data collecting in a laboratory. It was also possible to assess the monitoring system's efficiency thanks to the data collected. The suggested sentiment measure was validated using the remote subjective approach. As a result, both the first work in the lab and the distant approach proved the theory. Assessors who were fluent in Portuguese were used to gather the data. Table I shows the 146 assessors, 74 men and 72 women, ranging in age from 18 to 43 years old, with a variety of backgrounds, such as area of birth (north, south, and southeast of Brazil), educational level, and other characteristics. There were three sets of ages (A1, A2, and A3) and three topics (A1, A2, and A3) for the sentences (entertainment, work or study, and family). Assessors were asked to complete a web-based questionnaire in which they had to choose adjectives that best described their emotional state, such as stress or sadness. The user was also asked to pick between joyful, tranquil, soothing, or inspiring messages in the event of depression and stress; from which the user may choose one or two messages. The RS uses the messages that are selected by the users. In addition, users may choose how many messages they want to receive and when they want to get them. The results of the survey provided

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insight into how a person's character traits could influence a sentiment metre. Later, the evaluators used OSN to write sentences, which a script then collected. Both the author of the sentences and the Sentimeter-Br2 metric assigned a sentiment score to the sentences, ranging from -5 to +5.

TABLE I
PROFILES ANALYZED ON SOCIAL NETWORK AND RESPECTIVE VALUES

Parameter	Values
Gender	man, woman
Age	(ranges) A1: 18 – 26; A2:27 -35; and A3: 36 - 43
Themes	entertainment, work/studies and family
Geographic location	North, south and southeast
Educational Level	higher education, bachelor or equivalent, MSc or PhD

Remotely monitored communications from assessors were examined over a five-week period by both the Sentimeter-Br2 sentiment measure and by the assessor who wrote the message. The assessors returned to the lab at the conclusion of the five-week period to evaluate how well the KBRS performed in a regular mobile phone. The emotion measure was applied to a total of 27,308 sentences taken from the OSN. The subjective test results were used to build a sentiment adjustment factor based on the user's profile. It is possible to apply this modelled adjustment factor to more conventional mood indices. Specialists updated the Sentimeter-Br2 lexicon, taking into account new slang and phrases, by adding new terms and their ratings.

The Proposed Knowledge-Based Recommendation System

The KBRS incorporates an emotional health monitoring system that employs a deep learning model and a sentiment measure called eSM2 to track the emotional health of its users. According to Fig. 1, an overview of the KBRS architecture is presented.

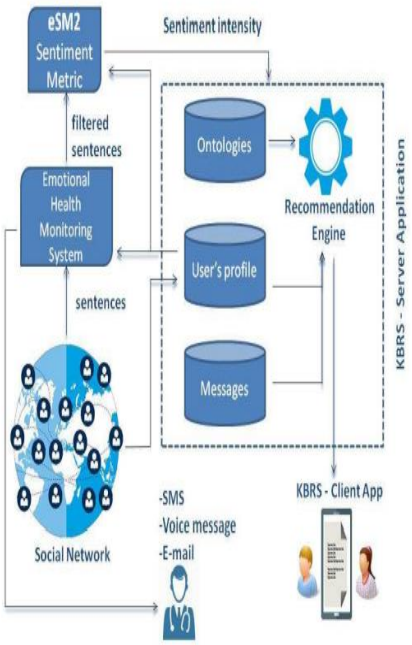

FIGURE 1: Architectonics of the proposed KBRS, which takes social network phrases into account.

Figure 1 depicts an OSN from which the sentences were taken. Sentences with a stress or depression content are identified utilising machine learning algorithms and the emotional content of the sentence. People who have already been enrolled with the monitoring system may get alerts through email from the system. Sentiment metre (eSM2) analyses the chosen phrases and uses the sentiment intensity as an input to the recommendation engine for further processing. According to their profile, ontology characteristics, and emotion value determined from their OSN phrases, users are delivered messages tailored to their unique needs and preferences by KBRS's server. The following are the parts of the system:

From the OSNs' data, a database of user profiles and information is constructed.

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• Messages: the recommendation engine will offer messages from a library of 360 messages, 90 of each kind (relaxing, motivating, cheerful, or tranquil messages). When a user is in a state of stress or sadness, they may choose one of two types of messages to receive. All of the messages were authored by three psychologists, and three additional psychologists verified their authenticity.

Sentences retrieved from OSN and filtered using machine learning to indicate depression or stress situations are used in this method. It's integrated into the system for keeping tabs on people's emotional well-being.

When using the eSM2 sentiment analysis, the phrases are narrowed down and given an overall sentiment score from -5 to +5. A number of prior research have examined and verified this range [3], [64]. To what degree is the message being conveyed depends on how strongly the phrase emotes its feeling. A message may be classified as extreme, moderate, or lower based on its degree of importance. A positive message is provided to the user if the monitoring system determines that he or she is under a lot of stress. Table II displays the range of sentiment intensity and the corresponding message intensity levels; the message intensity levels were selected based on the views of users. Intense adjectives like "much," "extremely," and "strongly" are examples of highly positive statements. In addition, the message's format is in line with the preferences identified during the first round of testing.

The recommendation engine uses ontologies, which are a system of classes, objects, and relations. The Ontology Web Language is used to express ontologies (OWL). Each class's data can be retrieved from the OSN. For health-related situations, the Nuadu ontology collection is used. The following courses from Nuadu were utilised in this study: There are a variety of ways to characterise a person's ontology. People's actions are documented in an ontology that explains them in detail. The entries might suggest a shift in a person's daily routine. A user's habits and timetables are documented in a sleep ontology. Risk ontology presents the facts regarding smoking and drinking alcohol, two harmful behaviours that have been linked to increased stress and the development of illness over time. An ontology that specifies the context in which a person exists (home, study, work, or travel). A lack of activity entries or a shift in sleeping hours may be explained by this information. As the name suggests, it is an engine that generates a recommendation set. Personal and contextual information about users on Facebook is utilised in the suggested solution. Facebook users, on the other hand, don't always share this information. Standard data, such as 8 hours of sleep, no bad behaviours and no preferences for work or study, are utilised when users do not provide their own information on their profile. According to our testing, just 5% of the users do not submit this information. An OSN-based content-based RS is also built, which feeds the system using just the terms that a user searches for on OSN. In order to keep things simple, we won't go into detail on the usual content-based RS in this part.

TABLE II
SENTIMENT INTENSITY RANGE AND RESPECTIVE MESSAGE INTENSITY LEVEL

Sentiment Intensity Range	Message Intensity Level
-5.0 to -3.0	An extreme level of positive message
-2.9 to -0.1	An intermediate level of positive message
0.0 to + 5.0	A lower level of positive message

B. Machine Learning-Based Emotional Health Monitoring System

Users' phrases are retrieved from an OSN and filtered using machine learning in the emotional health monitoring system. The KBRS is triggered in the event of a stress or depressive condition. Using the first-person pronoun, brief messages, unpleasant feelings, and low sentiment intensity are all symptoms of depression or stress. Different

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choices are used to provide warning messages when machine learning detects depressing phrases (voice message or e-mail). Only persons who have been previously approved by the system will get these communications. Sentences containing depressed, stressful, and non-depressive content were retrieved from an OSN using a machine learning technique. For example, "hate my life," "feeling sad," "I'm stressed," and other expressions of stress and depression were accessible in the models for recognising stress and depression expressions. Additionally, positive emotional expressions were weeded out to reduce the number of false positives in the diagnosis of depression. The emotional content of a statement is used to differentiate between depression and stress. Anger, contempt, and surprise are all connected with stress [6], [49]; whereas fear and melancholy are associated with depression [48]. As part of the training phase, 146 assessors wrote words on an OSN that were used to categorise stress, depression, and non-stress and non-depression expressions. As a whole, 27,308 categorised Facebook messages were utilised, with 23.70% of them relating to depression and stress phrases, respectively. Non-stress and non-depression sentences make up 50.103 percent of all texts. In the testing phase, 146 more assessors were included. SMO, Random Forest, and Na've Bayesian classification were employed in this study. Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMM) have shown promising outcomes in studies [65]. (GMM). This technique has poor accuracy and F1-score in early testing, though. In the next tests, they were no longer utilised. Theano [66] was utilised to build the deep learning architecture and other algorithms in this study. The accuracy of machine learning algorithms for stress and depression identification was tested and evaluated in all trials using 10-fold cross-validation. Binary attributes of depressed/non-depressed and stressed/non-stressed phrases were used in the categorization process. The character-level representation is computed by the CNN in the deep learning architecture, with characters acting as inputs. Convolutions for word characters are accomplished via the CNN's convolutional kernel, which generates ko for each

$$ko_i = htaf(M_i r_{ci} + b_i)$$

convolution I shown in the diagram (3).
htaf stands for the hyperbolic tangent activation function, and rci stands for the character-level representation of word I in parameter Mi, the parameter matrix. As in HTAF, the bias nodes on each network layer are linked to all other nodes. The HTAF is utilised in the hidden and output layers of the deep learning architecture to calculate the backpropagated error signal. According to, the Softmax layer is in charge of calculating the probability P of the relationship labels (4). The input letters are used to generate the layer h of concealed activation.

$$P = softmax(M_i h + b_i)$$

To compare performance, the SVM classifier was used instead of the Softmax algorithm in another test. BLSTM outputs were utilised to feed the HTAF layer, whereas the character-level representation and word embedding vectors were used to feed the BLSTM-RNNs in Fig. 2. To select the label sequence, the DE layer receives the output vectors from the BLSTM output layer. Information is captured in the next and reverse directions by the hidden states ha and hb. A neural network model's LSTM output does both bottom-up (h) and top-down (h) computation. The bottom-up records the current and prior stages in the neural network model, while the top-down computation creates information using the reversed inputs. The disease extraction is done in both the forward and backward orientations. The y parameter is the input vector in an LSTM unit, where y1 is the first word, y2 is the second word, and y3 is the third word; the subject of the sentence (imposition) represents a1 and the object of the sentence (stress) represents b1. In Figure 2, the DE layer produces the labels stress/non-stress. There were 10 batches,

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with a 0.8 momentum, 50 iterations, and a 0.5% dropout rate in the testing. Various combinations of these variables were tested until the best results were obtained before being settled on. Accuracy, precision, and the F1 score Machine learning algorithms were compared based on their Recall Area Under the Curve (PR AUC)[67], which was a performance parameter. Using the F1-score, recall and accuracy are combined into a single number. It is usual to use the PR-AUC incases of unbalanced data.

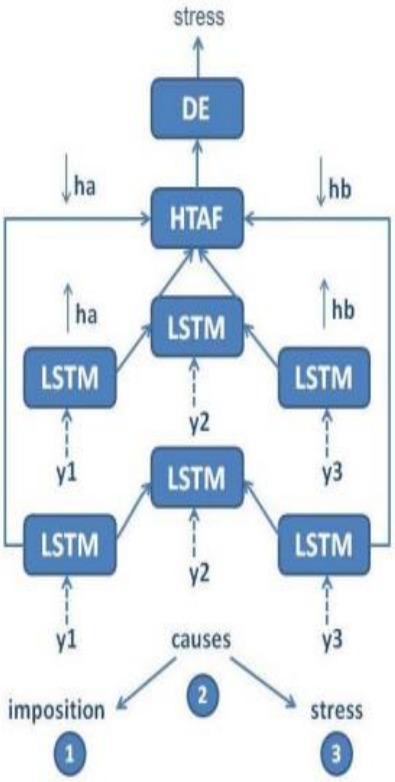

Fig. 2. The mechanism of the BLSTM-RNN method for classifying the relation of the sentence "'imposition causes stress"'.

B. eSM2 Sentiment Metric

In addition to the topic of the phrase, the correction factor is based on the person's age range, gender, theme, educational level, and geographic area. There were 146 volunteer assessors that contributed to this information. On the other hand, the app's UI might display this data. Because of this, users have the option of whether or not to provide their data in line with company privacy rules. For those who have a depressed profile, 29 of the assessors were asked to give the contact information of approved persons who would get warning letters to the email address provided. Accordingly, the correction factor for sentiment analysis is important since the user's characteristic and topic may affect how a phrase is assessed in terms of sentiment. Age, gender, educational attainment, and geographic region were all taken into account since early testing revealed that they had the most influence on the sentiment metric's overall score. PHP and AJAX programming languages may be used to extract these variables from OSN. An automated script based on keywords identifies the topic. The new eSM2 sentiment intensity measure, which takes an S-sentence into account, is presented in a new paper (5). A correction factor based on Sentimeter-Br2 and user profile characteristics is used in the eSM2. It was also tried using a second and third order polynomial function, but the exponential function performed better.

$$\begin{aligned} eSM2(S) = Sentimeter\_Br2(S) * C * exp(a_1 * A_1 ... \\ + a_n * A_n + g_1 * M + g_2 * F + e_1 * E_1 \\ + ... + e_n * E_n + t_1 * T_1 + ... + t_n * T_n \\ + l_1 * L_2 + ... + l_n * L_n) \end{aligned} \quad (5)$$

where:

• C is a scale constant;

As long as one of the a1... a factors is equal to 1, the other factors are all zeroes. Age-specific weight variables A1...An were used in this study, which focused on three age groups.

There are binary factors that are connected to gender; one of them equals one, the other is zero, and M and F are the weight factors for gender, man and woman.

It's important to note that t1...tn are binary factors, and if one of them is equal to 1, the others are zeros. Each topic has a different

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weighting factor, which goes from 1 to n. Entertainment, work/study, and family were all examined in this piece.

Geographic location is represented by the binary components l1...ln, which are all zero if l1 is equal to 1. Weight factors L1...Ln are the weight factors for each geographic area in Brazil (north, south, and southeast) that were examined in this study.

If one of the binary elements e1...en is equal to one, the other two are zeros; E1...En are the weight factors associated with each educational degree, respectively. Higher education, bachelor or equivalent, and master or superior were all included in this study, which was based on UNESCO educational levels.

The eSM2's performance was assessed in the laboratory by assessing the sentiment value of 20 sentences. With this data, each assessed phrase represents a 15-variable equation, resulting in 2920 equations and an overdetermined system. There are two steps involved in solving this problem: firstly, each equation is linearized, and then the least squares approach is utilised. The root mean square error (RMSE), the maximum and average error were used to evaluate the performance of (5).

The KBRS client-server architecture

Client and server applications for the KBRS are outlined below. A web application in Hypertext Preprocessor (PHP), JavaScript Object Notation (JSON) and HTML5 is used to deploy an application on a mobile device. Emotional health monitoring and the KBRS can only be used if the user grants the application authorization to view the user's profile information via the application interface on their device. Web servers, on the other hand, hold a variety of data, including user profiles and message databases. There are a number of other functions carried out by Web servers, such as recommendation engines and sentiment analysis metrics. In order to ensure that the user's device is not overwhelmed, it is vital to highlight that this device is only used to receive messages from other devices. An automated software regularly extracts the phrases and user profile from the Facebook social network. The eSM2 sentiment measure is used to assess the sentiment intensity of the filtered phrases, which are then used to diagnose sadness or stress. The user's application receives four sorts of messages, each with a different sentiment intensity level and ontology usage, depending on what the user selects. Sentiment analysis using eSM2 is used in the first message; sentiment metric and no ontology are used in the second message; and the third message does not have the sentiment metric but does have ontology. In the final message, sentiment metric and ontology are absent. A default affirmative message is given to the user's application client-side if the user does not input a sentence on an OSN.

EXPERIMENTAL RESULTS

Performance evaluations of emotional health monitoring systems, sentiment metric parameters, and a suggested KBRS performance assessment are discussed in this section.

The Emotional Health Monitoring System's Performance Evaluation

The training phase utilised 27, 308 tagged messages, as previously indicated. To train the deep learning model, preliminary findings revealed that utilising 75 percent of these messages yielded the same classification accuracy as using 100 percent of them. SoftMax's CNN BLSTM-RNN achieved the greatest results in this phase when all performance evaluation metrics were included. Additional 146 assessors took part in subjective assessments to evaluate the proposed model throughout the testing phase. Over the course of five weeks, 25,192 phrases were

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retrieved from an OSN. Table III displays the results of the testing phase's machine learning algorithms. According to Table III, we can see how the F1-Score, the accuracy and the PR-AUC of depressed, stressed, and non-stressed phrases are classified. According to Table III, the CNN BLSTM-RNN employing SoftMax performed the best. For sad, stressed, and non-stressed or non-depressed phrases, the findings showed an accuracy of 89.9, 89.9 and 93 per cent, respectively. Because of its back-propagation network optimization, Softmax achieved the best results [69]. Participants were observed and asked to classify their mood using an emotion icon after each day of the test period in order to assess the classifier methodology's performance (emoticon). All participants agreed that sending a notice message to the person in charge would be beneficial in the event of a depressed user. Messages like this were sent out by e-mail and text messaging. A stress and depression categorization accuracy more than 88% was achieved in this study, compared to comparable studies [11]–[17] and [19], respectively.

B. Definition of the eSM2 Sentiment Metric Parameters

There are average weight values for each parameter in eSM2 model that were derived from test results shown in Figure 3. Gender, age range, geographical location, and topic characteristics were shown to be the most significant determinants of sentiment. In order for the programme to collect user attributes, the user must provide their permission. To avoid violating ethical norms, the programme does not collect information on a user's religion or race.

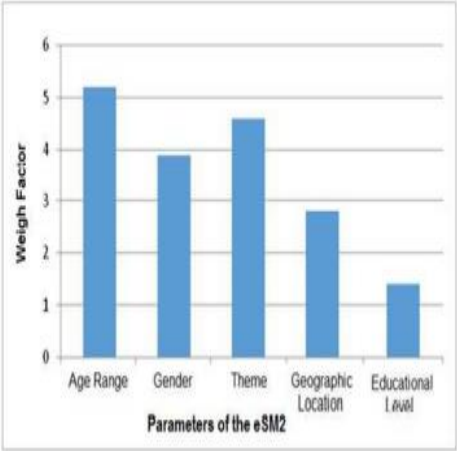

Fig. eSM2 sentiment metric weight factors are derived from subjective test results and are based on parameter weights.

According to Table IV, eSM2's performance is evaluated using RMSE, Maximum Error, and Average Error, as well as the sentiment intensity judged by the assessors in subjective, face-to-face evaluations.

Machine Learning Technique	F1-Score/Accuracy/PR-AUC for depressed users	F1-Score/Accuracy/PR-AUC for stressed users	F1-Score/Accuracy/PR-AUC for non-depressed and non-stressed sentences
CNN BLSTM-RNN using SoftMax	0.92/0.89/0.90	0.95/0.90/0.93	0.95/0.93/0.94
CNN BLSTM-RNN using SVM	0.90/0.87/0.88	0.91/0.88/0.89	0.92/0.88/0.91
SMO	0.83/0.84/0.82	0.84/0.85/0.83	0.85/0.85/0.83
Random Forest	0.79/0.81/0.78	0.80/0.82/0.79	0.82/0.83/0.80
Naïve Bayes	0.76/0.69/0.75	0.78/0.79/0.77	0.79/0.80/0.72

TABLE IV PERFORMANCE ASSESSMENT OF ESM2 CONSIDERING RMSE, MAXIMUM ERROR AND AVERAGE ERROR IN RELATION TO THE SENTIMENT INTENSITY SCORED BY THE ASSESSORS

Parameter	eSM2
RMSE	0.21
Maximum Error	0.34
Average Error	0.27

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C. Performance Evaluation of the Proposed Recommendation System

Testing of KBRS on a mobile device having a Wireless interface was done in a lab setting before it was made available to the public (Wi-Fi). One core of a 1400Mhz 32-bit Quad Core CPU, 1GB RAM memory is utilised for KBRS execution. For the purposes of calculating an average, the parameters were ranked on a scale of 1 to 5, with 1 representing the best outcomes and 5 representing the worst. Ontology and eSM2 were taken into account while calculating KBRS's energy usage and the apparent network resource consumption in Table V. These tests were carried out on the standardised equipment used by the assessors in the laboratory and the results are shown.

TABLE V
PERCEIVED VALUE OF CONSUMED RESOURCES IN THE ELECTRONIC DEVICE AND RESPECTIVE EVALUATION IN ACCORDANCE WITH A 5-POINT SCALE

Performance Regarding the Parameters	Perceived Average Value
Latency of the KBRS in general	4.2
Energy consumption of the KBRS application	4.2
Apparent network resource consumption	4.6

They also looked at ergonomic elements, with the assessors answering these questions on a scale from 1 to 6, with 1 denoting extreme dissatisfaction, 5 denoting extreme satisfaction, and 6 indicating a lack of an opinion.

• How long did it take you to acquire recommendations from others?

• How do you feel about the overall design and user experience?

What is your opinion on the suggested message variety?

In general, how would you rank the usefulness of the app? According to the findings of this study, 92% of the assessors were pleased with both the diversity in messaging and user interface of this programme. Nearly 90% of reviewers gave it an overall usability rating of five stars or above. We learned this by asking participants in the study whether they preferred to hear pleasant, tranquil, soothing, or inspiring messages while they were depressed or under stress. KBRS makes use of these messages. In addition, users may choose how many messages they want to receive and when they want to get them. To compare the findings of the eSM2 with the typical content-based RS, which is referred to as "no ontology," the KBRS, which is ontology-based, is utilised in Table VI. Using the eSM2 measure and ontology, 94% of KBRS users were happy with the findings. Table VI shows how satisfied people are with the message recommendations they get on their smartphone. According to the scale of adjectives, the response alternatives are very good, good, neutral and poor.

TABLE VI PERCENTAGE OF PERCEIVED VALUE OF FOUR KINDS OF RECOMMENDATION SYSTEM CONSIDERING AND NOT CONSIDERING THE ESM2 SENTIMENT METRIC AND CONSIDERING AND NOT CONSIDERING THE ONTOLOGY IN THE RECOMMENDATION SYSTEM

	Messages with eSM2 and ontology	Messages with eSM2 and no ontology	Messages without eSM2 and with ontology	Messages without eSM2 and no ontology
Very good	94%	89%	81%	69%
Good	3%	8%	8%	4%
Neutral	3%	3%	11%	2%
Poor	0%	0%	0%	21%
Very poor	0%	0%	0%	4%

Experiments that took into consideration the eSM were also undertaken in order to compare the performance of the eSM and the eSM2. With the exact test parameters as in Table VI, the eSM metric's results are presented in Table VII. The eSM measure

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and ontology were utilised in KBRS, and the data revealed that 89 percent of users were pleased.

THE PERCEIVED VALUE OF FOUR DIFFERENT TYPES OFRECOMMENDATION SYSTEMS IS SHOWNINTABLE VII. Recommendation systems may be improved by considering and not considering ESM's SENTIMENT METRIC and ontology.

	Messages with eSM and ontology	Messages with eSM and no ontology	Messages without eSM and with ontology	Messages without eSM and no ontology
Very good	89%	80%	74%	63%
Good	5%	4%	12%	2%
Neutral	2%	3%	4%	1%
Poor	2%	8%	8%	18%
Very poor	2%	5%	2%	16%

V. CONCLUSIONS AND FUTURE WORK

According to user profile information, geographical location and the topic of a phrase, the eSM2 was designed to assess the message's sentiment intensity. Current sentiment measurements do not take these two factors into account. A comparison of the eSM and eSM2 metrics' performance was carried out, and the eSM2's findings were found to be better in terms of perceptual evaluation. In light of this, it is clear that additional user profile characteristics may increase the sentiment metric's performance. In addition, the ontology notion was incorporated in the proposed KBRS. eSM2's user-profile-based adjustment factor may be used with different sentiment measures, which is an essential consideration. There are currently just a handful studies using OSN data to identify stress. CNN and BLSTM-RNN were used for character level representation and disorder entity identification to monitor OSN user sadness and stress, respectively, with an accuracy of 0.89 and 0.90, respectively. These findings are more accurate than those of previous studies. The proposed KBRS was tested against another KBRS that does not take into account a sentiment measure and ontology. The proposed KBRS surpasses the RS without sentiment metrics and ontologies, obtaining 94% and 69% of extremely pleased users, respectively. Users claim that a recommendation system (RS) that ignores ontology and sentiment metrics produces subpar suggestions, relying instead on generic and impersonal material. It is clear that ontology and tailored sentiment analysis are more successful than generic sentiment analysis when it comes to getting the greatest results from the KBRS. Researchers found that when appropriated users received suggested messages, they experienced an increase in their mental well-being. A key benefit of the proposed KBRS is that it does not rely on a complicated programming language to run on end-user devices, allowing it to take up less resources. Additionally, the client device interface is straightforward. As a consequence, the suggested KBRS may be used in various services, such as customer complaint systems and user assistance programmes, to identify rapid changes in consumers' emotions.

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