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Classification of Depression, Internet Addiction and Prediction of Self-esteem among University Students

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***Abstract*—Machine learning is massively used in the prediction of cognitive and psychological features in recent times. This research aims to find the predictability between leading disorders like Internet addiction, depression, and low self-esteem. For this purpose, 461 undergraduate students have been selected arbitrarily from several educational institutions of Dhaka city and voluntarily completed a standard questionnaire that was prepared based on the self-reported measures concerning the disorders mentioned above. Different standard psychometric scales such as Internet Addiction Test (IAT) by Dr. Kimberly Young, Self-esteem Scale by M. Rosenberg, PROMIS Emotional Distress Depression short-scale by PROMIS Health Organization have been used in the correlational survey. The internal consistency of the data has been proven by Cronbach alpha. Subsequently, the Shapiro-Wilk Normality test revealed the data to be non-parametric. Several essential features have been extracted to reduce the redundancy from the data using minimum-redundancy-maximum-reduction (mRMR) and Chi-square test. A prediction model has been devised using Logistic Regression, Naive Bayes, Random Forest, C4.5 Decision Tree, and k-Nearest Neighbors. The experimental result shows that Internet addiction and depression are interconnected with self-esteem, and thereby, the prediction model can be built to reduce the severity of these disorders.**

***Index Terms*—Internet addiction, depression, self-esteem, machine learning, prediction**

I. Introduction

The increasing impact of communication media, especially the Internet, harms people in their day to day life. Nowadays, it is observed that an individual's daily life faces profound changes due to the Internet. Although our life is made easy and straightforward through the Internet, it also brings a considerable risk of causing depression and low self-esteem among students [1], [2]. Internet addiction has been experienced by roughly 1.4-20.8% of teenagers and 8-13% of college students in their lifetime [1]. Also, people having psychological instability and issues with impulsiveness are obsessed with the Internet more than others [3].

One of the leading health problems in contemporary society is depression. The World Health Organization (WHO) performed a detailed study in 2016 that displays depression is a significant issue for about 350 million people in the whole world. Even though depression has been dealt with by the medical professionals in early times, however, machine learning is slowly gaining much popularity in early detection and prevention of this disorder. Many factors affect depression, among which self-esteem is a major one. Self-esteem reflects one's appreciation and approval of its characteristics though individuals self-assessment [4]. Reports display that self-esteem explains 38% of Internet addiction with contentment and remoteness, and correlate with time allocation troubles, interpersonal communications, and health issues [3]. Another finding suggests that people with low self-esteem are more addicted to the Internet. Internet addiction and self-esteem are measured with the help of the Internet Addiction Scale (IAS) and Coopersmith Self-esteem Scale for measurements in [5]. To conclude, usage of the Internet can influence both disorders, namely depression, and low self-esteem.

The main objective of this research is to indicate a fundamental review of any interconnection between the major psychological disorders like Internet addiction, low self-esteem, and depression by using different kinds of measures and find if another one can precisely predict one variable. Here, Internet addiction, self-esteem, and depression are considered as a single variable each. According to the studies above, depression and lack of self-confidence can be predictive of extreme Internet usage. This research represents the comparison of accuracies using different machine learning algorithms on a dataset of 461 undergraduate students.

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The rest of the study is arranged in the following order. Section II illustrates background studies. Research methodology has been described in section III, and section IV represents results and discussion of the study. Section 5 concludes the paper with future work.

II. Related Work

Several research efforts have been directed toward the everyday use of the Internet, depression, and self-esteem. The authors of [6] introduced a system called MONARCA that can do self-management, assess, and treat bipolar disease by using small sensors on the mentally disturbed patients. In [2], it is found that depression and Internet addiction is strongly correlated with each other. They show that in the way of dealing with Internet addiction, self-esteem and psychopathology can be considered as essential factors. They have used the Internet Addiction Scale (IAS), Symptom Checklist (SCL), and self-esteem scale developed by Rosenberg, and discovered that self-esteem decreases as the Internet Addiction Scale increases. The tested model used in one of the papers can predict 28% of the depression among adolescents. It also shows that daily Internet use and self-confidence can affect depression significantly [3]. Kruskal-Wallis test, Spearman's correlation, and Mann-Whitney U test analysis are used in another case study to correlate Internet addiction with depression to the university students and found that 8.3% of people on average were addicted to the Internet. They found a strong relationship between Internet addiction and depression (rs=0.804) where rs stands for Spearman's correlation coefficient [5].

Another research proposed a psychiatric state detection system through the usage of four wearable biosensors to predict the emergency psychiatric state of the patients [7]. They gained an accuracy level of 83% and designed the system to treat the disturbed patients in a homely environment. In another study, by analyzing correlation, Internet addiction is found to be severely related to depression, anxiety, and stress. They used Depression, Anxiety, and Stress Scale (DASS) to measure the correlations [8]. Another observation represents that regardless of gender, higher virtual social assistance creates more depressive symptoms in an individual's life [9]. In [10], they evaluated a health system via telephone, which keeps track of depression and stress of the mentally unstable patients. The system used a Patient Health Questionnaire (PHQ-9) and health survey questionnaire for veterans (SF36-V) to measure the depression and pain levels of the subjects. The study concludes that this system is recommended in monitoring the severity of pain and depression for medical purposes. Results of a study suggest that 40.7% of the students they examined have an Internet addiction. They used regression analysis that reveals the depression and self-esteem are capable of predicting the variance of daily Internet use [11].

Another study revealed that male university students are addicted to the Internet and face melancholy more than female students [12]. A significant relationship exists between Internet addiction and depression. The findings of the paper indicate that the level of self-esteem can be predicted from internet addiction and depression questions. Additionally, this paper combines both the statistical and machine learning measures to get the exact and precise level of dependency of the variables, which makes this research distinct from other studies.

III. Research Methodology

At the beginning of the study, a dataset has been prepared by collecting data from the undergraduate students studying in various educational institutes of Dhaka. Some exploratory analysis has been conducted to understand the demographic factors of the respondents. Later, we have measured Internet addiction, level of depression, and self-esteem score of the respondents using Internet Addiction Test (IAT), PROMIS Emotional Distress-Depression Short scale, and Rosenberg Self-esteem Scale (RSE) respectively. After preparing the data, statistical analysis has been conducted to find the internal consistency and distribution of the data. Finally, after processing the data and selecting the most relevant features, five machine learning algorithms such as Logistic Regression, Random Forest, Naive Bayes, C4.5 Decision Tree, and K-Nearest Neighbor run to build classification and prediction models based on accuracy, precision, and recall. Fig. 1 displays the sequence of operations of this research.

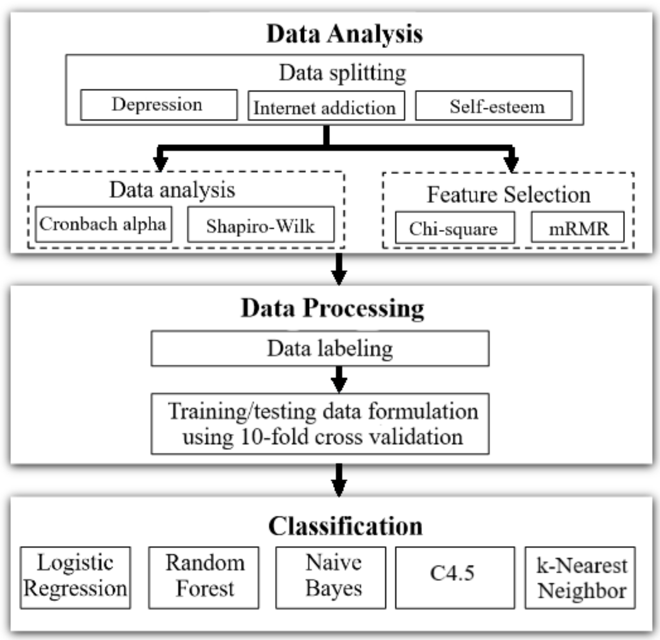

Fig. 1. Workflow of the research operations.

A. Data Collection and Exploratory Analysis

Participants are arbitrarily chosen using different social media and networking sites to partake in a 66-item survey measuring the levels of depression, Internet addiction, and self-esteem. Individuals between the age of 20 and 25 are involved in our study. Voluntary response sampling is used to select the participants. Four hundred sixty-one undergraduate students who are studying in different universities of Dhaka city complete the survey. Among these participants, 212 are male (46%), and 249 are female (54%) with an overall average age of 23 years. The majority of the participants are in their 1st year (25%) and 4th year (41%) of university life. Since participants are students, 75% of them are currently unemployed, and 23% of them are currently doing part-time jobs. Only nine students (1.95%) are involved in full-time jobs. Fig. 2 shows the demographic factors of the respondents.

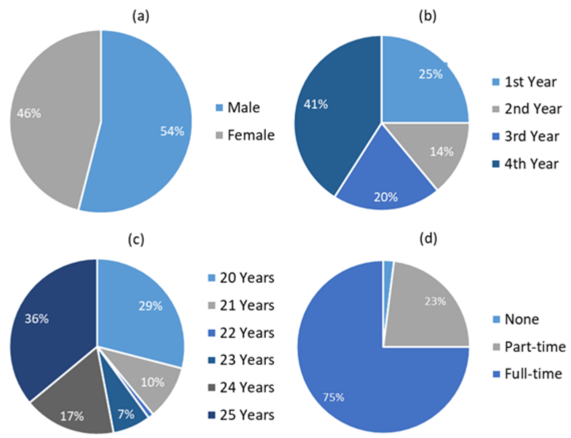

Fig. 2. Demographic factors of the respondents. (a) percentage of male and female respondents, (b) percentage of survey participants based on academic year of study, (c) percentage of the participants based on age, (d) percentage of the respondents based on their current employment.

The following sections explain the scales used to measure Internet addiction, depression, and self-esteem in detail. It also includes the details of the statistical analysis methods, feature selection methods like mRMR and Chi-square, and different machine learning models used so that this study is easily understandable by the readers.

a) Internet Addiction Test (IAT): The Internet Addiction Test measures the stage of web usage of an individual [13]. It contains 20 questions, and the scale provides a result ranging from 0 to 100. Those who acquire a score between 0-30 are normal Internet user; scores in between 31-49 represents a mild addiction level; 50-79 is considered a moderate addiction level; scores between 80-100 represents a severe addiction level of dependency upon the Internet [14].

b) PROMIS Emotional Distress-Depression Short Scale: The PROMIS depression instrument includes an eight-item short questionnaire [15]. At first, the raw score is calculated by adding all the questions and then finding the corresponding t-score from the t-score table to assess the depression level of an individual. The t-score is a standardized score metric, and like every other standardized score, the t-score has a middle score (mean) of the relevant reference population of a large sample. The score range of 0-54.9 is marked as having none to slight depression, 55-59.9 is considered to have mild depression, 6069.9 represents the moderate level, and above 70 interprets as a high level of depression.

c) Rosenberg Self-esteem Scale (RSE): The Rosenberg Self-Esteem Scale is a well-renowned measurement for assessing self-esteem [16]. It contains a ten-item questionnaire that includes a 4-point Likert scale with the score that stretches from 4-40 [17]. A higher score acquired by an individual represents high self-esteem. The score ranging from 0-15 indicates that one has low self-esteem.

B. Statistical Measures

The noted results of the statistical part are analyzed using SPSS (Statistical Product and Service Solutions) version 25.0. SPSS is chosen for the calculation of the statistical part of this research because it gives more efficiency, flexibility and it can generate results, charts, tables, plots from files containing data of almost all types.

a) Cronbach's Alpha: Cronbach's alpha is introduced by Lee Cronbach that measures the reliability of the dataset, how correctly tests identify what it should [18]. The formula for measuring Cronbach's alpha (α) is expressed in (1).

$$\alpha = \frac{N + \bar{c}}{\bar{v} + (N-1)\bar{c}} \tag{1}$$

Here, N is the total number of samples, $\bar{v}$ represents the average variance, and $\bar{c}$ is the average inter-sample covariance among the samples.

b) Shapiro-Wilk Normality Test: The normality of a dataset plays a significant role while conducting statistical tests, as many of them require parametric or non-parametric variables. Normally distributed population indicates that the samples are symmetrically distributed, and most values assemble around the mean. Non-parametric tests do not assume the reference population to be normally distributed [11]. To check if the dataset is normally distributed or not, the Shapiro-Wilk test is conducted in this research. The null hypothesis for the test is that the variables are normally distributed. If the probability value (p-value) is less than 0.05, then the null hypothesis is rejected, and the dataset is considered as non-parametric. Shapiro-Wilk test (S) is conducted using (2).

$$S = \frac{\sum_{i=1}^{n} a_i x_i}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{2}$$

Here, x_{i} represents the sample values in ascending order, n is the sample size from a normal distribution, and a_{i} is the constant generated from the mean, variance, and covariance of the order statistics.

C. Feature Selection

Before conducting classification and prediction, two feature selection methods have been applied to reduce irrelevant information and include only the meaningful information in the model. After evaluating the existing techniques for feature selection, we chose the Chi-Square test and mRMR because they are proven to be the most useful and proficient strategies.

a) Chi-Square: Chi-Square is a state-of-the-art feature selection method that ranks the features according to their corresponding chi-square statistic for the target (output). Firstly, the Chi-Square (χ) value is calculated for each of the features using (3).

$$\chi = \sum_{k=1}^{n} \frac{(e_k - f_k)^2}{e_k} \tag{3}$$

Here, e_{k} is the number of expected values, f_{k} is the number of observed values, and n denotes the total number of expected and observed value in a given data.

b) mRMR: Minimum-Redundancy-Maximum-Relevance (mRMR) is a feature selection algorithm that combines the two criterion functions of maximum relevance and minimum redundancy. It creates a feature subset that has maximum mutual information with the output, while also selecting distinct features with minimum similarities to reduce redundancy. Mutual information defines the maximum dependency among the target and the features. The mRMR algorithm can be expressed by (4).

$$J_{mRMR}(X_k) = I(X_k; Y) + \frac{1}{|S|} \sum_{X_k \epsilon S} I(X_k; X_j) \tag{4}$$

In (4), $I(X_{\mathrm{k}}; Y)$ indicates the feature relevance between the two features X_{k} and Y, and second term removes the features that has high mutual information with the selected feature, X_{k}. This algorithm provides a list of features in ascending order, with the most important feature residing in the first element of the list and the least important feature residing at the bottom of the list.

D. Data Formulation and Prediction Models

The machine learning part of this research represents the prediction level of the variables. The dataset used in this research requires a supervised machine learning approach since the outcome is labeled. The data is partitioned for training and testing through 10-fold Cross-validation since it results in a lower variance. Since our dataset does not contain any missing (or null values) and outliers (or extreme) values, it does not require removal or fixing data. Many algorithms are run on our dataset to predict the outcomes. Features are mixed and matched to improve accuracy. Additionally, Receiver Operating Characteristics value (ROC value), precision, and recall are used to define how many targets are being predicted correctly and thus provide a better model [19]. Fig. 3 represents the distribution of the data for depression, Internet addiction, and self-esteem.

Five machine learning algorithms, such as Logistic Regression, Random Forest, Naive Bayes, C4.5 Decision Tree, and K-Nearest Neighbor (K-NN) are run on the dataset to verify whether the three variables above can predict one another. First of all, Logistic regression is used in the dataset for predictive study. This method is used to correlate one or more independent variables to anticipate the outcome variable. Random forest algorithm is used as it is the most straight forward algorithm, and it joins several decision trees and generates an accurate result. Moreover, the Naive Bayes classifier is chosen because it is considered as one of the best algorithms for classification, and it uses Bayesian methods of probability.

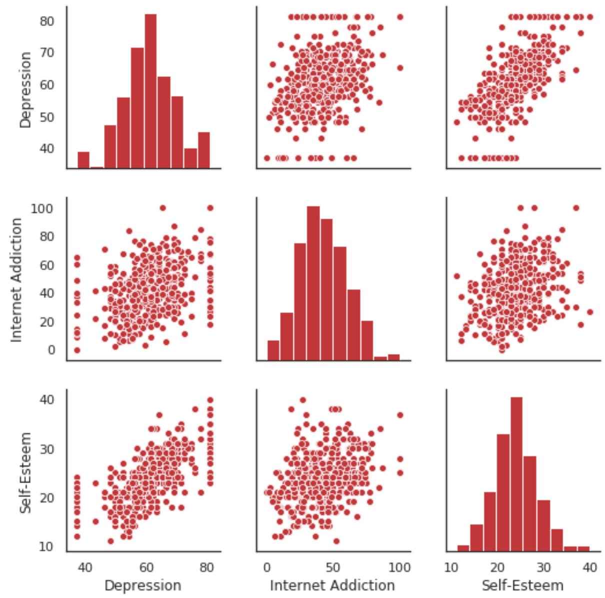

Fig. 3. Data visualization for depression, Internet addiction, and self-esteem distribution.

The C4.5 decision tree is used as it produces a decision from a simple tree that is created by minimal effort. Again, the K-NN algorithm is applied since it is a non-parametric method and suitable for medium length datasets, which satisfies the criteria of the dataset used in this research.

The machine learning algorithms have been applied by using Spyder IDE (Integrated Development Environment) and cross-checked using the data mining software Weka version 3.8.1. Weka is chosen because it has built-in sophisticated data mining algorithms, and it requires minimal effort to conduct data preprocessing.

E. Performance and Evaluation Methods

The results gained from the prediction model are evaluated based on their corresponding accuracy, precision, recall, and ROC curve values. These calculations require the number of correct and incorrect predictions of the model. The correctly predicted samples are denoted as true positive (TP) and true negative (TN), while the false predictions are denoted as false positive (FP) and false-negative (FN).

The accuracy of a model defines the rate of correctly predicted samples among the total samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Precision denotes the rate of correctly identified true positive values among the overall true values.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall, also known as true positive rate, denotes the rate of correctly identified true positive values.

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

ROC (Receiver Operating Characteristics) curve determines the capability of a model for correctly predicting the variables. It is drawn using the true positive rate, TPR against the false positive rate, FPR. If the ROC area is closer to 0, it indicates the model can distinguish between classes very well, a poor ROC value that is closer to 0 indicates a weak separability of the model.

IV. Results and Discussions

The dataset has been tested for internal consistency by calculating the Cronbach alpha for each of the variables, namely Internet addiction, depression, and self-esteem. Cronbach's alpha value closer to 1 indicates that the data is consistent. Table I represents the results of internal consistency and proves that the data is consistent.

TABLE I
INTERNAL CONSISTENCY OF THE VARIABLES

Variable	*Cronbach's Alpha*	*Consistency*
Internet addiction	0.89	Good
Depression	0.94	Excellent
Self-esteem	0.83	Good

The normality distribution of our data is evaluated using the Shapiro-Wilk test. Data is considered to be non-parametric if all the p-values of the Shapiro-Wilk test for all the variables are less than 0.05. Table II represents the result of the Shapiro-Wilk test for several variables. It is shown that the dataset is non-parametric.

TABLE II
SHAPIRO-WILK NORMALITY TEST RESULTS

Variable	*p-value*	*Normality*
Internet addiction	0.006	Non-parametric
Depression	1.63E-7	Non-parametric
Self-esteem	0.003	Non-parametric

The crucial features have been extracted from Internet addiction, depression, and self-esteem datasets to reduce the dimensionality of the prediction model. Feature selection using Chi-square and mRMR test returns a list of optimal features that contribute most to the target output and omits the irrelevant features. We need to examine the accuracy of the classification model. Fig. 4 shows the optimal number of features selected by mRMR for Internet addiction, depression, and self-esteem by comparing the accuracy results of different algorithms.

Similarly, optimal features have also been selected using Chi-square for these three variables. Table III represents the optimal number of features using Chi-square and mRMR for each of the variables: Internet addiction, depression, and self-esteem.

TABLE III
FEATURE SELECTION RESULTS

Variable	*Total features*	*Chi-square*	*mRMR*
Internet addiction	20	18	17
Depression	8	6	8
Self-esteem	10	8	8

After selecting the relevant features of the data, different machine learning approaches have been conducted to achieve

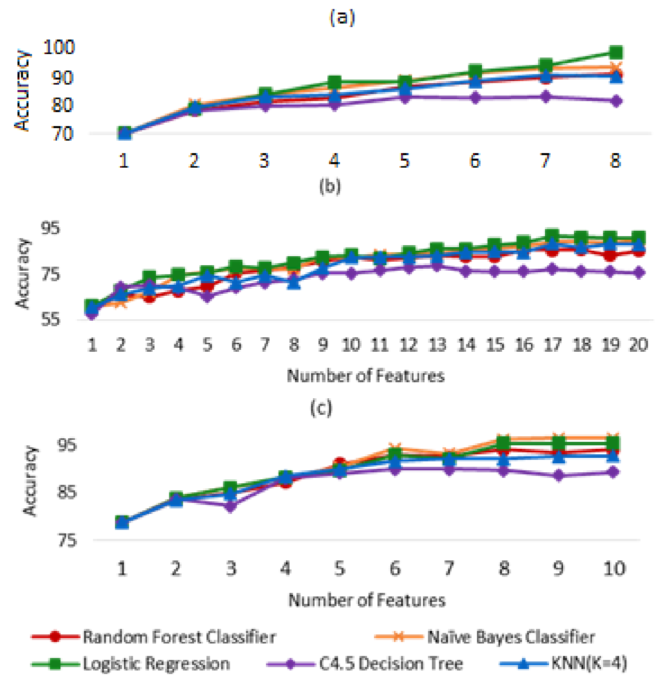

Fig. 4. Feature selection using mRMR of (a) depression (b) Internet addiction and (c) self-esteem.

prediction models. The following results have been observed. It is found that Internet addiction can predict the outcome of self-esteem. Therefore, by finding the Internet addiction level of the people, their level of self-esteem can be predicted. Moreover, depression and specific self-esteem questions can predict self-esteem. It means that if anyone is struggling with high, medium, or low depression, then his/her self-esteem level can be predicted, which can also be low, medium, or high.

Table IV displays the ROC value and accuracy of different algorithms. It is found that Logistic regression gives the most accurate result for the predictions by considering both the ROC area and accuracy. It is observed that self-esteem can be predicted 83% accurately on average from 8 questions of depression scale with the addition of 2 questions from the self-esteem scale. These two questions from the self-esteem scale have been added to gain better accuracy. Among the five algorithms, the best accuracy rate and ROC value for this prediction are produced by Logistic regression. Again, by adding three questions of self-esteem scale with the Internet addiction scale, better accuracy of more than 80% is gained

TABLE IV
RESULTS FROM ALGORITHMS

Independent variable	Dependent variable	Algorithm	ROC area	Accuracy (%)
Features of depression and 2 features of self-esteem	Self-esteem	Logistic Regression	0.933	86
		kNN	0.853	82
		Random Forest	0.918	84
		C4.5 Decision Tree	0.849	83
		Naive Bayes	0.889	82
Features of Internet addiction and 3 features of self-esteem	Self-esteem	Logistic Regression	0.94	82
		kNN	0.678	69
		Random Forest	0.925	83
		C4.5 Decision Tree	0.758	80
		Naive Bayes	0.841	76

from three algorithms for the prediction of self-esteem. Even though Random forest classifier gains the highest accuracy of 83% in this case, however, the best ROC area is generated from Logistic regression with 82% accuracy. Therefore, Logistic regression produces the best result for predicting self-esteem from Internet addiction.

Further observation of precision, recall, and f1-measure reveals that Logistic regression provides the best prediction models for the two models. Fig. 5 represents the comparison of these three variables for each of the algorithms. Among the five algorithms, Logistic regression performs the best for predicting self-esteem from both depression features, and Internet addiction features separately.

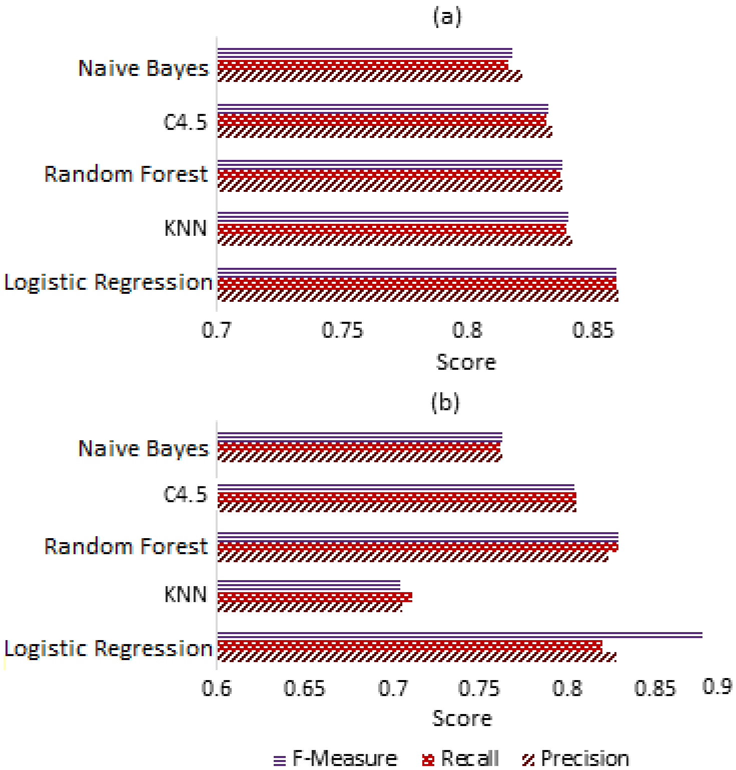

Fig. 5. Precision, recall and F1-measure for predicting (a) self-esteem from depression (b) self-esteem from Internet addiction

V. Conclusion and Future Work

The escalating use of the Internet is causing multiple mental disorders and effecting people's personality traits. The main focus of this research is to find whether Internet addiction, depression, and self-esteem are interconnected and influential on each other. Many intriguing results have surfaced in our study. Again, depression has a relation to Internet addiction and self-esteem. Self-esteem also has predictability with Internet dependency among university students. The most exciting finding of this study is that self-esteem levels can be predicted by depression and also by Internet addiction. In the future work, more in-depth analysis such as neural network, deep learning will be conducted to find out if there are any hidden layers or dependency between the variables. The range and age limit of the respondents can be broadened to get a more accurate and general result. A new algorithm can be proposed to determine the relationships and suggest the necessary measures that have to be taken to minimize the effects of these leading disorders.

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