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USER DEPRESSION AND SEVERITY LEVEL PREDICTION DURING COVID-19 EPIDEMIC FROM SOCIAL NETWORK DATA

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ABSTRACT

In recent times, depression becomes a major issue, which causes suicide, particularly among youngsters. During the Coronavirus disease (COVID-19) epidemic, many organizations suggested social distance and quarantine actions, which cause major attention to the mental health and depression of each individual. Most population express their emotions by using modern social media technologies like Twitter, Facebook, etc. By considering user tweets, a Long Short-Term Memory (LSTM)-based classifier was designed that learns rich attributes such as psychological, contextual, cognitive, person-level and distress-dependent n-gram attributes of each user for depression severity level prediction. But, it did not learn the social network structural properties of the most prominent communities, which influences the prediction outcomes. Hence in this article, a novel model is developed to predict the user's depression severity levels by considering the social network structure of most prominent communities and influence measures. At first, it analyses the physical characteristics of the most prominent groups based on their balanced local and global power distribution. Then, the influential users and communities are identified along with the rich group of attributes. Moreover, those attributes are provided to the LSTM classifier for the user's depression severity level prediction during the COVID-19 epidemic. Finally, the investigational outcomes exhibit that the presented model attains 93.53% accuracy and 0.4376 Root Mean Square Error (RMSE) contrasted with the conventional classifiers to estimate the user's depression severity level.

Keywords: COVID-19, Social networking, depression severity prediction, influential user, influential communities, LSTM.

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INTRODUCTION

Distress is one of the foremost underappreciated sources of pain and mortality worldwide, particularly amid youth. According to the WHO, around 264 million individuals are infected globally, and the number is growing by the day [1-2]. Depression is distinct from normal mood swings and fleeting emotional reactions. The pathetic person fails miserably at work and behaves badly with family and close friends [3]. When a pathetic people do not get an appropriate diagnosis, it may cause depression that is the second biggest reason of mortality in adolescents. The issue is particularly bad in India, China, and the United States.

India is considered to be the world's most depressed nation. Based on the WHO [4], India, China, and the United States have the highest rates of distress, schizophrenia, and bipolar illness. Notwithstanding the availability of excellent depression treatment, many people who are suffering do not have access to it. Only around 10% of people in many regions get therapy. The societal stigma associated with mental problems is the primary cause of these dismal numbers. Greater than 70% of individuals may not seek help from a psychologist in the premature stages of distress, worsening their mental health.

The current COVID-19 outbreak is influencing us not only physically, but also mentally. The social distance and quarantine measures imposed in some concerned nations have resulted in interpersonal separation and drastic alterations in our everyday lives. Another negative effect on individual's life includes unemployment, financial uncertainty, domestic violence and cybercrime. All of these disorders have prompted severe concerns about stress, anxiety and depression. With a heavy workforce in stressful conditions, healths are employees are also subject to depression, anxiety and fatigue [5-7]. To address fatigue and anxiety, a digital therapeutics corporation termed Big Health is providing free intellectual method-related treatments to address insomnia and distress. With such a huge necessity for distress therapy and restricted power under the difficult conditions of COVID-19, expertise-related assistance in the prognosis must be developed quickly.

In the recent digital world, Social networking platforms have evolved into a forum for individuals to share their opinions, current moods and feelings. Publishing and distributing material on online platforms reflects the individuals' everyday life and physiological states [8-10]. Researchers have routinely utilized meeting and survey-related schemes to determine the mental health of users on social media [11]. But, these schemes were costly and time-consuming. Also, it was complex to obtain adequate information to ensure the robustness of the model. Thus, online networking behavior-related has been developed to identify distress [12-15]. In contrast, according to these classical studies, depression is a disease, which may occur in a person at various stages or levels. During the premature phase, this severity is normally less and its level is obsessed by the condition being practised over period. The impacted people usually may need diagnosis based on the severity of depression or stress. So, identifying depression or stress in an individual is not often useful to recommend the proper diagnosis by a domain expert.

From this perspective, Ghosh *et al*. [16] developed a deep learner to predict the severity of distress by utilizing the information distributed by the person on online sites. In this model, a rich group of attributes such as psychological, contextual, cognitive, person-level and distress-dependent n-gram attributes was mined to define all users. Then, such attributes were fed to the small LSTM network using Swish as an activation factor to estimate the distress severities. On the other hand, most social networking data analytics models do not consider the structural properties of most prominent communities.

Therefore, this article develops a novel model, which considers the social network structure of the most prominent communities and influence measures along with the different rich groups of attributes to predict the depression severity level. To achieve this, the physical characteristics of the most prominent groups are analyzed regarding their local and global power. Also, the power distribution is balanced and the influential communities are identified. The influential communities are social activists, students, medical professionals, etc. Then, these characteristics along with the rich group of attributes are fed to the LSTM to estimate depression severity level. Thus, this model increases the accuracy of predicting the depressed users in the different communities with their depression severity level.

The rest of the article is arranged as the following: Section II studies the work associated with stress or depression detection using machine and deep learning algorithms. Section III explains the presented work and Section IV displays its effectiveness. Section V reviews the entire study and recommends upcoming improvements.

LITERATURE REVIEW

Cheema & Singh [17] developed an improved model for Phonocadiography (PCG) data to identify emotional anxiety depending on non-linear entropy-based characteristics by Empirical Model Decomposition (EMD). First, PCG data was utilized to obtain the interval of heart rhythms having successive S1 peaks to create an Inter-Beat Interval (IBI) data. The IBI data was split into subband data by the EMD to create Intrinsic Mode Functions (IMFs). Also, the non-linear characteristics were determined and provided to the Least-Square Support Vector Machine (LS-SVM) to categorize psychological stress. But, it was validated on a limited corpus. Also, it necessitates optimizing the selection of kernel functions.\
Low *et al.* [18] leveraged Natural Language Processing (NLP) to characterize changes in the globe's biggest intellectual fitness support communities on the Reddit including non-intellectual fitness communities in the primary phase of the epidemic. The trends from various text-derived attributes were analyzed by the regression. Then, the posts were classified into their corresponding support groups and interpreted significant attributes by supervised machine learning. But, it did not causally link any individual changes to specific events and also it was not characterized by formally documented medical diagnoses.

Li & Liu [19] designed a 1D CNN and a Multi-Layer Perceptron (MLP) to detect human stress. Initially, the stressed and non-stressed states were distinguished by the binary classification. Then, a 3-class classification was performed for emotion classification, where the networks classified baseline, stressed and amused states. But, the dataset used in this model was limited, which may not sufficient to define the overall human population.
Bobade & Vani [20] presented various machine and deep learning algorithms to detect stress on people by multimodal corpora. In this system, K-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA), Random Forest (RF), Decision Tree (DT), AdaBoost, Kernel SVM (KSVM) and feed-forward Artificial Neural Network (ANN) were utilized. On the other hand, these algorithms were not effective for a massive number of data.

Zhang *et al*. [21] developed a Two-leveled Stress Detection Network (TSDNet). Initially, the face and action-level interpretations were trained separately and their outcomes were merged via a stream-weighted integrator with local and global attention to identifying the stress. However, its accuracy was less because of a limited number of data. Billah et al. [22] analyzed the database to detect the level of distress amid pupils by MLP, Multi-objective evolutionary scheme and fuzzy unranked ruling generation scheme. But, the number of instances in the database was not adequate.

Albagmi *et al*. [23] predicted generalized anxiety levels during the COVID-19 epidemic based on the machine learning algorithm. In this analysis, 2-class and 3-class anxiety issues were categorized earlier by gathering the database during the COVID-19 epidemic in Saudi Arabia. The information was gathered from every area of the Kingdom through an online inspection comprising queries to recognize aspects impacting anxiety levels, after queries from the GAD-17, a monitoring device for generalized anxiety diseases. Then, the estimation systems were constructed by the SVM and J48 decision tree classifiers. But, the system complexity was increased while increasing the number of classes in the result parameter.

Blanco & Lourenço [24] developed a new deep learner to analyze how positive and negative emotions were communicated in tweets regarding COVID-19. In this model, a pre-learned BERT and a neural network were utilized to capture the semantic characteristics and analyze data from online posts. Also, a technique was presented, which integrates emotion identification and chat restoration to examine the impact of social relations on emotional shifts. But, it needs more characteristics related to the emotional chat to increase the model efficiency.

PROPOSED METHODOLOGY

In this section, the presented user's depression severity level prediction model is explained in brief. Figure-1 illustrates the entire pipeline of the presented model, which begins with data preprocessing and retagging into various stages of depression by determining

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the depression score for all users in the network. After that, influential user and communities are determined along with the rich group of attributes, as well as, an LSTM model is trained to estimate the resultant distress severity level of persons in the social network.

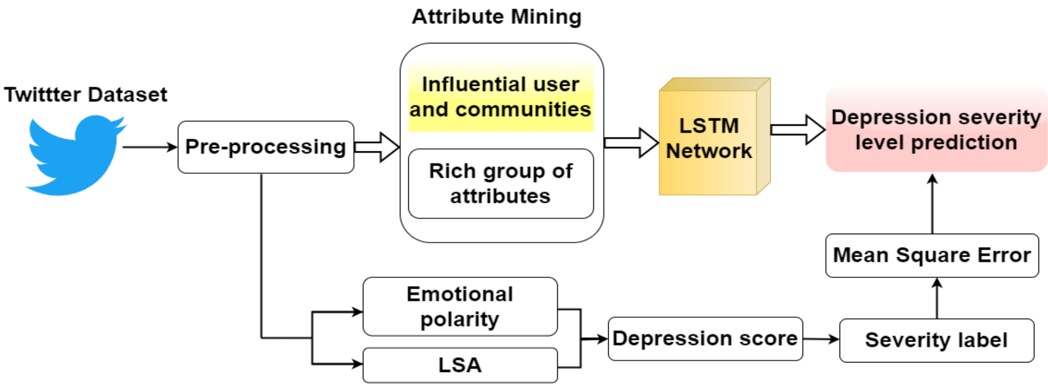

Figure-1. Entire pipeline of the presented depression severity level prediction model.

Database Description

The database is acquired from the Twitter account from March 2020 to December 2020, for around 6000 users. The dataset is compiled by web-crawling Twitter users' profile information and a timeline. It is also looking for an anchor tweet that defines the user's psychological condition. All tweets posted from the anchor tweet for 1 month were gathered. Users' tweets are categorized as depressed/stressed if their anchor tweets contain the regular language "(I'm/was/I am/I've been) declared distress." Users who did not publish any tweets containing the words "depress, or stress" were categorized as non-distressed. A non-distress dataset is also prepared in this manner. Because the dataset is poorly categorized into binary classifications of sad and non-distressed, these labels are ineffective for estimating distress severity. As a result, using the same dataset, an independent relabeling approach is devised. First, a distress score is calculated from tweets and LSA based on emotion polarity. The scores are then classified into 4 severity levels (e.g., no/minimal, mild, moderate and severe depression) [16].

Data Preprocessing and Attribute Mining

The collected data is pre-processed and the user tweets are aggregated to obtain a rich group of attributes. In this stage, the Emojis, punctuations, articles and special characters in tweets are eliminated. The tweet contents are tokenized, stemmed and lemmatized before preprocessing. The redundant or unwanted words mentioned in tweets like typographical errors or acronyms of frequent words are processed in this stage. After preprocessing, a few online behaviors of Twitter users are extracted such as physiological, incidences, intellectual, person-related attributes and usage of distress-associated sentences to estimate the distress severity level. So, a total of 527 attributes (12 emotion attributes, 25 event attributes, 5 online behavior attributes, 334 user-specific attributes and 151 depression-related -gram attributes) corresponding to all users are extracted [16]. In addition to these attributes, social network structural properties and influence attributes are obtained to train the LSTM network model. The determination of such additional attributes is described below.

Network Structure and Influence Measures for Influential Community Detection

In this stage, a retweet network is created by the collected tweets, concerning persons who are in a retweet correlation, i.e. an undirected edge between 2 persons represents either one person retweeted another or vice versa. It needs to obtain communities of persons that have related visions on specific themes in the large networks. Consider that retweeting is an alternative of defining opinion on the shared tweets; the retweet system is considered as the links among individuals who concur on a specific theme. As a result, the dilemma interprets into splitting the communities. In the context of multifaceted systems, the concept of "community" refers to a group of users that are compactly linked among themselves than with users outer the group.

Consider the retweet network as a directed graph G with edges$E(G)$. A directed edge $e_{x,y}$ from the person x to the person y represents that tweets of x were retweeted by y. Initially, a new clustering-based neighborhood recognition scheme is employed to this retweet network, which splits the nodes to increase the system's modularity. Modularity defines the rate of edges declining within communities of the system segregation than the predicted rate of edges in such communities, known an arbitrary allocation of associates in the system. This algorithm identifies modular communities by creating groups of densely connected nodes. It involves the following processes: (i) detecting the influential user depending on their influence, (ii) choosing a candidate adjacent to enlarge the community depending on the node similarity and (iii) aggregating the small community depending on the community similarity

A. Influential user detection depending on their influence

The influential user has the maximum influence in the network, which will attract its adjacent. Consider $w(e_{x,y})$ is the weight of $e_{x,y}$ defining the number of times that y retweeted the tweets of x, the person power $I(x)$ is described by

$$I(x) = \sum_{e_{x,y} \in E(G)} w(e_{x,y}) \quad (1)$$

Then, the users are sorted according to their influence to find the most influential user of the community

B. Community Enlargement depending on the user similarity

It is known that users within a community are more closely connected than those outside the community. To choose the candidate adjacent and enlarge the community, the similarity of the users and the mean similarity of every user with its adjacent are utilized. The similarity between 2 users is determined according to the local structure data as:

$$Sim(x, y) = \sum_{t \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log k_t} \quad (2)$$

In Equation (2), t is the familiar adjacent of users x and y, $\Gamma(x)$ and $\Gamma(y)$ are the adjacent group of x and y, as well as, k_t is the degree of t. The mean similarity is defined as the measure to reflect the mean similarity of all nodes with their adjacent, which is determined by

$$meanSim(., x) = \frac{1}{k_x} \sum_{y \in \Gamma(x)} Sim(x, y) \quad (3)$$

In this step, user x's adjacent y is added to the community if $meanSim(., x) < Sim(x, y)$. The reason for this is that the similarity among users in a similar community is greater than that of others that do not belong to that community. A greater similarity would guarantee that the community has users with a more dense connection. The dominant user's adjacent may not often belong to a similar community since it is the user with the maximum similarity. The similarity of connected nodes in a similar community is greater than the mean similarity

C. Aggregating small communities depending on community similarity

In this step, the community C_x with the highest number of users (Q) is chosen as the small community. It is observed that the nodes within a similar community are more closely connected. So, it is apparent that the small community is likely to aggregate with the community with the maximum similarity. The label propagation is used to determine the similarity between small communities and the other communities as:

$$S(C_x, C_y) = n_q\left(q \in C_y \cap \Gamma(t, t \in C_x)\right) \quad (4)$$

In Equation (4), n_q is the number of users that belong to the community C_y and are connected to community C_x. Thus, the user's communities in the network are identified effectively. Moreover, the variances in the structure of the identified communities $C_1, \dots, C_n$ are observed by the power of persons of a specific group C_k. This is addressed by determining the intra and inter-neighborhood power of all communities, and by determining the sharing of power amid the neighborhood's persons. So, the neighborhood power is the total power of each user.

$$I(C) = \sum_{x \in C} I(x) = \sum_{x \in C}\left(\sum_{e_{x,y} \in E(G)} w(e_{x,y})\right) \quad (5)$$

It is partitioned into the influence that the community users that within their community and the influence they expert outside their community. So, intra-community influence and inter-community influence are defined by

$$\mathrm{I_{intra}(C)} = \sum_{\mathrm{x \in C}} \mathrm{I_{intra}(x)} = \sum_{\mathrm{x \in C}}\left(\sum_{\substack{\mathrm{e_{x,y} \in E(G)} \\ \mathrm{y \in C}}} \mathrm{w(e_{x,y})}\right) \quad (6)$$

$$\mathrm{I_{inter}(C)} = \sum_{\mathrm{x \in C}} \mathrm{I_{inter}(x)} = \sum_{\mathrm{x \in C}}\left(\sum_{\substack{\mathrm{e_{x,y} \in E(G)} \\ \mathrm{y \notin C}}} \mathrm{w(e_{x,y})}\right) \quad (7)$$

The ratio between such two measures I_{inter}/I_{intra} discloses the scope to which a neighborhood is outer its edges versus its inside data prominent transmission. Typically, the users belonging to a similar community are more likely to have similar types of behavioral similarities. So, a higher value of $I_{intra}(C)$ defines $x \in C$ is more likely to be within the social community C. Likewise, a higher value of $I_{inter}(C)$ defines x is more likely to have higher behavioral similarity with users who are outside the social community C.

Thus, the most influential users and communities are detected and given as input to the LSTM model along with the other extracted rich group of attributes for depression severity level prediction

LSTM Model for Depression Severity Level Prediction

A 3-layer LSTM network [16] is applied, which learns the different attributes related to the user behaviors, social communities, etc., to predict the depression severity level. In this model, Swish is used as an activation function rather than Rectified Linear Unit (ReLU), described as $f(a) = 2a \cdot sigmoid(\beta \times a)$, where β is a training variable. If $\beta = 0$, the residual term becomes 0.5 that is $f(a)$ becomes linear. Likewise, if β is extremely large, the sigmoid term acts as a binary activation. So, the swish activation function $(\beta = 1)$ includes a flat shift between ReLU and linear activation margins.

Pseudocode for presented depression severity level prediction model

Input: Twitter dataset

Output: Depression severity levels (mild, moderate and severe)

Begin

1. Collect the tweets from the different Twitter users;
2. Tokenize, stem and lemmatize the collected tweets;
3. Pre-process the tweets to remove Emojis, punctuations, special characters and articles;
4. Remove typographical errors and acronyms of frequent words;
5. Determine the emotion polarity and LSA to obtain the depression score and severity label;
6. Extract the rich group of attributes for each Twitter user;
7. Construct the retweet network as a directed graph G with edges $E(G)$;
8. Split the network nodes (users) by the clustering-based community detection algorithm;
9. Determine the user's influence using Equation. (1) to identify the most influential user;
10. Determine the user similarity using Equations (2) & (3) to enlarge the community;
11. Calculate the community similarity using Equations. (4) to aggregate small communities;
12. Compute the community influence using Equation (5);
13. Determine the intra-community and inter-community influence using Equation (6) & (7);
14. Detect the most influential community;
15. Feed the rich group of attributes, most influential user list and most influential community list to the LSTM network;
16. Train the LSTM by the Swish activation to get the trained model;
17. Test the unknown tweets by the trained LSTM model to estimate the distress criticality level;
18. Evaluate the efficiency of prediction;
19. End

RESULTS AND DISCUSSIONS

In this section, the efficacy of the presented classifier called Multi-Feature LSTM (MF-LSTM) is assessed by implementing it in MATLAB 2017b. In this experiment, the considered Twitter dataset is briefly described in Section 3.1. From this dataset, 70% of tweets are taken for learning and the residual 30% are for testing. Also, by implementing existing classifier models such as LSTM [16], LS-SVM [17], MLP [19], KNN [20], KSVM [20], TSDNet [21] and J48 decision tree [23] on the considered dataset, a comparative study is presented to understand the prediction efficiency based on the accuracy, precision, recall, f-measure and RMSE.

- **Accuracy:** It is the proportion of exact prediction over the total data analyzed.

$$\text{Accuracy} = \frac{\text{TruePositive(TP)+TrueNegative (TN)}}{\text{TP+TN+FalsePositive(FP)+FalseNegative (FN)}} \quad (8)$$

In Equation (8), the amount of tags properly recognized as non-depression, while the amount of tags properly recognized as depression is TN. Likewise, FP is the number of depression labels predicted as non-depression, whereas FN is the number of non-depression labels predicted as depression.

- **Precision:** It determines the correctly predicted labels at TP and FP rates.

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

- **Recall:** It is the fraction of labels that are correctly recognized at TP and FN rates.

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

- **F-score ($\boldsymbol{F}$):** It is calculated by

$$F = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

- **RMSE:** It is the square root of the average of the square of every error. It is the variance of each observed label (l_o) and predicted label (l_p).

$$RMSE = \sqrt{\sum(l_o - l_p)^2} \quad (12)$$

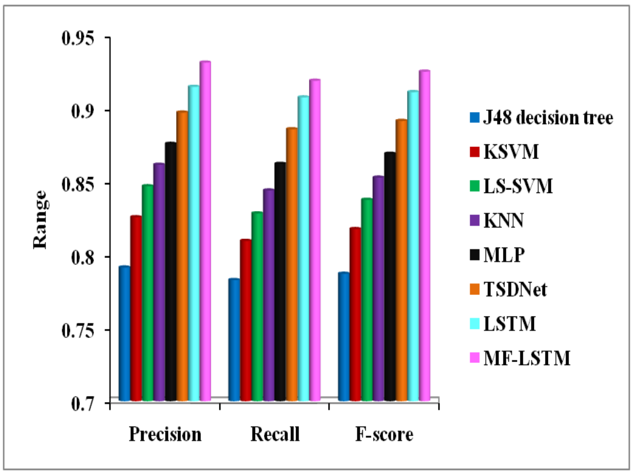

Figure-2. Comparison of precision, recall and f-measure for proposed and existing depression severity level prediction models

Figure-2 demonstrates the efficacy of the different classifiers applied to the Twitter dataset to predict the depression severity levels. It observes that the effectiveness of the MF-LSTM model in terms of precision, recall and f-score is greater than the other classifiers because of combining structural and influence measures of the Twitter network for training the LSTM

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model. So, this scrutiny indicates that the precision value obtained by the MF-LSTM is 17.71% higher than the J48 decision tree, 12.81% higher than the KSVM, 9.99% higher than the LS-SVM, 8.11% higher than the KNN, 6.35% higher than the MLP, 3.81% higher than the TSDNet and 1.81% higher than the LSTM models. The recall value obtained by the MF-LSTM is 17.42% larger than the J48 decision tree, 13.54% larger than the KSVM, 10.96% larger than the LS-SVM, 8.9% larger than the KNN, 6.6% larger than the MLP, 3.75% larger than the TSDNet and 1.26% larger than the LSTM models.

Similarly, the f-score value obtained by the MF-LSTM is 17.57% greater than the J48 decision tree, 13.17% greater than the KSVM, 10.47% superior to the LS-SVM, 8.5% superior to the KNN, 6.46% superior to the MLP, 3.78% superior to the TSDNet and 1.54% superior to the LSTM models.

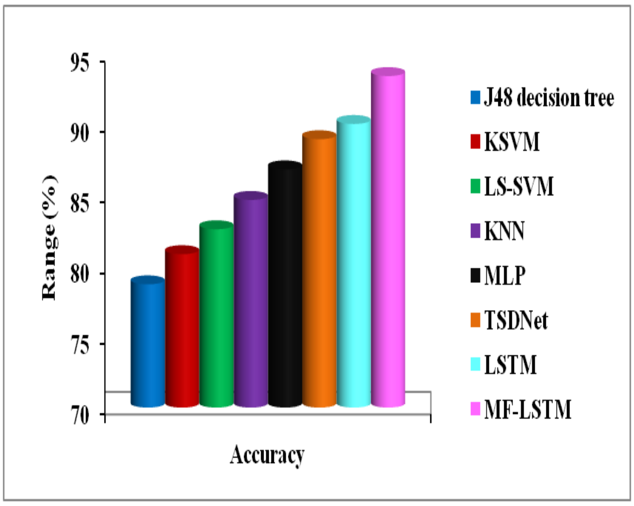

Figure-3. Comparison of Accuracy for Proposed and Existing Depression Severity Level Prediction Models.

Figure-3 exhibits the accuracy (in %) of various classification models applied to the Twitter dataset to predict the user's depression severity levels. It observes that the accuracy of the MF-LSTM is 18.77% better than the J48 decision tree, 15.63% better than the KSVM, 13.15% better than the LS-SVM, 10.37% better than the KNN, 7.62% better than the MLP, 5.03% better than the TSDNet and 3.77% better than the LSTM models. Thus, it indicates that the MF-LSTM network training using the multiple attributes including the structure and influence measures of the Twitter network achieves a higher efficacy in predicting the user's depression severity levels compared to the other classifier models.

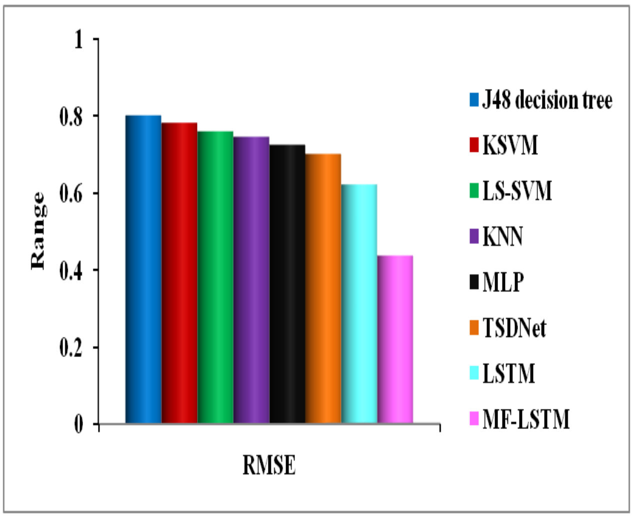

Figure-4. Comparison of RMSE for Proposed and Existing Depression Severity Level Prediction Models.

Figure-4 portrays the RMSE of various classification models applied to the Twitter dataset to predict the user's depression severity levels. It observes that the RMSE of the MF-LSTM is 45.43% less than the J48 decision tree, 44.07% less than the KSVM, 42.47% less than the LS-SVM, 41.35% less than the KNN, 39.67% less than the MLP, 37.65% less than the TSDNet and 29.66% less than the LSTM models. So, it is summarized that the MF-LSTM network model can predict the depression severity level of each user on the social media efficiently compared to the other classifier models without considering the network structure and influence measures.

CONCLUSIONS

In this study, a new model was presented for increasing the efficiency of predicting the online user's depression severity levels based on the social network structure and influence measures of the most influential communities. Primarily, the network structure and similarity measures for all users were determined according to their balanced internal and external influence distribution. Afterward, the influential users and communities were detected along with the rich group of attributes. Further, such attributes were used to train the LSTM model for estimating the depression severity level of each user in the social network during the COVID-19 outbreak. Finally, the testing solutions revealed that the MF-LSTM on the considered Twitter corpus has an accuracy of 93.53% and an RMSE of 0.4376 compared to the existing models for user's depression severity level prediction.

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