Depression Screening in Humans With AI and Deep Learning Techniques

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***Abstract*— Social media platforms have been widely used as a communication tool where most of the population expresses their feelings and shares life experiences. Along with general information about the public, these platforms hold an ample amount of content related to depressed users and thus can generate sensitive social signals indicating if a person is suffering from some serious issues, such as self-harm, suicidal thoughts, or intention for an unlawful act. Early depression detection using advanced natural language processing (NLP), deep machine learning, and transfer learning techniques can assist in designing an efficient system to detect major depressive systems at an early stage. The current depression detection models are not enough to capture sensitive social signals indicating the true mood, personality, and behavior of an individual. Thus, making the current systems unsatisfactory. To address this life-threatening human-health problem, we propose an efficient artificial intelligence (AI) and deep learning (DL)-based model for identifying depressed individuals on social media platforms. The model employs hybrid feature-based behavioral-biometric signals captured using Word2Vec, term frequency-inverse document frequency (TF-IDF) models to learn a convolutional neural network (CNN) and long-short term memory (LSTM) models. The data are captured from multiple sources using advanced crawling strategies to have data variety in the corpus. Thus, making the proposed system effective across platforms. The Dataset produced by this study is the first of its kind with a variety of depressive signals from online social network (OSN) platforms including Facebook, Twitter, and YouTube. The experiments have shown that both DL models LSTM and CNN, and the hybrid (CNN + LSTM) models achieved promising results on all individual as well as combined datasets. Out of 24 experiments for Word2Vec LSTM and Word2Vec (CNN + LSTM) models, we achieved the accuracy of 99.02% and 99.01%, respectively, and recorded as best results outperforming all the existing approaches on performance measures such as recall, precision, accuracy, and *F*1-score. The Word2Vec-based features have been proved optimal features for detecting depressions symptoms on Facebook corpus (FC) and YouTube corpus (YC) by achieving an accuracy of 95.02% (with CNN) and 98.15% (with CNN + LSTM), respectively.**

***Index Terms*— Artificial intelligence (AI), behavioral-biometric signals, convolutional neural network (CNN) and long-short term memory (LSTM), deep learning (DL), depression detection, mental health, social media.**

I. Introduction

MENTAL health is a behavioral disorder posed by individuals that causes them distress and impairment of their physiological functions. It disturbs their overall wellbeing including their thoughts, behaviors, and mood. As per the study [1], about 971 million (approximately) people across the world suffer from mental disorders. In the United States 1 in 6 children aged 2–8 years (17.4%) suffered from mental disorders [2]. These mental disorders can be of different categories such as depression, anxiety, schizophrenia, dementia, and bipolar disorder. A majority of these individuals remain untreated [3]. Due to the rise in competition and societal pressure to perform well, depression is increasing at an alarming rate amongst young college-going students. This leads to decay in performance, and overall learning capabilities of students and ultimately has an impact on the physical health of these young individuals. Even though depression is a preventable disorder [4], the social stigma surrounding it prevents them from seeking professional help. Furthermore, the individuals do not share their feelings even with their families and close friends. These issues prevent such patients from getting timely treatment, this aggravates their condition, increases their anxiety levels and in some cases leads to suicidal attempts [5], [6]. Thus, it is very important to identify such patients and provide them with timely professional help, as early detection of such disorders can reduce the damages caused due to depression [7]. An increasing number of college students and individuals in general suffering from these mental aliments use social media platforms such as Reddit, Twitter, YouTube, and Facebook to express their feelings, experiences, and challenges of mental disorders. Anonymity enables them to fully express themselves. Thus, the use of social media as a tool for early detection of depression has become very popular and effective. Since this data is massive in size,

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therefore, it becomes increasingly difficult to identify suicidal or depressed individuals manually. Thus, in this case, natural language processing (NLP) can be used as an effective technique to detect depressive users on social media. The natural language of an individual affects their personality, psychology, and overall, well-being. Thus, the study of linguistic styles used by people can divulge a lot about them. There have been many studies in the literature which use NLP for predicting and detecting mental disorders. Some of these studies use single platforms such as Reddit to detect depression [8]. Some use single features such as bag of words (BoW) [9], linguistic inquiry word count (LIWC) [10] or latent Dirichlet allocation (LDA) [11]. While others use a combination of multiple features such as BOW + LDA [12] and term frequency-inverse document frequency (TF-IDF) + LDA [13]. The authors of a rigorous survey [14] presented a systematic literature review on computational methods and technologies employed by several researchers for the detection of mental disorders. This study provided several observations such as the self-diagnosis tools such as questionnaires and rating scales employed for mental disorder identification are not enough as they are inconsistent and static. Furthermore, there are no normal generalized methods to detect mental disorders. They require hybrid methodologies which may use data from physiological signals, behavioral patterns, and even data online social media platforms to efficiently and early and effectively detect mental disorders. Even with significant research being done in this field, the challenges still remain.

This article is thus an attempt to search for a solution for depression detection. It identifies depressive users on multiple social media platforms such as YouTube, Facebook, and Twitter unlike the works in literature which focus mostly on single platforms. This system will be helpful for medical practitioners or psychologists to readily identify depressive users based on the language used. Furthermore, it will also be used for timely flagging of depressive users so that parents, friends, and well-wishers of such users can take the necessary actions to help such patients.

A. Contributions

This study has the following major contributions.

1) *System:* The design of an artificial intelligence (AI)-based system to detect depression symptoms in users on Facebook, Twitter, and YouTube with an accuracy of 99.02%.
2) *Dataset:* The dataset produced by this study is the first of its kind with annotated samples from popular social media platforms such as Facebook, Twitter, and YouTube.
3) *Data Collection (DC):* A hybrid approach combining techniques and tools such as Netvizz, iMacros, and tweepy and different strategies to collect the data (depression-related) from a variety of sources is explained.
4) A DL-based major depressive disorder detection system (MDDDS) is designed to show the performance of these hybrid features for achieving better accuracy and high performance.
5) *Social Signals:* A set of vocabulary terms and vocabulary behavior has been identified on each mentioned social media platform to distinguish between normal and depression-related textual samples, thus, acting as social signals to assist in designing an efficient depression detection system.

The rest of the article is organized as follows: In Section II presents recent background studies about depression detection. In Section III, we discuss the working architecture of the proposed MDDDS. Section IV discusses DC and preprocessing of raw data for the experiments. In Sections V and VI, we perform feature engineering (FE) and discuss the experimental setup for DL, respectively. The results obtained and analysis of the outcomes is presented in Section VII. In Section VIII, we perform a comparative study between the proposed approaches and the popular ones in the literature. We finally conclude our study with the conclusion of our work and future research directions in Section IX.

II. Background Study

There have been several studies done in the literature relating to mental health and spoken language. Many theories connecting depression with sociology and psychology have been defined in the literature. According to a cognitive theory [15], individuals suffering from depression usually use negative terms to express themselves and the environment around them. They mostly use negative words and the first person in writing or in speech. These individuals tend to isolate themselves from society and do not socialize. Based on the different theories relating mental disorders to the natural language many researchers have worked on relating word usage with mental illness. For instance, Adhikari *et al.* [16] have studied linguistic patterns of Alzheimer's disease patients in the Nepalese language. Rude *et al.* [17] have studied language used by college students who are vulnerable to depression. A study of word usage by suicidal and nonsuicidal patients has been done in [18] by analyzing the word usage of 300 poems written by nine suicidal and nine nonsuicidal poets from the early, middle, and late periods. As per their work suicidal patients use more self words or personal pronouns and few collective words. These individuals are aloof from society and are self-preoccupied. Furthermore, Ghosh *et al.* [19] proposed a multitasking framework to detect depression, and suicide notes using the existing standard emotion annotated corpus of suicide notes in English, CEASE, with additional 2539 sentences collected from 120 new notes. Another study [20] employed linguistic and acoustic aspects of speech to detect depression using bidirectional long short term memory (BiLSTM) on a corpus containing 59 interviews including 29 persons who are diagnosed with depression by medical experts and 30 control participants.

With the increased usage of social media and the internet as platforms for expressing opinions, feelings, and ideas, newer challenges have been built up to deal with mental health disorders. These platforms such as Twitter, Facebook, and YouTube act as a source of data to study the users' mental health. These data have been analyzed using NLP techniques to study their

TABLE I
DIFFERENT STUDIES WHICH HAVE BEEN CONDUCTED IN THE AREA OF MENTAL HEALTH DISORDERS DETECTION USING SOCIAL MEDIA PLATFORMS

Study	Data Source	Mental Illness Type	Technique(s)	Performance Measure	Remarks
Tsugawa et al. [21]	Web based questionnaire on Twitter	Depression	SVM, LDA	Accuracy and F-measure	• Features based on user activities have been used to predict depression • Topic modeling can improve the accuracy of the model • Minimum of 2 months of data is required for predicting depression
Wang et al. [22]	Twitter	Anorexia or eating disorder	Naive Bayes, an SVM with various kernels, and K-NN.	Accuracy	• Predict Anorexia or eating disorder based on 11 behavioural features • 6 social-status features • 80 psychometric features Linguistic Inquiry and Word Count (LIWC) lexicon
Shen and Rudzicz [23]	Reddit	Anxiety	logistic regression (LR), a linear kernel SVM, and a neural network (NN)	Accuracy, Precision	• Generate features that accurately classify posts related to binary levels of anxiety • Used topic modeling and emotional normalization for feature generation. • Features used: word2vec embedding combined with LIWC features • N-gram probabilities combined with LIWC.
Birnbaum et al. [24]	Twitter	Schizophrenia	Gaussian Naïve Bayes, Random Forest (RF), Logistic Regression (LR), and SVM. TF-IDF LIWC	Accuracy and F-measure	• Detects schizophrenia symptoms in patients • Feature filtering has been performed using ANOVA F-test to reduce number of features
Sekuli¢ et al. [25]	Reddit	Bipolar Disorders	SVM, LR, and RF	Accuracy and F1-score	• Detects bipolar disorders based on psycho-linguistic features • Features used include pronouns and articles, topical features and psychological features such as emotions based on LIWC categories, and words based upon similarities using Empath lexicon • lexical features used comprised of TF-IDF weighted bag-of-words
Ramírez-Cifuentes et al. [26]	Reddit	Anorexia	SVM, LDA	F1, precision, and recall	• Proposed methods for early detection of anorexia-related categories such as anorexia, body image, food intake etc • Based on TF-IDF and features such as LIWC and text length threshold
Zhou et al. [27]	Twitter	Anxiety disorder, Bipolar disorder, Depressive disorder, etc.	Stochastic, Gradient Descent	F1, precision, and recall	• Detects people with high probabilities of having five categories mental disorders such as anxiety, bipolar, depressive, obsessive-compulsive disorder, and panic disorder.
Tadesse et al. [8]	Reddit	Depression	SVM, LR, RF, AdaBoost, and Multilayer Perception	Accuracy and F1-score	• Used features such as Bigrams, LIWC, and LDA to distinguish between depressed and non-depressed users
Jagtap et al. [28]	Facebook	Depression	Ensemble learning, NLP,	Accuracy	• Depression detection using machine learning based techniques.
Eichstaedtet al. [29]	Facebook	Depression	LDA, Machine learning	Accuracy, F1-score	• Performs depression detection based on linguistic features such as expression of sad emotions, usage of interpersonal words such as loneliness and self-preoccupation. • Features used include unigrams, LIWC and bigrams. • Concluded that social media can replace existing screening procedures for mental illness detection.
El-RAmly et al. [30]	Twitter	Depression	BERT	Accuracy, precision, recall and F1-Score	• Performs depression detection for Arabic language. • Provided better results than lexicon and machine learning based techniques.

impact on the mental health of its users. Table I shows details of different works which have been done in the area of mental health disorder detection using social media platforms such as Twitter, Reddit, and Facebook. It provides us with insights

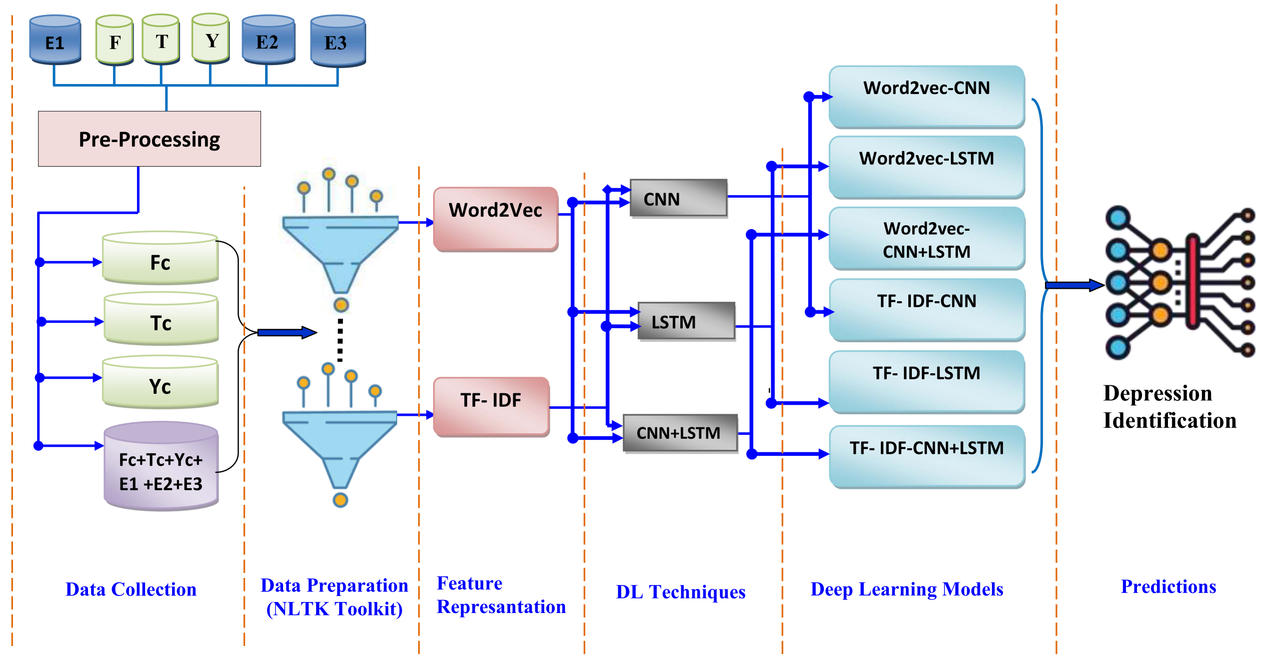

Fig. 1. Working architecture of MDDDS.

into how depression and the language used are interrelated to one another. It shows the social media data sources which were studied, the mental illness type investigated such as depression, anorexia, schizophrenia, anxiety, and bipolar disorders. The different machine and DL techniques, performance measures, and results obtained have also been discussed.

III. MDDDS: Working Architecture

This study is aimed to design a DL-based intelligent system to identify depressive symptoms in netizens using their publicly available text content on social media platforms. The whole system architecture as shown in Fig. 1 is divided into six modules starting with a collection of raw data related to depression from multiple existing repositories and social networking websites to training and designing of a classification system for the identification of depressive symptoms in the future user-generated text.

Each module is responsible to perform a certain set of specific tasks in order to prepare input for the next module excluding the final prediction system. We name these six modules as DC module, FE module, DL module, trained deep models (TDMs) module, and finally the classification/prediction (C/P) module. Each of these modules are discussed in several sections including Sections IV, VI, and VII.

IV. DC and Preprocessing

For conducting the experiments, the primary need and the main ingredient is the data. Quality of data is the recipe for the accurate results. The process of DC for this research is one of the main contributions of this study as the dataset prepared is the first of its kind for the discussed problem. The data have been collected from several sources such as existing repositories, publicly available datasets, and online social media platforms including Facebook, Twitter, and YouTube. For every source, a different set of strategies has been employed to collect the adequate amount of samples suited to our experiments as discussed below. The word-clouds shown in Figs. 4, 5, and 9, presents the vocabulary terms used on Facebook, Twitter, and YouTube respectively. The size of each word indicates its frequency in the particular dataset.

A. DC From Existing Sources

Since the content related to depression disorders is a sensitive data, therefore not easily available in adequate quantity. Very few possible datasets which best suit our problem domain we came across include small noisy depression dataset [31] on GitHub repository, we refer it dataset E1, and depressive tweet content corpus [32], referred as dataset E2. The former contains around 4k tweets expressing depressive mode of the twitter user and the later with 7k instances written by general public on social media and were identified as users with depressive disorders by medical experts. The dataset E1 holds the columns including id, data, content, text, time, time_zone, user_name, and label out of which the columns of our interest were the content (topic of the text), text (user text), and the label (depressive/non_depressive). The second dataset holds the columns such as user_id, u_name, message, and label. Here, the columns of our interest are user_id, message, and label. It is to be noted that both the datasets are used to study for depression detection in online users, therefore contains depression and normal instances. We realized that the two datasets have more depression-related samples than the non_depression ones. Therefore, we collected and combined more normal instances from a third dataset namely the "SMILE Twitter Emotion Dataset" [33], referred as E3 in this study. Apart from user_id the columns in this dataset include happy, not_relevant, angry, sad, and surprise. Since we need the normal (nondepression related) samples, therefore we discarded the instances with label angry, sad

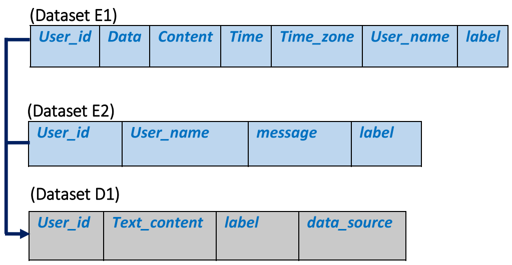

Fig. 2. Normalization of existing datasets E1 and E2 into D1.

and not_relevant, and stored the happy and surprise-related instances in the dataset D1 with an additional column namely source which holds the source information of each instance for our reference as depicted in the figure below.

B. DC From Online Social Media Platforms

To bring the variety in the dataset, the samples related to depression symptoms have also been collected from the popular social networking platforms as these sources hold the most recent and updated information about their users. It has been seen that these online social networks (OSNs) play an important role in daily social activities, and also, it has also been observed that most of the users suffering with depression express their feelings online, therefore, these OSN platforms holds important social signals to identify the moods and emotions of the users. We collected the data from popular social media platforms such as Facebook, Twitter, and YouTube. For Facebook and Twitter, we scrapped the data using Netvizz app [34] and tweepy and TWINT packages [35] framework based on the topmost keywords in the existing depression-related datasets. The word clouds shown in Fig. 3 depicts the most frequent vocabulary terms found in two existing datasets including few new key phrases used to collect the data.

After performing the exploratory data analysis (EDA) of both datasets individually we found a lot of vocabulary terms and phrases as social signals to identify the depression symptoms in the users. Apart from a number of distinguishing dictionary terms the words such as *“Alone,” “loss,” “Sad,” “Hopeless,” “Depress,” “Stress,” “failure,” “end_of_life,” etc.*, has been found as the top most terms used by people in both the corpse’s. The examples from the both the corpse’s are shown in Table II.

It has been observed that people on pure social networking platforms like Facebook are more open and much expressive then the ones on Twitter. In other words, we can say people discuss about lot of stuff going in their lives such as family issues, relationship issues, career-related problems, and health issues. Whereas blogging websites like Twitter, people are not much expressive, therefore talk about very few topics like career issues, job and unemployment problems, etc. Some of most frequent words found Facebook corpus (FC) include *jobless, cheating, fake_people, God, quit, loss, depress, empty, scary, hopeless, dishonest, Low_energy, pain, crisis, fatigue, etc.* On the other hand, the words like *aimless, jobless, unemployment, uselessness, stress, pressure, Sad, directionless, anxiety, poverty* as can be seen in the table we have

Fig. 3. Depressive symptoms word-cloud presenting most frequently used depression-related vocabulary terms found on social media platforms.

Fig. 4. Facebook word-cloud showing most frequently used depression related vocabulary terms on Facebook social network.

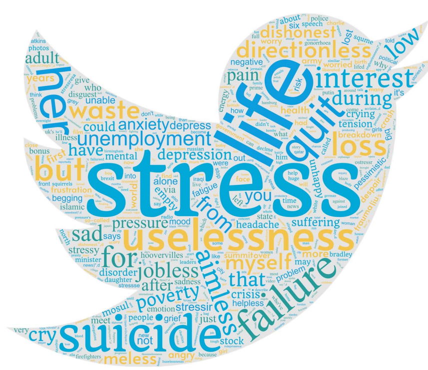

Fig. 5. Twitter word-cloud presenting most frequently used depression related vocabulary terms on Twitter blogging website.

categorized the vocabulary terms in several categories including Mood_vocab, Body_vocab, Relationship_vocab, Offensive_vocb, and vocabulary for personal pronouns (PP_vocab) as per their semantic information. The table also presents the vocabulary terms mostly used by users while expressing their depressive behavior online.

For the YouTube, we employed a slightly different strategy to extract the data. Since we know that the YouTube is

TABLE II
EXAMPLES OF SENTENCES SOCIAL SIGNALS FOR IDENTIFYING DEPRESSIVE SYMPTOMS FROM FACEBOOK AND TWITTER SOCIAL MEDIA PLATFORMS

Corpus	Vocabulary Term(s)	Example Sentence (from dataset)	Vocabulary Category
Facebook Corpus (FC)	Hopeless, Helpless, Sad, Angry, Disgust, Frustrated, etc.	*"I am hopeless now… looking for some sun to heal me up", "Life is disgusting like hell, it is like not living anymore. . ."*	Mood_vocab
Facebook Corpus (FC)	Head, Eyes, Chest, Throat, Tongue, etc.	"*My head will explode with depression" "… with all the pain in my chest*"	Body_vocab
Facebook Corpus (FC)	Family, Parents, Partner, Mother, Girlfriend, Boyfriend, etc.	"*Life is beautiful with an honest partner, without it is hell like mine*"	Relationship_vocab
Twitter Corpus (TC)	Curse, Hell, F***, fatigue Trauma, bloody, failure/fail etc.	*"Hell with this life. . ." "F***ed up my entire career. . ." "I am cursed with my success" "I have proved to be a failure in life"*	Curse_vocab
Twitter Corpus (TC)	obscene, vulgar, toxicity kill, harm, illegal, end_of_life, etc.	*"Naked like evil, life is ending me up. . ." "All alone in peace, checking on my blood color. . ." "All problems vanish with you as you leave the world" "Death, the end_of_life seems to be the only solution . . ."*	Offensive_vocab
Twitter Corpus (TC)	I, me , myself, our, us, etc.	*"People like us should not breathe anymore" "Am I the only with such an unbearable pain in my chest. . . " "It is me the reason for all bad things happening in the family. . "*	PP_vocab (Personal Pronoun)

neither a pure social networking platform like Facebook nor a blogging site like Twitter, YouTube is a website mostly used for sharing video. Millions of users have created their accounts on the YouTube allowing them to upload videos that anyone can watch. It has been observed that every minute of a day, 35 h of video is being uploaded to this site [36]. People can share these videos and write comments of unlimited size as well in different languages. To extract the depression-related textual comments we identified most depressive songs, or depressive lyrics on YouTube and created a list of 100 songs in English, and Hindi with their titles along with their page links. Using iMacros technology-based crawler each collected link is visited to extract the comment content on the page. iMacros is a browser add-on [37] which enable us to write different scripts to crawl and scrap data from web pages. Some of the examples of depression-related songs on YouTube are shown in Table III.

The comments are scrapped from the link one by one automatically by iMacros scrapper based on several filters such as language = "English," special_sumbls = "discard," etc., the pseudo for the iMacros crawler for YouTube on collected links is shown in Fig. 6.

The input file in the algorithm (*depressive_liks.csv*) contains YouTube links of manually selected depressive or anxiety-related songs or lyrics. As can be noted from the algorithm the basic filter such as if the comments to the song are in English is filtered, otherwise the comment is discarded in the final processed file. The more details on the description of the collected datasets used in this study are given in Table IV.

Algorithm: *YouTube Content Crawler* (Y_{CC})

```
Input: 'depressive_links.csv','depressive_vocab(ngrams).csv'
Output: depressive_comments.csv
Begin
  For each instance in depressive_links.csv do
    CrawlTo comments_section do
      u − name = scrap(user − name)
      content = scrap(comment − text)
      #replies = scrap(number of comments)
      #views = scrap(number of views)
      #likes = scrap(number of likes)
      agg_reply_text = scrap(reply comments)

      depressive_comments.csv =
          add.(#replies, content, #views, #likes)
  end for
  depressive_comments
          = depressive_comments .csv

  For each tuple in depressive_comments do
      if tuple['content'].language == Eng
          depressive_comments = depressive_comments .add(tuple)
          else tuple['content'] = discard
          end else
      end if
  end for
  return depressive_comments.csv
End
```

Fig. 6. Algorithm: YouTube Content Crawler (YCC).

C. Data Preprocessing

It has been observed that most of the machine and DL algorithms show poor performance with processing raw data as these content is not properly machine understandable. Therefore, before feeding such data to a learning algorithm it must be preprocessed. In this study, we have conducted a meticulous preprocessing of raw data as shown in Fig. 7.

As can be seen in Fig. 1, the raw data coming from different resources is stored in individual databases (.csv sheets) and then first passed through general data cleaning normalization and preprocessing filters including noisy data removal, missing data handling, and inconsistency handler filters. In the case of removing the noisy and unwanted data tokens like html tags, extra white spaces, special symbols, and digits have been removed from each instance. The missing data handler is responsible to deal with empty cells, NaN values, etc. The instances with more than 50% of missing cell values (tokens) or filled with NaN entries are discarded from dataset, otherwise filled with the value calculated either from the mean

TABLE III
EXAMPLES OF DEPRESSIVE SONGS, DEPRESSIVE LYRICS ON YOUTUBE PLATFORM

Song Title	Language	Link	Views	Comments	Likes
I hate myself	English	https://www.youtube.com/watch?v=FskL-2jrgF0&t=31s	30M	820k	741k
Depression songs for Depressed people	English	https://www.youtube.com/watch?v=NMCgN4QK1Gw&t=480s	27M	48k	532k
Alone Sad Jukebox	Hindi	https://www.youtube.com/watch?v=TCFuCCY-pxc	17M	18k	428k
Broken Hearts hindi	Hindi	https://www.youtube.com/watch?v=-F8spsC9eFw&t=	32M	13k	239k
NF - Goodbye	English		20M	21k	416k
Best Of Breakup Mashup	Hindi	https://www.youtube.com/watch?v=iyBbXFKEmUs	23M	11k	409k

TABLE IV
DESCRIPTION OF DATASETS AFTER BALANCING AND NEWLY CREATED DATASETS

Dataset/Corpus	**#Depressive-instances**	**#Non-Depressive-instance**	**Total #instances**
Twitter Corpus (TC)	6080	5510	11590
Facebook Corpus (FC)	2700	3000	5700
Youtube Corpus (YC)	7520	6509	14029
Dataset (E1) [31]	4078	4000	8078
Dataset E2 [32]	5550	4500	10050
Smile Annotation Dataset(E3) [33]	NA	3497	3497
Total	**25928**	**27016**	**52944**

of associated cells or with a least value, thus not effecting the statistics of the modified sample. It should be noted that other data cleaning and preprocessing techniques have been introduced in the feature selection Section V as well. Finally, the duplicated instances (posts, tweets, and user text) have been removed from the collected samples.

In the second phase as shown in Fig. 7, the cleaned data has been passed again through the pipeline of natural language tool kit (NLTK) libraries to further process it for analysis. The basic filters in NLTK toolkit include normalization, tokenization, stop word removal, stemming, and lemmatization. Normalization converts all the text into the same case (small case in our study), tokenization is responsible for breaking the raw text into words, sentences called tokens. These tokens help in understanding the context or developing the model for the NLP. NLTK has a very important module called tokenize which further consists of models such a word tokenize and sentence tokenize. Stop words in English are commonly used words for example, "the," "is," and "and.". As these stop words appear in great quantity, hence providing little to no meaningful information for classification task, therefore are removed from the text before training a model. Finally, stemming is responsible for reducing words to their root forms such as mapping a group of words to the same stem even if the stem itself is not a valid word in the language. An attempt has been made to explain these NLTK filters using the help of a figure with example sentence as shown in Fig. 8. It should be noted that in the instances for which the labels are not present, for example, the newly collected instances the formal annotation process is applied followed by a manual human

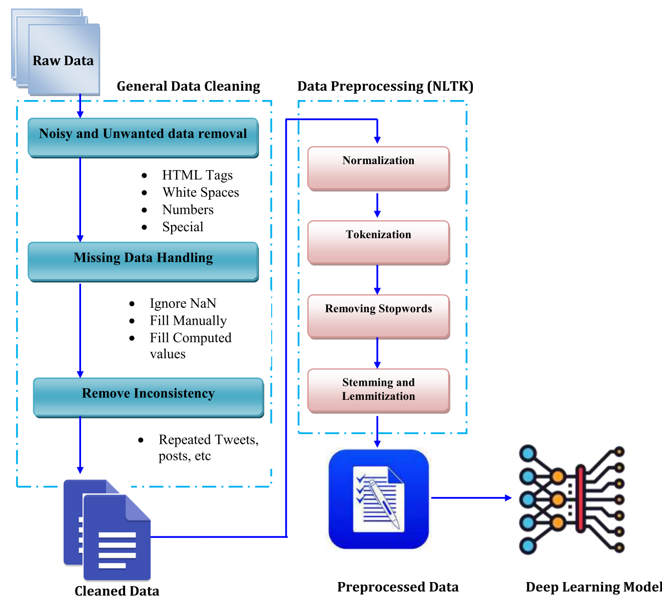

Fig. 7. Cleaning and preprocessing of raw data for analysis.

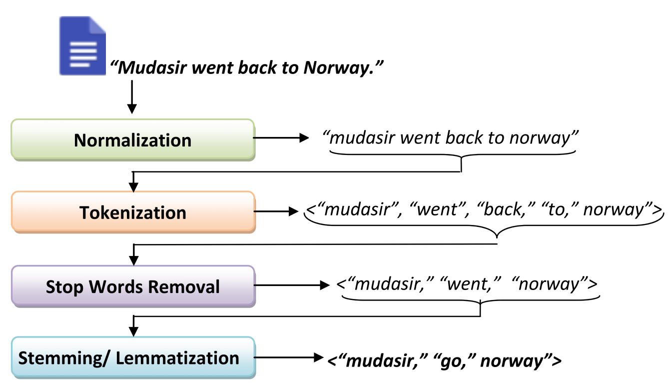

Fig. 8. Preprocessing of user data with NLTK libraries.

check. Otherwise, the labels are not modified at any stage of experiments and are kept the same as were in the existing datasets.

V. FEATURE ENGINEERING

Once the adequate amount of data to train a DL model is collected, the next step in process is to extract features out of it which provide most discriminating information of classes. Since the proposed study is an attempt to identify depressive symptoms in online users from the textual content is more like a vocabulary analysis. Therefore, to know and understand this behavioral pattern in using vocabulary, we employed two basic models, viz., TF-IDF [38] and Word2Vec [39] model to derive the features from the collected dataset. Both the two feature selection and extraction techniques are briefly discussed as follows.

A. Word2Vec-Based Feature Representations

Word2Vec model is implemented to extract the relationship between words within corpuses. It makes use of neural networks (NNs) models to learn the word embeddings with one input layer, one hidden layer, and final output layer. It takes input as a text corpus and generates an output vector. The output vector is generated in such a way that similar words stay close to each other in the vector space. The NN inside Word2Vec performs mathematical operations on tokens (words) to detect the word similarities. The two main training algorithms for Word2Vec model include continues BoW (CBoW) and skip-gram [40]. The former is using the context to predict a target word (w) and later is using a word (w) for the prediction of target context, i.e., neighbors. In mathematical terms, we can say

$$\text{if } w_{i-1},\ w_{i-2}, w_{i+1}, w_{i+2} \text{ are given words} \\ -\text{the Word2Vec CBoW will provide } w_i \quad (A)$$

Similarly for the word2Vec skip-gram model can be mathematically stated as follows:

$$\text{if } w_i \text{ is given word the Word2Vec Skip} - \text{Gram} \\ -\text{will provide } w_{i-1},\ w_{i-2}, w_{i+1}, w_{i+2} \quad (B)$$

The output of Word2vec model is a set of word-vectors where vector close to each other in the vector space have the similar meaning, and the vectors away from each other have different meaning. For example, the words like *crying* and *pain* will be close in the vector space while as the words such as *Orange* and *India* will be seen apart in vector space.

The CBoW model has been applied to extract the vocabulary terms used in depressive posts, tweets, and normal (non_depressive) text. The most commonly used terms such as *depression(4321), quit(3259), pain(1785), headache(1212), disgust(1201), negative(1189), and helpless(1339)*, have been found in depression-related content collected from Facebook, Twitter, and YouTube, etc., as shown in the word-cloud in Fig. 3.

Furthermore, we also observed a difference in the vocabulary terms used across three platforms. For example, the most frequently dictionary terms used by people on Facebook social network include *fake(7432), Suicide(6551), die(7012), sadness(4470), quit(2440), pain(3507), dishonest(4025), pressure(786), fatigue(1097)*, etc. While terms like *stress(4023), life(4084), failure (3897), uselessness (2920), unemployment(1701), aimless (986), loss(808), waste (681)*, etc., have been seen as the most frequent terms used by people on the Twitter site. Similarly, the different set of vocabulary

Fig. 9. YouTube word-cloud with most frequently used depression-related vocabulary terms found in YouTube comments.

terms have been found in YouTube comments. For example, the terms such as *Hell(5020) trauma(4972), curse(4817), worse(4017), death(3986), naked(3905), f***(3881), broken(3808), her(3010), mood(2972), myself(2766)*, etc., are observed as the top most keywords in the data collected from YouTube. The word-clouds for top most vocabulary terms is shown in Figs. 1–3 for Facebook, Twitter, and YouTube corpus (YC), respectively.

B. TF-IDF-Based Feature Representations

TF-IDF technique has been also used to derive the discriminating features to distinguish between depression and nondepression-related instances. TF-IDF is basically a statistical measure to estimate how relevant a word is to a document in a collection of documents. It is achieved by performing the product operation on two matrices-how many times a particular word (w) is present in a document (TF) and the number of documents ($|D|$) in which the word appears (IDF).

In formal ways, we can state as follows:

$$T_f = (\#\text{ repetitions of a given word } w \text{ in a document } (d)/ \\ -(\#\text{ unique terms in a document } (nd)) \quad (C)$$

and

$$ID_f = \log(\#\text{ total documents } (D)/ \\ -(\#\text{ of documents containing word } (nd \in D)) \quad (D).$$

To sum-up TF-IDF model in more formal and understandable manner, TF-IDF value of a word w in a document d from a set of documents D can be calculated as follows:

$$T_f - ID_f(w, d, D) = T_f(w, d) * ID_f(w, D)$$

where

$$T_f(w, d) = \log(1 + \text{frequency}(w, d))$$

and

$$ID_f(w, D) := \log\left(\frac{|D|}{|d \in D : w \in d|}\right). \tag{1}$$

We applied TF-IDF technique to the user instances to associate the words to their most relevant document. The highest scoring word or token for a document are the most relevant to the topic or to the document. It has been observed

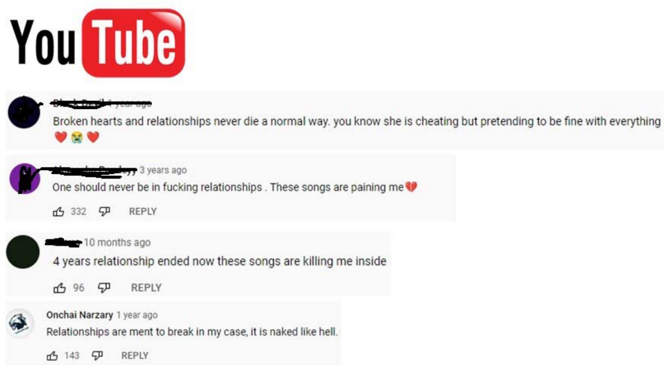

Fig. 10. Example showing vocabulary behavior followed my users on YouTube.

that people with depressive symptoms use negative terms such as crying, dark, quit, lost, etc., in a very frequent manner rather than normal (nondepressive) words like cinema, family, adjust, food, etc. It has also been observed that most of the key-terms used in depression-related posts belong to either sad or disgust emotion categories. Therefore, techniques like TF-IDF can learn keywords used in one class in order to better distinguish it from other classes. Also, on YouTube there is no concept of individual text posts like with Facebook and Twitter. Users watch a shared video and can read the comments from other users. A trend is being observed within these users, they mostly write their comments with all the previous comments in mind. An attempt is made to make it more clear with Fig. 10 where a screen-shot of some comments are taken from a selected sad song on YouTube in which several users make use of vocabulary term relationship by following the prior user comments.

It is clearly visible that the users are using somewhat the same pattern by following each other on YouTube. This pattern can be better learned by TF-IDF technique to know the topic and the course of the post or comment.

VI. Experimental Setup for DL

The prime objective of this article is to identify the people with major depression disorders on social media help them with early medical remedies and consultations. Thus, protects an individual from committing serious actions, such as suicide. Our aim here is to design a DL-based system to automatically identify a user with depression symptoms from a piece of text or say a paragraph he or she has posted. The whole experimental setup for the proposed study is shown in Fig. 1. The alphabets F, T, and Y in the figure represent the dataset collected from Facebook, Twitter, and YouTube, respectively. After applying the basic preprocessing the tasks these three corpora are represented as FC, Twitter Corpus (TC), and YC, respectively.

To conduct experiments in this direction, we initially started with three newly created datasets (FC, TC, and YC) for this study based on several rules as discussed in the DC Section IV. As mentioned in the section, the three datasets contain user post, tweets, and comments with other columns collected from Facebook, Twitter, and YouTube, respectively,

TABLE V

Possible Combinations of 24 Experiments Conducted in Three Phases Toward Identification of Depression Symptoms

Phase	Model	Corpus
Phase 1	Word2Vec-CNN	Facebook Corpus (FC)
Phase 1	Word2Vec-LSTM	Facebook Corpus (FC)
Phase 2	Word2Vec-CNN+LSTM	Facebook Corpus (FC)
Phase 1	Word2Vec-CNN	Twitter Corpus (TC)
Phase 1	Word2Vec-LSTM	Twitter Corpus (TC)
Phase 2	Word2Vec-CNN+LSTM	Twitter Corpus (TC)
Phase 1	Word2Vec-CNN	YouTube Corpus (YC)
Phase 1	Word2Vec-LSTM	YouTube Corpus (YC)
Phase 2	Word2Vec-CNN+LSTM	YouTube Corpus (YC)
Phase 3	Word2Vec-CNN	Combined (FC+TC+YC+E1+E2+E3)
Phase 3	**Word2Vec-LSTM**	**Combined (FC+TC+YC+E1+E2+E3)**
Phase 3	**Word2Vec-CNN+LSTM**	**Combined (FC+TC+YC+E1+E2+E3)**
Phase 1	TF-IDF-CNN	Facebook Corpus (FC)
Phase 1	TF-IDF-LSTM	Facebook Corpus (FC)
Phase 2	TF-IDF-CNN+LSTM	Facebook Corpus (FC)
Phase 1	TF-IDF-CNN	Twitter Corpus (TC)
Phase 1	TF-IDF-LSTM	Twitter Corpus (TC)
Phase 2	TF-IDF-CNN+LSTM	Twitter Corpus (TC)
Phase 1	TF-IDF-CNN	YouTube Corpus (YC)
Phase 1	TF-IDF-LSTM	YouTube Corpus (YC)
Phase 2	TF-IDF-CNN+LSTM	YouTube Corpus (YC)
Phase 3	TF-IDF-CNN	Combined (FC+TC+YC+E1+E2+E3)
Phase 3	TF-IDF-LSTM	Combined (FC+TC+YC+E1+E2+E3)
Phase 3	TF-IDF-CNN+LSTM	Combined (FC+TC+YC+E1+E2+E3)

based on topmost keywords related to depression extracted from existing datasets E1 and E2. The experiments have been performed in three phases as discussed as follows.

At phase 1 the experiments have been performed on individual datasets using CNN and long-short term memory (LSTM) deep machine techniques and the features have been extracted using most common TF-IDF and Word2Vec attribute representation models as discussed in Section V. With two DL techniques, three datasets, and two feature representation methods we conducted two sets of six experiments with all possible combinations, comprising of total 24 experiments as shown in Table V.

To analyze the potential of designed features and the power of DL and transformers we attempt to perform the experiments by combining CNN and LSTM techniques, and evaluating the combined performance of the hybrid model over three (FC, TC, and YC) individual datasets comprising of two sets of three experiments each namely Word2Vec-CNN + LSTM (FC), word2Vec-CNN + LSTM (TC), word2Vec-CNN + LSTM (YC), and TF-IDF-CNN + LSTM (FC), TF-IDF-CNN + LSTM (TC), TF-IDF-CNN + LSTM (YC)-based on Word2Vec and TF-IDF features, respectively. Therefore, a total of $2 \times 3 = 6$ tests have been performed at this phase. Since we are dealing with deep machine learning models, therefore, the collected instances from social media platforms were not enough to derive enough insights. And DL models mostly perform poor on such dataset size. To get rid of dataset size we combined few existing datasets (both depressive (E1 and E2) and non_depressive (E3) samples) to have a comparatively larger dataset. It should be noted here at stage 3 all the newly designed corpuses are combined with existing datasets to conduct the experiments on a larger data corpus with the individual (CNN or LSTM) as well as hybrid (CNN + LSTM) deep trained models. At this stage, a total of six experiments have been performed on Word2Vec and TF-IDF features.

In three phases, a total of 24 experiments have been performed with all the possible combinations to evaluate the distinguishing potential of two feature representation techniques for the identification of major depression symptoms in users on social media platforms. The best performing technique is used to test the newly collected test samples, and to evaluate the performance of proposed system against the start-of-the-art approaches. A quick glance at the 24 experiments discussed above is presented in Table V. It can be clearly noticed that there are 12, 6, and 6 experiments conducted in phase 1, phase 2, and phase 3, respectively.

To analyze the potential of Word2Vec and TF-IDF-based features in designing the system for the identification of depression symptoms we perform experiments using CNN and LSTM by supplying individual and combined datasets. The training data in all the experiments are split into the ratio of 80:20 for training and validation, respectively. Finally, all the algorithms are evaluated and tested on a separate subset of original dataset.

To evaluate the performance of the model we used commonly known performance measures such as accuracy, precision, and recall. Based on the confusion matrix given in Table VI, the formula for calculating each of the metrics are as follow:

$$\text{Accuracy (A)}: = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2}$$

$$\text{Precision (P)}: = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{Recall (R)}: = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{4}$$

To analyze the balanced performance using both precision and recall we have used F-score. The F-measure or F-score estimates the performance of model on a given dataset by combining the precision and recall of the model and is defined as the harmonic mean of model's precision and recall. The formula for calculating F-measure is as follows:

$$F_\beta\text{-score} = (1 + \beta^2) * \frac{P * R}{\beta^2 * P + R}. \tag{5}$$

The F_β-score is a generalization of the F-score which adds a configuration parameter called beta (β). The default value is 1.0, which is the same as the F-measure or referred as $F1$-score. A smaller beta value (such as = 0.5) gives more weight to precision and less to recall, whereas a larger beta value (such as = 2.0) favors recall more than precision. It is helpful to use both precision and recall, but slightly more attention is needed on one or the other, such as when false negatives are more important than false positives or vice versa. The better way to calculate the $F1$-score for our study is mentioned in the following equation:

$$F1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 * \text{TP}}{2 * \text{TP} + \text{FP} + \text{FN}}. \tag{6}$$

VII. Results and Analysis

From the experimental setup section, we now clearly understand that all the collected datasets are normalized and combined together to be fed into the DL algorithms for training, evaluation, and final testing. It is also now understood that all the six different datasets (YC, TC, YC, E1, E2, and E3) are converted into two (Word2Vec and TF-IDF) machine representations to perform the experiments. A total of 24 experiments have been conducted with the help of these six (three new, and three existing) datasets as presented in Table VI. The main aim is to investigate and analyze the potential of Word2Vec and TF-IDF-based features to develop an efficient classification model to identify depressive content in the user text. The performances of the learned models have been evaluated using precision, recall, accuracy, and $F1$ evaluation metrics. The results in the table shows that all the approaches have achieved significantly good results on six datasets while classifying the depressive content in the user text. Talking about the accuracy performance metric the Word2Vec LSTM and Word2Vec (CNN + LSTM) has achieved the accuracy of 99.02% and 99.01%, respectively, and recorded as best results out of all the 24 experiments on the combined dataset. On individual corpuses Word2Vec-based features have been proved better for FC and FC by achieving accuracy of 95.02% (with CNN) and 98.15% (with CNN + LSTM), respectively. For TC, the accuracy recorded with CNN, LSTM, and CNN + LSTM were 91.48%, 92.19%, and 85.87%, respectively. One of the reasons for recording comparatively lower performance on TC can be the limited length of on Tweets allowed by service provider. As users mostly cannot express much about their feeling in 280 characters allowed in a tweet, which is not case with the other two social media platforms. The same pattern has been observed in the results achieved on TF-IDF features. As can be clearly seen that out of all the nine experiments on individual datasets the lowest accuracy has been found as 88.69%, 89.09%, and 88.70% using CNN, LSTM, and CNN + LSTM, respectively. While as the accuracy scores on FC and TC has been recorded as 91.02%, 94.56%, and 97.79%, 98.38%, 97.89% using CNN, LSTM, and CNN + LSTM, respectively, which are clearly higher than results obtained on TC. Here, it can be stated that Word2Vec features have the enough potential to distinguish two class instances than the TF-IDF-based features. In the case of TF-IDF-based features on individual corpuses the LSTM model has outperformed the CNN and the combination of CNN and LST (CNN + LSTM) by achieving the accuracy value of 94.56%, 89.96%, and 98.38% on FC, TC, and YC, respectively.

TABLE VI

RESULTS OF 24 EXPERIMENTS CONDUCTED IN THREE PHASES TOWARD THE EVALUATION OF DEPRESSION SYMPTOMS IDENTIFICATION USING CNN, LSTM, AND CNN + LSTM ARCHITECTURES USING WORD2VEC AND TF-IDF FEATURES

Phase	Model	Corpus	Recall	Precision	Accuracy	F1-Score
Phase 1	Word2Vec-CNN	Facebook Corpus (FC)	0.9257	0.9730	0.9502	0.9487
Phase 1	Word2Vec-LSTM	Facebook Corpus (FC)	0.9293	0.9344	0.9353	0.9319
Phase 2	Word2Vec-CNN+LSTM	Facebook Corpus (FC)	0.9251	0.9737	0.9502	0.9488
Phase 1	Word2Vec-CNN	Twitter Corpus (TC)	0.9140	0.9245	0.9148	0.9192
Phase 1	Word2Vec-LSTM	Twitter Corpus (TC)	0.9211	0.9309	0.9219	0.9260
Phase 2	Word2Vec-CNN+LSTM	Twitter Corpus (TC)	0.9038	0.8176	0.8587	0.8585
Phase 1	Word2Vec-CNN	Youtube Corpus (YC)	0.9636	0.9900	0.9746	0.9766
Phase 1	Word2Vec-LSTM	Youtube Corpus (YC)	0.9634	0.9892	0.9741	0.9761
Phase 2	Word2Vec-CNN+LSTM	Youtube Corpus (YC)	0.9704	0.9959	0.9815	0.9830
Phase 3	Word2Vec-CNN	Combined (FC+TC+YC+E1+E2+E3)	0.9705	0.9707	0.9706	0.9701
Phase 3	**Word2Vec-LSTM**	**Combined (FC+TC+YC+E1+E2+E3)**	**0.9901**	**0.9904**	**0.9902**	**0.9902**
Phase 3	**Word2Vec-CNN+LSTM**	**Combined (FC+TC+YC+E1+E2+E3)**	**0.9901**	**0.9920**	**0.9901**	**0.9910**
Phase 1	TF-IDF-CNN	Facebook Corpus (FC)	0.9173	0.8925	0.9102	0.9047
Phase 1	TF-IDF-LSTM	Facebook Corpus (FC)	0.9536	0.9314	0.9456	0.9424
Phase 2	TF-IDF-CNN+LSTM	Facebook Corpus (FC)	0.9126	0.8893	0.9072	0.9008
Phase 1	TF-IDF-CNN	Twitter Corpus (TC)	0.8873	0.9043	0.8896	0.8957
Phase 1	TF-IDF-LSTM	Twitter Corpus (TC)	0.9005	0.8901	0.8908	0.8953
Phase 2	TF-IDF-CNN+LSTM	Twitter Corpus (TC)	0.8855	0.9010	0.8870	0.8932
Phase 1	TF-IDF-CNN	Youtube Corpus (YC)	0.9641	0.9957	0.9779	0.9797
Phase 1	TF-IDF-LSTM	Youtube Corpus (YC)	0.9755	0.9947	0.9838	0.9850
Phase 2	TF-IDF-CNN+LSTM	Youtube Corpus (YC)	0.9644	0.9975	0.9789	0.9807
Phase 3	TF-IDF-CNN	Combined (FC+TC+YC+E1+E2+E3)	0.9764	0.9681	0.9729	0.9722
Phase 3	TF-IDF-LSTM	Combined (FC+TC+YC+E1+E2+E3)	0.9845	0.9692	0.9774	0.9768
Phase 3	TF-IDF-CNN+LSTM	Combined (FC+TC+YC+E1+E2+E3)	0.9966	0.9735	0.9854	0.9849

On combined dataset, the hybrid approach (CNN + LSTM) achieved an accuracy of 98.54% and outperformed the individual DL models CNN and LSTM with accuracy 97.29% and 96.92%, respectively, on TF-IDF-based features. While as on Word2Vec-based features the LSTM model and hybrid approach (CNN + LSTM) performed almost same with accuracy 99.02% and 99.01%, respectively, outperforming the CNN approach with accuracy value of 97.06%. Here we can conclude that the Word2Vec-based features have the enough distinguishing capabilities when it comes to identification of depressive and nondepressive symptoms from public text on social media. One of the reasons can be that TF-IDF features are a kind of statistical measurements and cannot help bring semantic knowledge from the text. It considers the importance of the words in a sentence and weighs them accordingly, but is unable to derive the contexts of the words and understand significance in that way. While as Word2Vec is capable of capturing context of a word in a document, semantic and syntactic similarity, relation in other words, etc. It produces one vector per word, whereas TF-IDF generates a score for the frequency of words in a document. Word2vec is the optimal choice for going deeper into the documents for identifying content and subsets of content. Its vectors represent each word's context. (i.e., the *n*-gram). TF-IDF is a word-document mapping where it ignore the order of words and produces a matrix of size $M*N$ where N is number of words in the vocabulary and M is number of documents. Whereas Word2Vec model produces a unique word-vector for each word based on their neighboring words. In comparing the performance of selected individual models and the hybrid (CNN + LSTM), we observe several things such as the Word2Vec-based CNN model has performed better on Facebook and YC. In contrast, TF-IDF-based LSTM models have performed better on all the individual corpora.

Since CNN models employee convolutional layers and maximum pooling layers to extract higher-level features, while LSTM-based models capture long-term dependencies among word sequences, therefore are better for text classification. On the other hand, the hybrid model outperformed the individual models in most of the experiments. One of the reasons can be that the CNN is great at learning the special structure from the data and convolutional layer by taking its advantage learns some structure from the input and use the power of LSTM to record long-term dependencies among tokens to enhance the performance of the hybrid model. CNN with LSTM provides a better test accuracy as compared to LSTM or CNN alone with approximately same weights and lesser training time. Therefore, faster training is possible with CNN, thus reducing the training time required for large dataset. One of the reasons to prefer to use CNN over LSTM could be the amount of time for training the model. The current DL hardware are basically Nvidia graphics cards, optimized to process data with extreme parallelism and speed which is being utilized by CNN architecture. Whereas LSTMs does the processing in a sequential manner, therefore, DL hardware does not increase its speed during the training phase of the network. In order

TABLE VII
PERFORMANCE COMPARISONS BETWEEN PROPOSED APPROACH AND THE EXISTING METHODS ON DEPRESSION IDENTIFICATION

Study/ Method/Feature(s)	Recall	Precision	Accuracy	F1-measure
Micheal et al. [8]				
Linguistic Inquiry and Word Count (LIWC)	0.69	0.95	69%	0.80
Linear Discriminant Analysis (LDA)	0.84	0.82	77%	0.83
unigram	0.97	0.93	68%	0.80
bigram	0.78	0.81	80%	0.79
LIWC+LDA+unigram	0.81	0.88	88%	0.84
LIWC+LDA+unigram+bigram	0.62	0.89	89%	0.89
N.S. Alghammdi et al. [41]				
Bow-Char(ADA)	0.75	0.95	72%	0.73
TF-IDF (DT)	0.56	0.69	65%	0.62
TF-IDF (KNN)	0.61	0.74	69%	0.67
Bow-Char(RF)	0.62	0.75	70%	0.68
SGD(Pipeline Union)	0.69	0.70	70%	0.70
TF-IDF (SVM)	0.70	0.74	72%	0.72
Wang et al. [22]	0.92	0.77	97%	0.84
El-RAmly et al. [30]	0.97	0.97	97%	0.96
Proposed Approach				
Term Frequency - Inverse Document Frequency-LSTM(TF-IDF-LSTM)	0.98	0.97	98%	0.97
Term Frequency - Inverse Document Frequency-CNN+LSTM (TF-IDF-CNN+LSTM)	0.99	0.97	98%	0.98
Word2Vec-LSTM	**0.99**	**0.99**	**99%**	**0.99**
Word2Vec-CNN+LSTM	**0.99**	**0.99**	**99%**	**0.99**

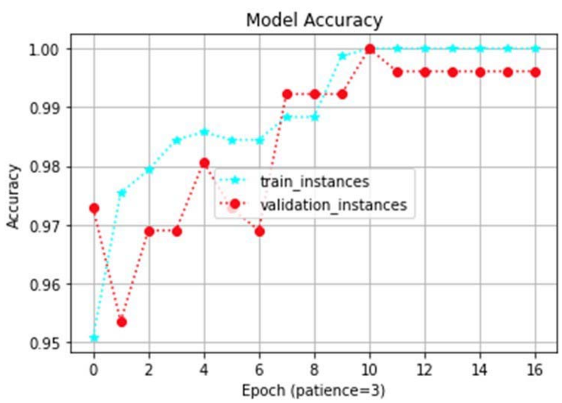

Fig. 11. Word2Vec-LSTM model accuracy.

to get more insights of the best-performing (Word2Vec-LSTM) model, we have presented its accuracy and validation loss models in a graphical representation as shown in Figs. 11 and 13, respectively.

It can be observed from the accuracy plot of the model that after nine epochs, the model is settling down, and this is the point from which we recorded the accuracy of the model on training as well as validation instances as 100% and 99.02%, respectively. Similarly, it can be observed from error plot of the model as shown in Fig. 13, the validation loss after epoch number 9 is 0.0048. The architecture of best performing hybrid CNN + LSTM model is shown in Fig. 12. As shown in the figure the tokenized input text is fed into the embedding layer to get an embedding vector. Then we added the convolutional layer of CNN to learn the special structure from the input vector. The output of the convolutional layer is provided as an input to the LSTM layer which produces input for the output dense layer. Finally, in the output dense layer, the sigmoid function is used for the prediction task. Max pooling layer is used to help over-fitting by providing an optimal form of the representation from the feature set.

VIII. COMPARATIVE STUDY

This study aims in identification of depressive symptoms from user text available online in order to predict netizens suffering with depressive disorders and help psychiatrists, mental health experts in providing early treatment and care to such patients. From the literature, we were able to find a number of studies by employing different machine and DL techniques as depicted in Table I. Here, in this section, we will conduct a comparative analysis between results presented by popular existing approaches developed in this direction and the proposed approach to evaluate the performance of developed system in the current study.

Table VII presents the comparison between the results obtained by existing studies and the proposed one based on performance measures such as accuracy and F-measure. As shown in the table the prior studies have employed a number of features including LIWC [42], unigram, bigram, and TF-IDF, approaches to distinguish instances with depression symptoms from normal instances. For example, Tadesse *et al.* [8] had tried features like LIWC, LDA [43], unigram, bigram, and the possible combinations of these features to learn several variants of machine learning models. Out of all the approaches, the best results presented in the study include 0.95, 0.97, 89%, and 0.89 for precision, recall, accuracy, and $F1$-score, respectively. Similarly, the study [41] has employed features like BoW, TF-IDF with different versions to predict depression symptoms in Arabic psychological forums and obtained the best values for recall, precision, accuracy, and $F1$-score as 0.70, 0.95, 72%, and 0.73, respectively. Comparing the results obtained by the proposed approach using TF-IDF features, the results show that the proposed approach has outperformed all the experiments conducted both in study [8] and [41] by obtaining scores as 0.98, 0.96, 0.99, and 0.99 for recall, precision, accuracy, and $F1$-measure, respectively, with LSTM technique. It has been seen that the study approaches presented in [22] has performed

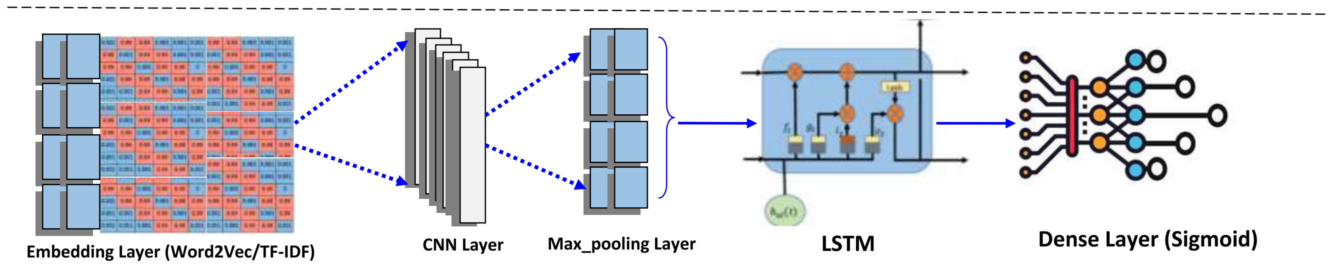

Fig. 12. Architecture of hybrid CNN + LSTM model.

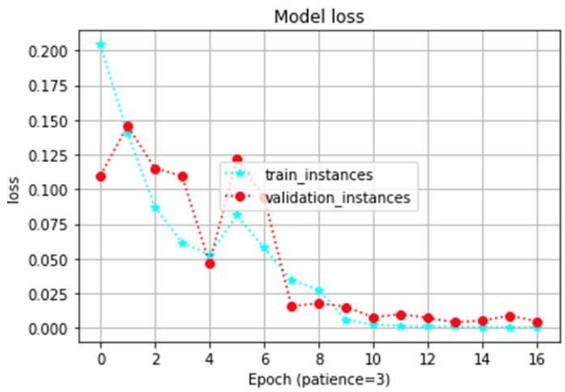

Fig. 13. Word2Vec-LSTM model-loss.

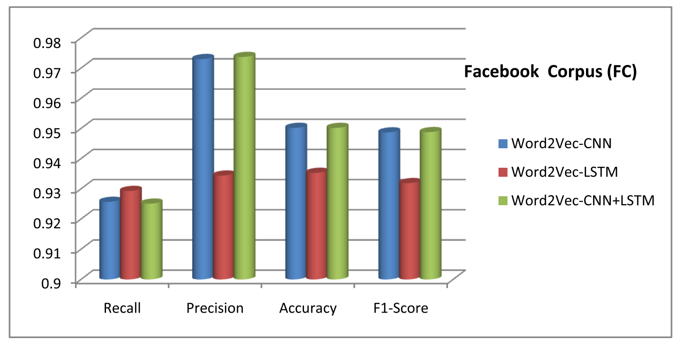

Fig. 14. Performance of CNN and LSTM using Word2Vec features on Facebook Dataset.

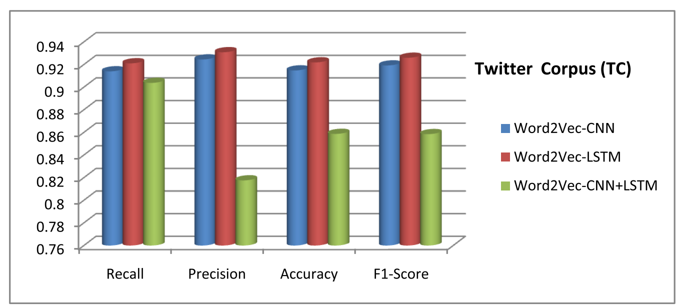

Fig. 15. Performance of CNN and LSTM using Word2Vec features on Twitter Dataset.

comparatively better than the first two studies shown in the table by incorporating 11 user behavioral features with six social-status behavior and 80 features-based of LIWC tool to detect Anorexia (or eating disorder) on Twitter blogging site. The study has recorded the results as 0.92, 0.77, 97%, and 0.84 for recall, precision, accuracy, and $F1$-score, respectively. It can been seen that, however, the accuracy score of this study (97%) is almost the same as with the proposed study (97.74%) but the other values such as for recall, precision, and $F1$-score is found higher in proposed study.

Talking about the best approach in the selected literature the authors in [30] have shown very good results by incorporating the bidirectional encoder representations from transformers (BERT) [44] based features to detect the depression in Twitter users particularly for Arabic language. The study reported the results as 0.97, 0.97, 97%, and 0.96 for recall, precision, accuracy, and $F1$-measure which are seen slightly better than the scores we obtained for our TF-IDF-based LSTM model but on the other hand, the proposed Word2Vec-based LSTM model outperformed this in all the performance measures by obtaining the scores as 0.99, 0.99, 99%, and 0.99 for recall, precision, accuracy, and $F1$-score, respectively. It can also be observed that the proposed Word2Vec-based LSTM + CNN model outperformed and surpassed all the existing approaches on performance measures such as recall, precision, accuracy, and $F1$-score as shown in the table. To extend it further, it can be clearly noticed that proposed Word2Vec-based LSTM and Word2Vec-based LSTM + CNN model has achieved 2% higher accuracy than the best model in the literature. Similarly, for other performance measures the best performing models, i.e., Word2Vec-based LSTM, and Word2Vec-based LSTM + CNN the recall precision and $F1$-measure is recorded as 2%, 2%, and 3%, respectively, higher than the top performing approaches in the mentioned literature.

On comparing the best model among the proposed approaches, we can observe from Figs. 14–19, the Word2Vec-based CNN, and hybrid CNN + LSTM model has performed better by achieving accuracy scores as 0.9502 and on the Facebook dataset. While as the individual CNN and LSTM models have performed better than the hybrid model CNN + LSTM by achieving accuracy scores of 0.9148 and 0.9148, respectively, on the Twitter corpus. For YouTube data, we have recorded the highest accuracy 0.9815 by the hybrid CNN + LSTM model. Similarly, we recorded the accuracy of TF-IDF-based features by the same DL models and observed that the LSTM model performed better in all three individual datasets by obtaining accuracy of 0.9456, 0.8908, and 0.9838 for Facebook, Twitter, and YC, respectively.

Thus, it is better here to conclude that and is clearly seen from the table that proposed Word2Vec-based LSTM and Word2Vec-based (LSTM + CNN) approaches have outperformed all the mentioned studies on performance measures

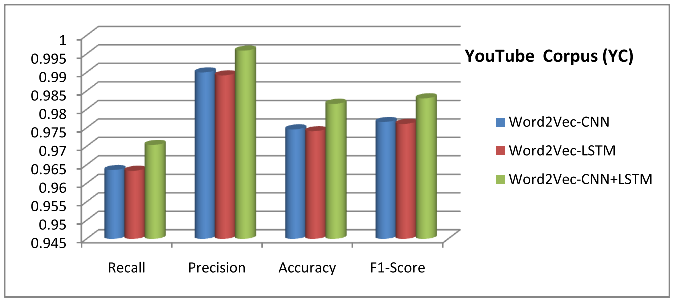

Fig. 16. Performance of CNN and LSTM using Word2Vec features on YouTube Dataset.

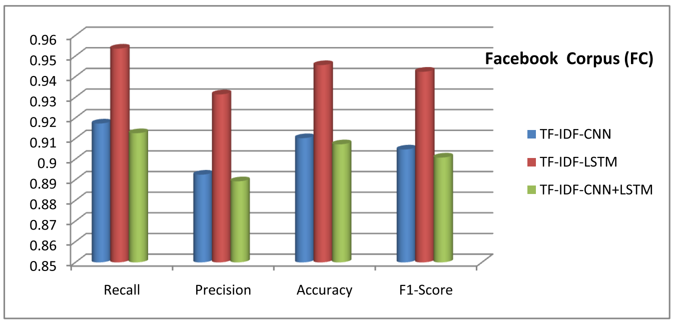

Fig. 17. Performance of CNN and LSTM using TF-IDF features on Facebook Datasets.

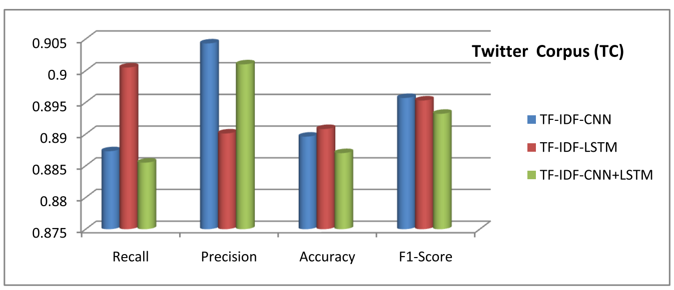

Fig. 18. Performance of CNN and LSTM using TF-IDF features on Twitter Datasets.

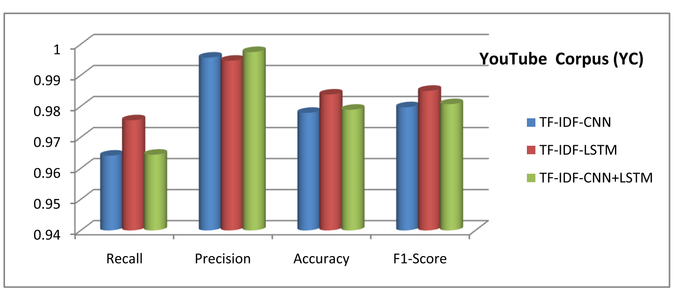

Fig. 19. Performance of CNN and LSTM using TF-IDF features on YouTube Datasets.

on all the performance measures. In contrast to the existing studies, the proposed approach made use of Word2Vec (skim-gram and BoW) features and combination of LSTM and CNN for detecting depression in users on the social media platforms such as Facebook, Twitter, and YouTube. It has been seen that DL models usually are good in performance if provided much and diverse content while training, and in our experiments, the DL models are supplied heterogeneous as it comes from multiple sources.

IX. Conclusion and Future Scope

The main aim of this study is to detect depression in users on social media. The article primarily focuses on extracting the Word2Vec-based features and TF-IDF-based representation of user content written in English to train a DL model for detecting and classifying depression symptoms on social media particularly on popular sites such as Facebook, Twitter, and YouTube. A large dataset has been designed by merging three existing datasets, out of which two datasets (E1 and E2) contain depression-related instances and one dataset (E3) holds normal (nondepressive) instances. Apart from this new instances are collected from the Facebook, Twitter, and YouTube websites using tweepy,[1] TWINT[2] (python package), Netvizz app, and iMacros[3] (browser add-on) technology, respectively.

Identifying the people with major depressive disorder symptoms on social media will assist in providing early medical remedies and consultations through proper channels. This early detection also protects a depressed individual from committing serious actions, such as suicide, etc. The Word2Vec and TF-IDF-based feature sets are used for training DL models such as LSTM and CNN. A total of 24 possible combinations of experiments were conducted in three phases toward the evaluation of depression symptoms identification using CNN, LSTM, and CNN + LSTM architectures on the individual as well as a combined dataset.

It has been observed that both the feature representations proved fruitful for the identification task, therefore considered as potential features to detect depression on social media. Also, both DL models LSTM and CNN, and the hybrid (CNN + LSTM) models achieved good results on all individual as well as combined datasets. Talking in terms of accuracy on individual corpora Word2Vec-based features have been proved better for FC and FC by achieving an accuracy of 95.02% (with CNN) and 98.15% (with CNN + LSTM), respectively. For TC the accuracy recorded with CNN, LSTM, and CNN + LSTM were 91.48%, 92.19%, and 85.87%, respectively. With Word2Vec LSTM and Word2Vec (CNN + LSTM) models, we achieved the accuracy of 99.02% and 99.01%, respectively, and recorded as best results out of all the 24 experiments on the combined dataset. The proposed Word2Vec-based LSTM + CNN model outperformed surpassed all the existing approaches on performance measures such as recall, precision, accuracy, and $F1$-score.

This study was an attempt to demonstrate the use of Word2Vec and TF-IDF-based attributes in depression detection tasks. Although we received very promising results from all the experiments defeating start-of-the-art studies, still the future scope of this research can be seen in terms of detecting depression from a multilingual corpus as the present study supports English language only, thus, it will be a future

[1] https://docs.tweepy.org/en/stable/api.html
[2] https://pypi.org/project/twint/
[3] https://www.progress.com/imacros

direction to detect depression in different languages and analyze the depression diffusion between these languages for example, from English to the Arabic Language. Furthermore, the depression symptoms vary between individuals, therefore, it will be a nice idea to perform user behavior profiling and analyze the patterns of depression within them across different social media platforms.

Data Availability

The link to the data repository related to this project can be made available upon request. If required will be made publicly available on the GitHub profile (https://bit.ly/3jku4En, accessed on June 2022) under the title of the article.

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