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A Review on Depression and Stress monitoring System via Social Media Data using Deep learning Framework

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Abstract: *Stress and depression are prevalent mental health conditions that significantly impact society. The use of automated health monitoring systems can be vital in improving the detection and management of depression and stress through social networking. Sentiment analysis involves natural language processing and text mining techniques that aim to identify emotions and opinions. Emotional computing is the development and study of devices and systems that can recognize, interpret, process, and mimic human emotions. By using sentiment analysis and deep learning techniques, effective algorithms and systems canbe created to target the assessment and monitoring of mental health disorders, especially depression and stress. This paper discusses the application of sentiment analysis and deep learning methods in detecting and monitoring depression and stress. Additionally, the paper proposes a basic design for an integrated multimodal system for stress and depression monitoring that incorporates sentiment analysis and emotional processing techniques. Specifically, the paper outlines the key issues andchallenges involved in developing such a system.*

Keywords: stress and depression; health; sentiment analysis, socialmedia, deep learning

I. INTRODUCTION

Social media is a valuable source of user-generated text, including opinions, feedback, and critiques that reflect attitudes and sentiments towards various topics. This paper presents a knowledge-based system that includes an emotional health monitoring system for detecting users with possible Psychological disorders, especially depression and stress. These disorders are often observed passively, making them difficult toidentify using standard diagnostic criteria questionnaires. Therefore, the author argues that online social behavior extraction provides an opportunity to actively identify psychological disorders at an early stage.

Depression and stress are common and disabling mental disorders that have a significant impact on society. Current methods for detecting and diagnosing depression and stress relyon self-reporting combined with healthcare practitioners' assessments. Effective health monitoring systems and diagnostic aids could be crucial in improving healthcare professionals' work and reducing healthcare costs. Sentiment and deep learning technology could help achieve these objectives by providing effective tools and systems for objective assessment, which support healthcare professionals' decisions.

This paper proposes a new and innovative approach to psychological disorder detection that does not rely on self-disclosure of psychological factors through questionnaires. Instead, it suggests using a machine learning technique to detect psychological disorders in social networks by exploiting the features extracted from social network data to identify potential cases of disorder with precision. The paper performs an analysis of the characteristics and applies machine learning to large- scale datasets to analyze features of the two types of psychological disorders. Sentiment analysis on Twitter uses several approaches, and deep learning models such as LSTM and RNN are gaining great results in emotion recognition. The paper focuses on classifying user emotion in Twitter messages using deep learning models such as LSTM and RNN..

II. BACKGROUND AND RELATED WORK

2.1. Sentiment Analysis

Sentiment analysis involves identifying the positive, negative, or neutral opinions expressed in text generated by users. This analysis can be performed at different levels: aspect or feature level, sentence level, or document level. Three main approaches to sentiment analysis exist: lexicon-based techniques, machine- learning-based techniques, and hybrid approaches. Hybrid approaches often combine lexicon- and machine-learning-basedapproaches, with sentiment lexicons frequently used in these strategies.

Before training data can be used to create a sentiment classification model, it must be cleaned. Tweets, for example, typically contain punctuation marks, non-characters, Retweets (RT), "@ links," and stop words, which can be removed using libraries such as Beautiful Soup. After cleaning, tweets can be split into individual words, which are then transformed into their base form using lemmatization, and converted into numerical vectors using word embedding or term frequency- inverse document frequency (TF-IDF) methods.

Word embedding is a language modeling and feature learning technique that maps each word to a vector of real values, such that words with similar meanings have a similar representation. This can be done using neural networks, and a commonly usedsystem is Word2vec (Glove or Genism). TF-IDF is a statisticalmeasure that reflects the importance of a word to a document ina corpus, based on its frequency in the target document and other documents in the corpus.

Both word embedding and TF-IDF are used as input features indeep learning algorithms for natural language processing (NLP). Sentiment analysis tasks transform raw data into vectorsof continuous real numbers, and can include objective or subjective classification, polarity sentiment detection, and feature- or aspect-based sentiment analysis. The subjectivity of words and phrases may depend on their context, and an objective document may contain subjective sentences. Aspect- based sentiment analysis focuses on sentiments expressed towards specific aspects of entities, while polarity and intensityare used to score sentiment analysis, indicating whether the sentiment is negative, neutral, or positive and the strength of thesentiment..

2.2 Application of Sentiment Analysis

Sentiment analysis has become increasingly valuable across various domains, such as business, government, and biomedicine. In the business intelligence and e-commerce fields, sentiment analysis can help companies better understand their customers' opinions and feedback to improve customer support, build better products, and enhance marketing strategies. For instance, Jain and Dandannavar [43] proposed ascalable and flexible framework for sentiment analysis of Twitter data using machine learning methods and Apache spark.

Sentiment analysis is also beneficial for recommender systems,as demonstrated in the work of Preethi et al. [12], where recursive neural networks were used to analyze sentiments in reviews to improve and validate restaurant and movie recommendations of a cloud-based recommender system. In commodity markets, sentiment analysis is an efficient tool for behavioral analysis [7].

In the medical domain, sentiment analysis has potential applications for analyzing opinions in health-related texts on social media and blogs [8]. The author proposed a medical lexicon to support experts and patients in describing symptomsand diseases using traditional machine learning and text processing techniques. Sentiment analysis is also applied to Patients' posts on social media in the field of mental health as asupplement or replacement for questionnaires [9]..

III. LITERATURE REVIEW

To achieve accurate sentiment classification, researchers have made significant efforts to integrate deep learning and machinelearning concepts in recent years. This section provides an overview of various studies on sentiment analysis of web content, including users' opinions, emotions, and reviews on various topics and products, using deep learning techniques. Deep learning models such as CNN, RNN, DNN, recurrent neural networks, and DBN have been extended to perform sentiment analysis tasks effectively. Researchers have also explored hybrid neural network approaches that incorporate multiple models to achieve better results..

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3.1 Convolutional Neural Networks (CNN)

The convolutional neural network (CNN) is a specialized type of feed-forward neural network that was originally used in various fields such as computer vision, natural language processing, and recommender systems. It is a deep neural network structure that typically includes convolutional and pooling/subsampling layers to generate inputs for a fully-connected classification layer. By filtering inputs, the convolutional layers extract features that can be combined from multiple filters. To increase CNN's robustness to noise and distortion, pooling/subsampling layers reduce the feature resolution. Fully connected layers are responsible for performing classification tasks. To prepare the input data for the embedding matrix, it was preprocessed by reshaping. The figure depicts an input embedding matrix that is processed through four convolution layers and two max pooling layers. The first two convolution layers have 64 and 32 filters, respectively, used to train different features, followed by a max pooling layer to reduce complexity and prevent overfitting. The third and fourthconvolution layers have 16 and 8 filters, respectively, followedby a max pooling layer. Finally, the fully connected layerreduces the vector's height from 8 to an output vector of one because there are two classes to predict (Positive, Negative)

3.2 Recursive Neural Network (RNN)

The Recursive Neural Network (RNN) is a type of supervisedlearning model that utilizes a tree structure with different matrices assigned to each node. Unlike other models, RNN doesnot require input reconstruction. In [29], a Treebank for Chinese social data sentiment was built to address the lack of labeled and large corpus in existing models. To predict sentence-level sentiment labels, the Recursive Neural Deep Model (RNDM) was proposed and achieved better performance than SVM, Naive Bayes, and Maximum Entropy. 2270 movie reviews werecollected and segmented using the Chinese word segmentation tool ICTCLAS. The proposed model improved sentiment label prediction for 13550 Chinese sentences and 14964 words. In contrastive conjunction structures, ME and NB performed better than baselines. In [30], a model comprising of RNTN (Recursive Neural Tensor Network) and Sentiment Treebank was proposed to effectively express the compositional effects at different levels of phrases, i.e., positive and negative phrases. The RNTN achieved 80.7% accuracy in sentiment prediction by performing fine-grained labeling over all the phrases and outperformed previous models. The study highlights the need for more influential composition models, as the meaning of long phrasescannot be effectively expressed by semantic word spaces in existing models, requiring richer and more supervised evaluation and training resources.

3.3 Deep Neural Networks (DNN)

Deep neural networks have become increasingly popular in recent years due to their ability to solve complex problems, such as image recognition, natural language processing, and speech recognition. The hidden layers in a deep neural network allow it to learn and extract features from raw input data, which can then be used to make predictions or classifications. This is achieved through a process called backpropagation, where the network adjusts its weights and biases based on the error between its predicted outputs and the actual outputs. The use ofdeep neural networks has led to significant improvements in many fields, including healthcare, finance, and autonomous vehicles.

3.4 Other Neural Networks

In this study [40] to overcome the complexity in word- levelmodels the character-level model have been proposed. The motivation of proposed model CDBLSTM is an existing modelthat is DBLSTM neural networks [41]. The focus of this work is only on textual content and on the polarity analysis of tweetsin which a tweet is classified into two classes, i.e., positive andnegative. There can be more options than positive and negativesuch as natural and finer but here the model is restricted only to positive and negative classes to compare with existing published results. The tweets are encoded from character level

3.5 Hybrid Neural Networks

This study [8] has proposed two deep learning techniques for the sentiment classification of Thai Twitter data, i.e., Convolutional Neural Network (DCNN) and Short Term Mem-ory (LSTM). Data processing was conducted properly. Data was collected from the users and their followers of Thai Twitter. After filtering the data, only the users with Thai

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tweets and tweets with Thai characters were selected. Five experiments were conducted to achieve finest parameters for deep learning, to compare the deep learning with classical techniques and to achieve the words sequence importance. Three-fold cross validation was used to verify the process. The results concludedthat the accuracy is high in DNN than LSTM and both techniques of deep learning are higher in accuracy than SVM and Nave Bayes but lesser than Maximum Entropy. Higher accuracies were found in original sentences than shuffled sentences so the words sequence is important.

In this research study [39] a hybrid model has proposed which consists of Probabilistic Neural Network (PNN) and a two layered Restricted Boltzmann (RBM). The purpose ofproposing this hybrid deep learning model is to attain better accuracy of sentiment classification. The polarity, i.e., negativeand positive reviews vary according to different context in orderto solve this type of problem this model performs well, neutral reviews are not considered. Experiments have done with datasets of Pang and Lee and Blitzer, et al., binary classificationimplemented on every dataset. The accuracy has been enhanced for five datasets by comparing with the existing state-of-the-art Dang, et al. [13]. There are no outer resources in proposed approach such as POS tagger and sentiment dictionary etc therefore it is faster too than competitor. To attain a reduced number of features the dimensionality reduction has been implemented as previous study used a complex strategy for feature selection.

IV. SYSTEM ARCHITECTURE

Pre-processing of train data uses NLP, which is a technique accustomed to perceive the computer information and handle the human interactions. The text comments that are given to the model is additionally being pre-processed. Both informations are passed to the sentiment library where the feature extraction of the pre-processed information is being done. From this, we tend to get the trained model for the knowledge sets. The system architecture is depicted in Figure

The classification is finished using LSTM that is another version of Recurrent Neural Network. The classifier takes the input and then classify them as positive and negative emotions. These data are then passed onto the another classifier for further classification of positive and negative emotions. The positive features are then classified as enthusiasm, fun, love, happiness, neutral, relief and surprise. The negative features are classified into angry, boredom, hate, emptiness, sadness and worry.

The classifier then predicts the output of the test input, whichprovides the results of the model. The text comments from the tweets undergo the pre-processing, since it contains URL id. Since we tend not to think about any address, we eliminateall the URLs and avoid all unwanted areas.

These processes are done in the pre–processing stage.

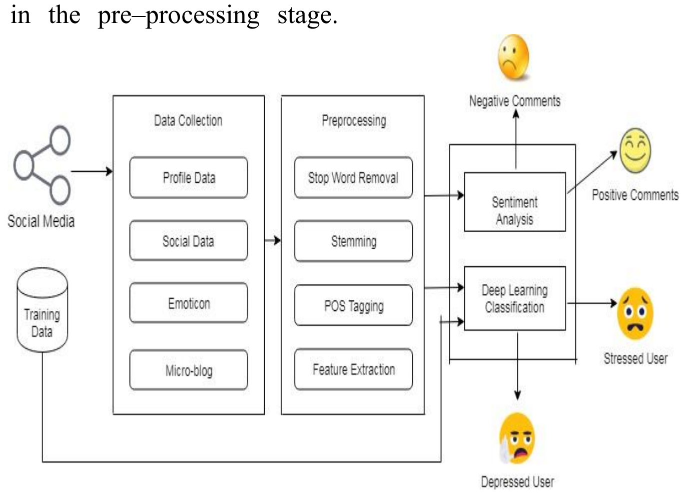

Fig. System Architecture

4.1 Proposed Approaches

In the proposed systemic approach, we formulate the task as aclassification problem to detect four types of detection of psychological disorders in social networks using the sentimentanalysis and deep learning framework:

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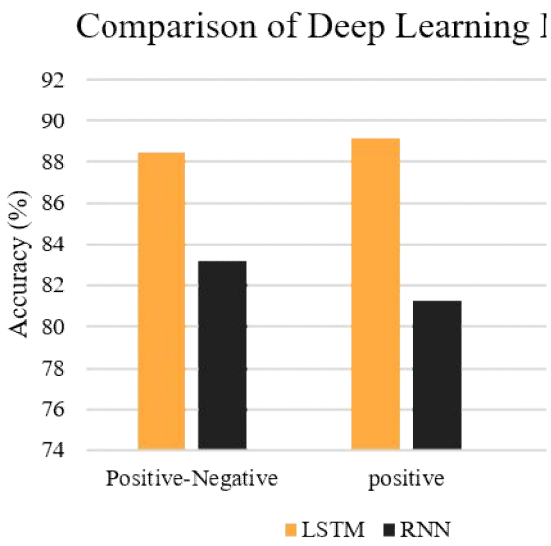
- Stress
- Depression
- Positive comments
- Negative comments



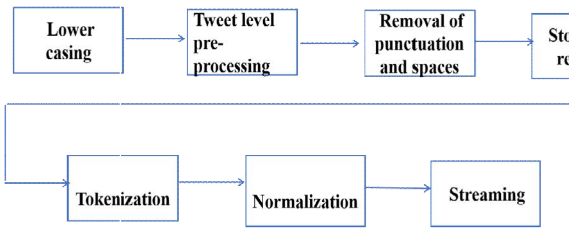
An innovative solution to monitor and detect potential users with emotional disorders, according to the classification of sentences with depressed or stressed content.

V. METHODOLOGY

5.1 Dataset

Obtaining accurate sentiment labels for tweets is a challengingtask that requires expertise in the field. Although datasets are available on social networking platforms, manual determination of tweet sentiment is time-consuming and not always accurate. For our experiments, we used three differentdatasets. The first dataset contained comments classified as positive or negative, the second dataset contained positive comments with labels of different positive emotions, and the third dataset contained negative comments with labels ofdifferent negative emotions. We had 100,000 data points in our positive-negative classification dataset.

To perform emotion analysis, we pre-processed the Twitter data to reduce noise and normalize the data for easier analysis.Tweets from Twitter are often noisy with unwanted emoticons, symbols, retweets, personalized wording, and other special characters. Hence, we performed pre-processing tasks to remove these unwanted elements. We used various pre-processing methods such as converting words to lower case, replacing additional dots with spaces, and removing unwanted spaces and special characters..

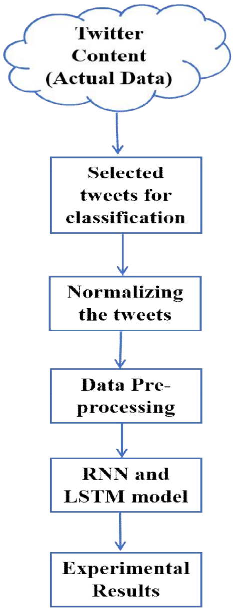


Pre-processing is an important step in analyzing Twitter data as the tweets are often noisy and informal. To make the analysis easier, we perform several pre-processing tasks such as converting words to lowercase, replacing multiple spaces with a single space, and removing unwanted special characters.

URLs are removed from the tweets as they lead to sparse results. We replace them with the expression ((www\. [\S] +))). User tagging using the @ symbol is replaced with the word USER-MENTION using the regular expression @[\s]

+. We use two types of substitutions, EMOJ-POSITIVE and EMOJ-NEGATIVE, for positive and negative emotions respectively, to represent smiley symbols and hand gestures.

Hashtags are removed from the tweets by removing the # symbol and replacing them with the word which comes after the symbol. The regular expression used to match the hashtags is # (+). Retweets are represented as \brt\b and are removed during pre-processing.



Finally, we clear all punctuation in the tweets using regular expressions such as ’’‘! ()-[]{};:’"\, <>. ? @%ˆ* ”’ /. will move to other tweets that also have the same hashtag. So, these are from the same area of interest. For replacing and giving a common format for these hashtags, we will remove the hash symbol and replace the hashtag with the word which comes after the hash symbol. The regular expression used to match the hashtag is # (+)

It is common to resend the tweets which we have already received from other users for many reasons. This gives more flexibility to the use of tweets and make this platform more interesting. Normally these retweets begin with the letter RT and during the pre-processing phase these RT will be removed as it is not relevant for the classification of tweet emotions. After removing URLs, hashtags, and retweets, the main step in tweet processing is removing punctuation marks from the tweets. This involves rephrasing the tweets, for instance, a tweet like "Oh my God!! I cannot believe this." will have its punctuation removed. All punctuation marks, such as "‘! ()- []{};:'"\, <>. ? @%ˆ*”’ /, will be removed to obtain better features for classification.

In addition, Twitter users often use various expressions to convey their emotions, such as using repeated letters in a word like "sooooo" to emphasize their feelings. During word-level processing, these duplications should be ignored. Other word-level processing steps include removing characters like "-" and"'", which are commonly used in expressions like "t-shirts" and "can't". These are represented in a more generalizedmanner as "t-shirt" and "cant".

VI. RESULTS AND DISCUSSIONS

In our experimental setup, we utilized the Kaggle dataset andevaluated our model's performance based on the accuracy of classification for positive and negative tweets. To compare ourresults with those of Ming-Hsiang Su et al., 2018, and Zhao Jianqiang et al., 2017, we used the same models, namely RNN and LSTM, on different datasets. Table II presents the accuracymetrics obtained for both LSTM and RNN across different classifications.

Our experimental results indicate that the LSTM model outperforms RNN and CNN classifiers in terms of accuracy. We successfully trained the LSTM model using the Twitter dataset and obtained three datasets for positive-negative, negative, andpositive classification, respectively.

During accuracy measurement, there may be a chance of misinterpreting predictions. For example, actual defective results being identified as true cases are termed as True Positive (TN), while some correct cases being recognized as

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negative arecalled False Positive (FP). We achieved a training accuracy of 88.47% and testingaccuracy of 79.16% for the positive/negative binaryclassification. For negative classification, we obtained a training accuracy of 89.13% and testing accuracy of 87.46%. For positive classification, we achieved a training accuracy of 91.32% and testing accuracy of 90.75%. These results clearly demonstrate the superiority of LSTM-based sentiment analysisover RNN.

Our proposed method incorporates both semantic word vector and emotional word vector, resulting in a remarkable improvement in system performance. We utilized Doc2Vect forfeature extraction in the word sequence for LSTM-based modellearning. Thus, its performance is better than that of RNN-basedstructures, which model the spatial relationship of the word sequence. Additionally, LSTM effectively addresses the vanishing gradient problem that RNN suffers from, where the model fails to learn and adapt even with significant changes in the weights. Moreover, LSTM performs better than conventional RNN in classifying the emotion of long sentences.

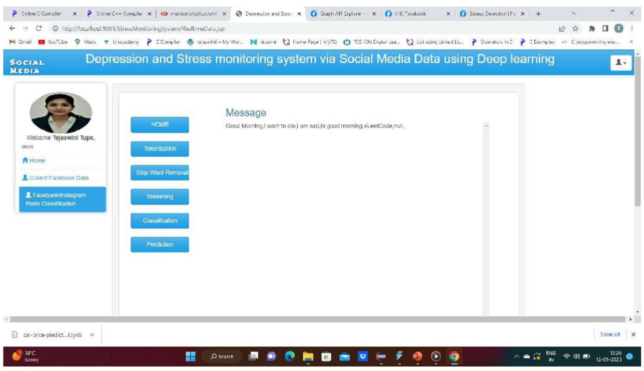
VII. CONCLUSION

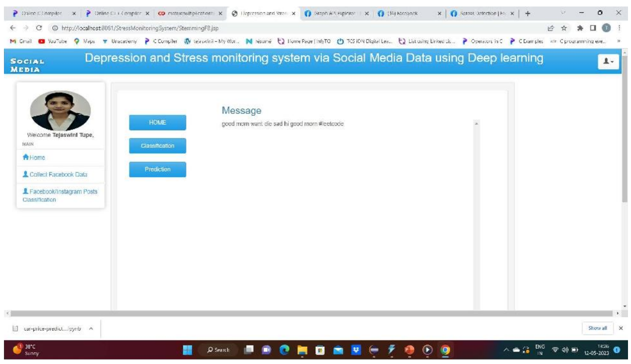
The proposed system aims to automatically identify potential online users with depression and stress, in order to help them before they take any drastic steps that could have a long-lasting impact on their health. We analysed a mixture of different wordsand emoticons in the tweets using deep learning techniques suchas RNN for modelling the classifier. By extracting features andgenerating a vector as input to the classification model, we achieved better results in classifying emotional messages on Twitter. In the future, we plan to investigate the personality of users based on their tweets to make the system more personalized.

VIII. ANALYSIS

This review summarizes several studies related to sentiment analysis using deep learning models, as shown in Table VII. The findings suggest that deep learning methods can achieve more efficient and accurate sentiment analysis. This is becausedeep learning models mimic the human mind's prediction abilities, making them better suited for predicting user views. Deep learning networks are also superior to SVMs and normal neural networks because they have more hidden layers. Additionally, deep learning networks can be trained in both supervised and unsupervised ways, and they carry outautomatic feature extraction, saving time on feature engineering. However, there are some limitations to deep learning models, such as the need for large datasets and the highcost of training. Training these complex models can take weeks, and it requires expensive GPUs. Overall, deep learningmodels have shown to be a powerful tool for sentiment analysis, capable of addressing different problem statements with little alterations to the system itself

IX. SCREENSHOTS





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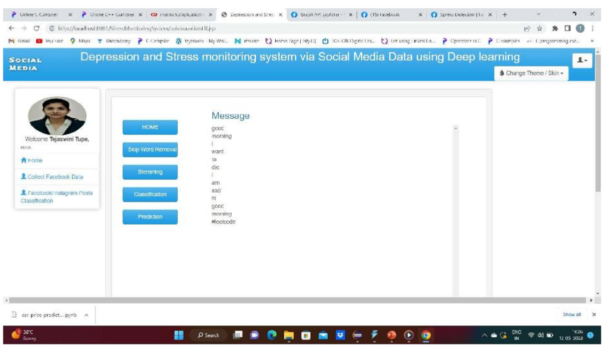

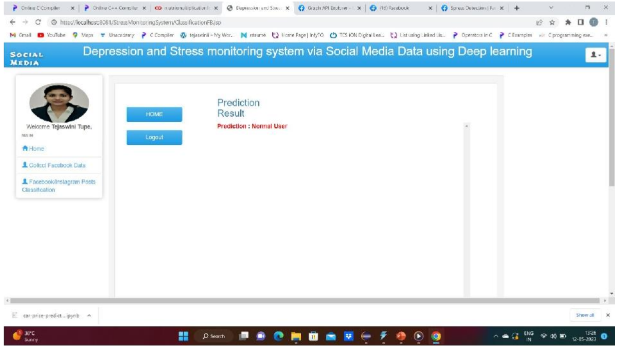

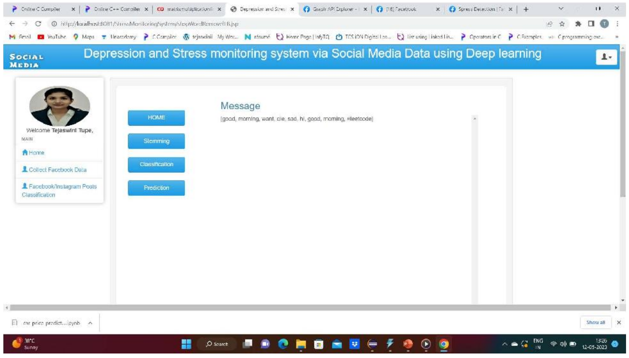

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