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Detecting Self-Esteem Level and Depressive Indication Due to Different Parenting Style Using Supervised Learning Techniques

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***Abstract*—Uprising a child is a psychological construct of parents, which is a combination of factors that evolves over time with the growth and development of the child. Parenting techniques can approach depressive symptoms in children's mind, which also influences their self-confidence level. The main objective of this research is to use supervised learning models to detect different parenting styles, depression indications of adolescents due to parenting, and the level of their self-esteem. Due to the absence of publicly available data, we created our own dataset of about 500 survey responses. Additionally, eleven psychological and nine linguistic attributes of Linguistic Inquiry and Word Count(LIWC) have been utilized to identify depression indications. Among all the supervised models, the Logistic Regression(LR), Gradient Boost Classifier(GBC), and Bi-Directional LSTM(Bi-LSTM) provide better results than other models. This research can improve parents' understanding of their child's psychology and encourage deeper conversations on practical life.**

***Index Terms*—Machine Learning, Deep Learning, LIWC, NLP, Depression, Parenting style, Self Esteem**

I. Introduction

The attribute of parenting is to process the development of a child's growth, education, and health which is implicated in the child's life undertaken by the parental figure [1]. Parenting style can be described as a set of methods that the parents use to raise their kids. Baumrind found three central controls of parenting: Authoritative, Authoritarian, and Permissive [2]. In addition, Maccoby and Martin figured out one more parenting style named Uninvolved [3]. Each parenting style has a unique approach to raising children, and these differences can be seen in various ways. Numerous studies have discovered a connection between parenting styles and children's mental health. Certain parenting styles can be a risk factor for mental and behavioral disorders in children, which can last till adulthood [4]. As parental activity affects mental health, it also influences one's self-esteem [5] and decision-making abilities. According to a report by WHO, one out of every seven(14%) adolescents is associated with depressive symptoms [6]. According to a study by Harter et al., low self-esteem affects one-third to one-half at early adolescence where a large number of them go unnoticed. Self-esteem has only been mentioned once or twice in AI literature as part of a debate on depression. In an interview, BRAC University Counseling Unit claimed that adolescents are not comfortable sharing their personal information. The fundamental goal of this research is to identify various parenting methods, as well as depression indications due to different parenting styles and self-esteem levels using different classification frameworks and data analysis approaches by filling up some Open-ended questionnaires.

The following are the major contributions of this work:

(1) A survey was conducted using a questionnaire consisting of some open ended questions which were inspired by DASS42, PAQ, and Rosenberg's self-esteem questionnaire. Around 500 responses were utilized to build a ground truth dataset. The BRAC University counseling team reviewed the questionnaire and based on their suggestions, we labeled the dataset.

(2) The LIWC package was used on the collected data. We utilized the eleven psychological and nine linguistic features for characterizing the

user's responses. By using these features, another dataset was developed to build and test the models.
(3) Finally, several supervised models were implemented on these three datasets to detect parenting style, depression indications due to parenting, and levels of self-esteem.

II. Literature Review

To detect low self-esteem in youths, Zaman et al. have used several machine learning algorithms and also applied the LIWC text analysis toolkit to find different variables [7]. Christopher Rauh and Laetitia Renee chose unsupervised machine learning(ML) algorithms to classify parenting behavior by the following dataset of children aged between 5 to 29 months [8]. Furthermore, Machine Learning algorithms were applied in the research of Choudhury et al. for predicting Depression in Bangladeshi undergraduates, and datasets were collected through survey questionnaires inspired by the DASS21 and Beck Depression Inventory [9]. Nimi, Y. & Miyaji, Y., two Japanese researchers conducted a study to identify depression in Japanese sentences from the Largest site Tobyo by implementing a Machine learning model [10]. The preprocessing was done by using a Japanese Tokenizer called Sudachi5.
Nowadays, emotional texts posted on social media have gained the focus of researchers. Islam et al. considered social networks as a promising instrument to detect depression [11]. LIWC was used to analyze the raw data, and then he built the ground truth dataset. He has discussed the temporal process, linguistic style, and emotional process for classifying depression indicative posts. Tadesse et al. focused on detecting depression-related posts based on a list of terms among Reddit users [12]. To evaluate the performance of the applied Machine learning models, he has utilized both single features (bigram) and combined features (LIWC+LDA+unigram). Uban, A.S. & Rosso, P. conducted a study to predict self-harm and depression levels among social media users considering Machine learning classifiers and Deep Learning(DL) architectures [13]. Style, content, emotion, sentiment, and the LIWC feature were taken into consideration to determine self-harming inclinations among Reddit users.

III. Methodology

Figure 1 represents the proposed architecture diagram of our research. After creating the dataset, it was analyzed and labeled accordingly. Following the completion of the preprocessing, the features were retrieved using several methods from these labeled data. Afterwards, the data were used for training the classification models. The performance of these models was compared and evaluated through different performance metrics.

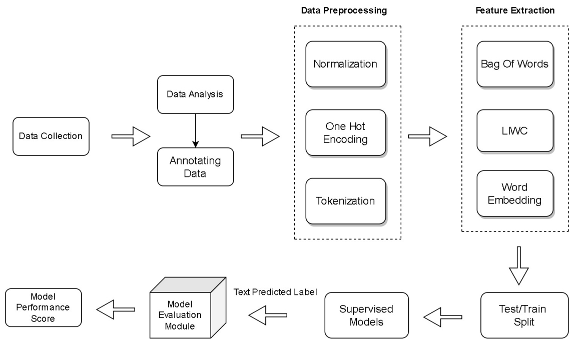

Fig. 1: **Proposed architecture diagram**

A. Dataset Collection

In the AI literature, the discussion about self-esteem and depression due to parenting style is hardly found. Due to the lack of a publicly available dataset, we conducted a survey through google form for this study. In the questionnaire, five multiple choice questions were used to identify the different parenting styles which were inspired by the Parental Authority Questionnaire(PAQ). Then a total of eight open-ended questions were given about depression and self-esteem. The DASS21, DASS42, and Rosenberg's Self Esteem Scale were used to create these open-ended questions [14][15]. While providing the questionnaire, the participants were requested not to overthink and answer the questions honestly, as the survey was conducted anonymously. A total of 712 people's responses were gathered after the survey was conducted.

B. Data Filtering

The audience used different approaches while filling out the survey. The responses which were given into Bangla and transliterated Bangla were eliminated. Also, the emoticons, punctuation marks, and responses of less than two words were removed from the dataset. Lastly, the stopwords were used to eliminate the responses which don't bear much meaning. After filtering out the data, 500 responses were eligible for conducting the survey. Among these responses, the male response is 207, and the female response is 293.

C. Annotation Guidelines

For further procedure, the datasets must be labeled in order to complete the annotation process. Suggestions from the counseling unit of BRAC University were taken about how the responses will be labeled. Responses related to parenting methods have been labeled as authoritarian, authoritative, permissive, and uninvolved. The options of each multiple choice questions represent the individual parenting style. The characteristics that portrayed the parenting style mostly from the audience's response were labeled accordingly. The effects of parenting on the mental state have been labeled into two categories-

- **Depression Indicative**: The responses of sadness, irritability, restlessness, and anxiety are labeled as depressive. Besides, hopeless and worthless reactions are also counted as depressive.
- **Non Depression Indicative**: The happy, hopeful, joyful, and grateful responses are labeled as non-depressive.

The responses that were collected for self-esteem are mainly used for personal evaluation. Through this, the idea of one's confidence level and self-worth can be obtained. Parenting styles have been shown in numerous studies to have a tremendous impact on developing a child's self-esteem. Moreover, self-esteem have been labeled into two categories-

- **High Self Esteem**: The responses that portray one's belief in him/herself are mainly addressed as high self-esteem. Even after knowing and admitting one's weakness, he/she does not give up and goes on. These types of responses are labeled as high self-esteem.
- **Low Self Esteem**: The responses that show a lack of confidence and belief in themselves and tend to focus only on weakness are labeled as low self-esteem. Their responses contain disappointment, frustration, and gloominess.

D. Dataset Statistics

Considering the parenting style, there are 132 authoritarian responses, 285 authoritative responses, 36 permissive responses, and 47 uninvolved responses. Regarding the mental state section, it contains 244 non-depression indicative and 256 depression indicative responses. At last, the self-esteem section consists of 293 high and 207 low esteem responses.

Table I illustrates the length-frequency distribution of depression indication and self-esteem dataset, respectively. The average length of the replies indicates that the audience described their feelings in a detailed way.

TABLE I: **Length-Frequency distribution of depression indication and self-esteem dataset**

Category	Datasets	Q1	Q2	Q3	Q4
Maximum Length	Depression	142	109	74	93
	Self-Esteem	173	106	107	126
Minimum Length	Depression	1	1	1	2
	Self-Esteem	1	1	1	2
Average Length	Depression	19	17	12	12
	Self-Esteem	14	12	17	18

E. Feature Extraction

To increase the accuracy of learned models and eliminate data redundancy, the techniques that were used for extracting the features are N-gram, LIWC, and Word Embedding.

As the data set contains plain text, the n-gram model is used for exploring depression indications from the responses of the audience. For this study, the types of n-gram used are unigram and bigram. The LIWC is a widely used application in computational studies and psychological analysis. This tool extracts textual features by calculating the number of words that belong to LIWC lexicon categories. Then it delivers the percentage of words within that text that belong to one or more categories after the derivation. There are about 80 psychological, linguistic and thematic categories that represent diverse cognitive, social, and affective processes. Among these, a total of eleven features are found to be more correlated to depression and self-esteem than other features (tone_pos, tone_neg, emo_pos, emo_neg, emo_anx, emo_ang, emo_sad, feeling, focus past, focuses, family). Additionally, nine more features are selected for linguistic features to characterize the user's responses.

Words are represented as vectors by word embedding, which has been trained beforehand. When training on contextually relevant data, these word embeddings show implicit relationships between words.

F. Classification Framework

Machine Learning classifiers are now widely utilized in various sectors, including medical prognosis. So this work makes use of several popular supervised machine learning classifiers, including Logistic Regression, Decision Tree

Classifier(DT), Multinomial Naive Bayes(MNB), Gradient Boosting Classifier(GBC), and Support Vector Machine. The ML classifiers have used the TF-IDF and Count-Vectorizer(CV) to find the best model. Machine learning algorithms used N-Gram and LIWC to identify text features. The features were encoded for the parenting detection dataset and then applied to these models. Dataset is split into 80% for training and 20% for testing. To mitigate overfitting in ML algorithms, the K-Fold cross-validation method was implemented. Here the value of K is 10.
Traditional Natural Language Processing(NLP) features were mostly handcrafted, imprecise, and time-consuming to develop. Neural networks can learn multilayer properties automatically and offer better outcomes. For this NLP task, there is the use of models such as Recurrent Neural Network(RNN), Gated Recurrent Unit(GRU), LSTM, and several versions of LSTM such as Stack LSTM and Bidirectional LSTM.

IV. Result and Analysis

The performance of the classification models that are used in this study is evaluated using Accuracy(ACC), F1 score(F1), and Recall. Table II and Table III illustrate the performance of the classifier models that have been used for detecting parenting style, depression indication and self-esteem level. Table II displays the performance of ML classifiers in different datasets. In parenting detection dataset, the Gradient Boosting Classifier(GBC) stands as the best performing classifier with an accuracy and F1 score of 95.00 and 83.28 accordingly. The ML classifiers that have been used after the count-vectorizer show better performance than the TF-IDF in both depression indication and self-esteem dataset. Based on the scores of LR with the count-vectorizer and LIWC from Table II, it can be concluded that it has performed better than the other two algorithms. The accuracy and recall score for depression indication dataset are 83.00 and 76.80. The scores are same for the self-esteem dataset as well. With LIWC, the LR algorithm has the best performance compared to GBC and SVM classifiers. The Figure 2 represents the LR algorithm with count-vectorizer accurately found 46 high self-esteem samples within 57 and 23 low self-esteem samples among 27 samples.

The Table III portrays the comparison between different classifier models, where Bi-LSTM model gains the highest accuracy among all other classifiers in the depression indication dataset. After

Fig. 2: **Confusion matrix of LR with count-vectorizer for self-esteem detection**

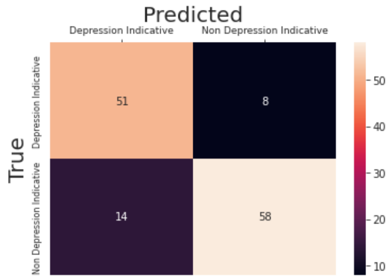

Fig. 3: **Confusion matrix of Bi-LSTM depression indication detection**

observing this Fig 3, we can state that this model correctly identified 51 (TP) depression indications out of 65 (TP+FP) samples and 58 (TN) non-depression indications out of 66 (FN+TN) samples. Following these insights, we can conclude that this model performs well with our requirements. With the use of word embedding technique, this model gets the better performance with the 83.21 accuracy and 83.50 recall score. Furthermore, Fig 5 represents the AUC-ROC graph, where it is clearly visual that Bi-LSTM line is more far away from the random prediction line than other algorithms. It actually demonstrates the supremacy of Bi-LSTM model for depression indication dataset. For further measurements of Bi-LSTM model's performance, we plotted out the loss graph shown in Fig 4. Moreover, the downward tendency and minimization of gap between train and validation curves in each epoch represents the gradual improvement of Bi-LSTM model's performance. In addition, stacked LSTM shows better performance in parenting detection and LIWC featured depression indication dataset with the accuracy score of 77.58 and 74.81 respectively, shown in Table III. Although, LSTM got 67.39 accuracy and 66.09 F1 score in self-esteem dataset, indicates this model outperforms all other deep learning models in self-esteem dataset.

TABLE II: **Performance analysis of ML classifiers**

Datasets	LR			GBC			SVM		
	ACC	Recall	F1	ACC	Recall	F1	ACC	Recall	F1
Parenting Detection	87.00	65.07	66.53	95.00	82.40	83.28	87.00	64.75	67.30
Depression Indication (TF-IDF)	77.00	78.40	76.80	73.00	65.4	70.90	76.00	72.00	74.60
Depression Indication (Count-Vectorizer)	83.00	79.50	76.80	77.00	77.60	73.80	76.00	69.20	67.40
Depression Indication(LIWC)	82.27	86.86	84.44	81.01	79.74	80.20	79.74	79.18	79.34
Self Esteem Indication (TF-IDF)	74.70	51.30	58.50	73.60	59.70	70.00	81.80	74.80	76.20
Self Esteem Indication(Count-Vectorizer)	83.00	79.50	76.80	77.00	77.60	73.80	76.00	69.20	67.40

TABLE III: **Performance analysis of DL classifiers**

Datasets	LSTM			Stacked LSTM			Bi-LSTM		
	ACC	Recall	F1	ACC	Recall	F1	ACC	Recall	F1
Parenting Detection	75.15	74.75	75.05	77.58	76.50	77.26	71.52	71.94	72.05
Depression Indication (Word Embedding)	78.63	78.41	78.41	80.51	80.41	80.10	83.21	83.50	83.16
Depression Indication(LIWC)	71.76	70.17	70.19	74.81	74.64	74.60	72.52	71.94	72.05
Self Esteem Detection(Word-Embedding)	67.39	66.01	66.09	63.04	61.42	61.33	63.77	62.41	62.43

Fig. 4: **Loss Graph of Bi-LSTM for Depression Indication Detection**

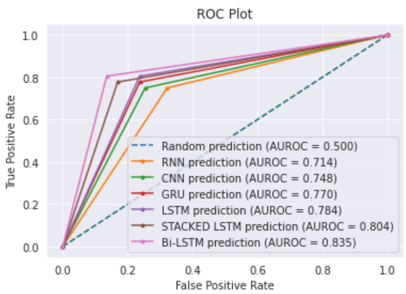

Fig. 5: **AUC-ROC Graph for Depression Indication Detection**

V. Conclusion

To conclude, this research applied supervised algorithms to assess parenting style, depressive indications related to parenting, and self-esteem among young individuals. The dataset was created through an online survey because of the scarcity of publicly available datasets. Furthermore, LIWC was applied in the dataset to detect depression indications. The research can be enhanced and developed in the near future by using advanced transformers and hybrid models. To enrich the dataset, more responses from the survey would be gathered. In addition, we gathered information about the audiences' residences from the survey. Geographically, the pattern of different parenting styles and psychological conditions of adolescents due to their parents can be identified resultantly. The supervised models can also be implemented to detect depression from social media posts. Nowadays, people express their emotions not only through texts but also through posting images. Thus various computer vision techniques can be utilized to predict depression from images.

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