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Using Advanced Analytical Models to Assess Self-Esteem and its Important Predictors in Undergraduate Students

Zahid Khan
Department of Statistics, University of Malakand, at Chakdara, Pakistan
Email: zahid.uom1@gmail.com
Sulaiman Khan
Department of Statistics, University of Malakand, Chakdara, Dir Lower, Pakistan
Email: sulaimankhan9806@gmail.com
Jawad Ahmad
Department of Statistics, University of Malakand, Chakdara, Dir Lower, Pakistan
Email: jawa05321@gmail.com
Haroon Ur Rahid
MS Scholar, School of Mathematical Sciences, Zhejiang Normal University, Jinhua 321004, China
Email: haroonurrashid@zjnu.edu.cn
Niaz Muhammad
Department of Statistics, University of Malakand, Chakdara, Dir Lower, Pakistan
Email: niaznm596@gmail.com

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Corresponding Author:
Zahid Khan
Email: zahid.uom1@gmail.com

ABSTRACT

Self-esteem is an important psychological concept that plays a major role in determining academic achievement, emotional state and social adaptation among college students. This paper examine the occurrence of self-esteem and the factors which impact self-esteem with key factors identified in undergraduate students in universities at the Malakand Division, Pakistan using machine learning models. A cross-sectional survey was done and a representative sample of students was gathered with the help of which demographic, academic, social, and psychological data were obtained. The data were analyzed using machine learning models, Random Forest, Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Logistic Regression. Confusion matrix were used to assess the performance of these four machine learning models. The study show that 55.70% students have normal self-esteem and 44.30% student have low self-esteem. The results show that there is a significant difference in the level of self-esteem amongst students and is largely influenced by various factors, including income, GPA and weight of the students. Machine learning models were found to be quite efficient at detecting complex and nonlinear associations amid predictors and showed much higher accuracy levels than conventional statistics. The outcomes can be used to underscore the usefulness of data-driven methods in the study of psychological constructs and emphasize the importance of specific interventions as the means of boosting the self-esteem of the students.

The work is informative to the university administrators, policymakers and mental health professionals, and offers an evidence-based model of what counseling programs, peer support programs and academic mentoring strategies can be designed to achieve the goals of promoting student well-being in culturally and socioeconomically divergent settings.

Introduction

Self-esteem, which is generally described as a subjective appraisal of personal value, is a necessary psychological concept that determines a vast number of emotional, behavioral, and mental consequences (Rosenberg, 1965; Orth and Robins, 2014). In the case of undergraduate students, the self-esteem factor is especially important since it determines the level of academic interest, motivation, coping mechanisms, social adaptation, and psychological wellness in the long term (Lane et al., 2004; Marshall et al., 2014). The life of the university is a critical stage of development, which is associated with greater independence, academic changes, exploration of identity, and social problems. Therefore, the concept of self-esteem as students is both scholarly and essential in planning proper support systems in institutes of higher learning. The problem of the Malakand Division Pakistan, is of particular interest as per the cultural requirements, socioeconomic inequalities, academic stresses, as well as the lack of mental-health facilities that distinctly influence the psychological functioning of students.

The Malakand Division, which is a culturally rich but economically poor area of Khyber Pakhtunkhwa, exhibits distinctive environmental and social interactions that could affect the self-esteem of students. The students of this region have to struggle with financial constraints, lack of exposure to psychological services, conservatism, and strong demands of family-based expectations, which can all affect variable self-esteem (Shah & Nisar, 2021; Bano and Malik, 2014). Institutions of learning in remote or developing regions do not have well-organized psychological counseling facilities, peer support systems, or co-curricular activities to promote the development of confidence. Additionally, a number of students are long distance commuters, have low internet access and an extreme academic rivalry on a limited budget and this creates an atmosphere in which the negative self-perceptions can easily arise. A study conducted in Pakistan has indicated that the prevalence of psychological constructs like stress, anxiety, depression, and social pressure is higher in the semi-urban and rural areas among students (Khan et al., 2019; Malik et al., 2020), which implies that such a study should be conducted in regions like the Malakand Division.

Research in the global scene has always shown that self-esteem in the case of university students is correlated with numerous demographic, psychological and environmental forecasts. One of the most researched variables is gender, where female students were found to have lower self-esteem in traditional societies because of more social limitation, role expectations, and lack of opportunities to express themselves (Zafar et al., 2020; Arif and Naqvi, 2016). Self-esteem also depends on age and the year of study, as first-year students generally have more problems with adjustment, whereas senior students slowly build identity clarity and academic confidence (Orth et al., 2016). The other background that can affect the performance is the socioeconomic background, in which students with low-income families tend to experience a lack of financial security that can damage their feeling of competence and academic stability (Pasha and Munaf, 2013). Peer relations, parental involvement, academic performance, self-efficacy, and the presence of social support systems are considered to be other important predictors (Chemers et al., 2001; Marshall et al., 2014).

In addition to demographic and psychosocial factors, academic-related stresses have a great influence on self-esteem of the students. Pakistani students often complain about excessive workload, stress before exams, a lack of teacher-student contact, and poor academic feedback, which can cause a decrease in confidence levels in students and unfavorable self-comparisons (Malik et al., 2020; Bano and Malik, 2014). Research indicates that, students who underperform in studies usually grow to have a low self-esteem, and those students who are able to perform well in school usually strive to have a high self-worth (Lane et al., 2004). Besides that, peer comparison, which is typical of collectivist societies, may have a significant effect on the way students assess their competencies. It has been found that in many cases, students who compare themselves to other students and find themselves less successful tend to demonstrate low self-esteem even when their abilities are considered (Valkenburg et al., 2017; Robins et al., 2001).

The other level of research in self-esteem is associated with exposure to digital media. The use of social media and especially the high social comparison social media platforms have been associated to have a negative impact on the self-esteem of students (Valkenburg et al., 2017). Literature in the developing world illustrates that online content has been making youthful adults measure their lifestyles, looks, and success against the virtual images and falsely evaluate themselves. In areas such as Malakand where digital literacy is on the rise, but there are less regulatory tools, exposure to unrealistic online norms can serve to exacerbate feelings of incompetence or societal pressure.

Although there has been extensive research done in the past on the factors utilizing the traditional psychological and educational research, the recent developments in the sphere of data analytics have presented new opportunities to explore them in greater detail. Machine learning (ML) provides advanced mechanisms with the ability to create complex and nonlinear associations among many predictors and psychological outcomes like self-esteem (Yarkoni and Westfall, 2017; Bzdok and Meyer-Lindenberg, 2018). Random Forest, Gradient Boosting Machines, Support Vector Machines and other ML algorithms are able to recognize any subtle interactions that might go unnoticed with the traditional statistical methods. In addition, using the ML techniques

enables the researcher to achieve greater accuracy in classifying individuals as low self-esteem, moderate self-esteem, or high self-esteem, which is beneficial to the institutions in identifying at-risk students.

Over the past years, the use of ML in mental-health and psychological studies has increased at a very high rate. The researchers were able to predict depression, anxiety, suicide risk, academic stress, and personality traits with great accuracy using ML algorithms (Chakraborty et al., 2020; Iqbal et al., 2021). The fact that they can handle large datasets, multivariate types of variables and are capable of identifying latent patterns of behavior has made these models have a high predictive performance. Nevertheless, in spite of these developments, the number of studies that apply ML directly to self-esteem prediction among students both on a worldwide and near-absolutist Pakistani level are minimal. This disparity shows the necessity of local and data-intensive studies.

Some studies conducted in the study area but self-esteem data is not yet analyzed using machine learning models (Akhtar et al., 2016; Khan et al., 2021; Khan & Ali, 2022; Haq et al., 2022; Khan et al., 2022a, 2022b, 2022c, 2022d, 2022e, 2022f, 2022g, 2022h, 2022i, 2022j, 2022k; Khan et al., 2023a, 2023b, 2023c, 2023d; Cheema et al., 2024; Haq et al., 2024; Khan & Ali, 2024; Khan et al., 2024a; Khan et al., 2025a, 2025b, 2025c; Shakoor et al., 2025). The current research paper attempts to answer three big gaps. The first one is that scanty empirical research exists on the prevalence of levels of self-esteem among undergraduate students within the Malakand Division. Second, there is a lack of information regarding the comparative meanings of academic, demographic, social, and psychological predictors in this cultural setting. Third, machine learning models in predicting self-esteem have not been evaluated in a systematic study of students in Pakistan. Through the use of ML, this research improves the prediction efficiency of self-esteem classification in addition to determining the variables with the greatest effect, thus adding to a broader picture on psychological well-being in university students.

It is anticipated that the results of this study will assist academic institutions in creating strategic mental-health interventions, including peer mentoring programs, stress-management workshops, counseling centers, and academic support services. The findings can also help policy makers' better plan and allocate resources for education by educating them about the psychological difficulties faced by students in remote areas.

Methods and Materials

To determine the prevalence of self-esteem among Pakistani undergraduate students in the Malakand Division of Pakistani universities and the influence of factors on it, this research design was cross-sectional. The sample size was selected as two distinguished universities in the region which included the University of Malakand and the University of Swat as the representative sample of the undergraduate student body in the region.

A cluster sampling was adopted in order to ensure the viability of data collection and a representative sample of the students. The two universities were considered to be the major clusters during the first stage. Each university was randomly selected as well as the departments within the university and then classes within the departments were randomly selected. Students attending these classes were open to participate in the study. The multistage cluster sampling method proved to be very effective as it was able to include numerous students across different academic disciplines and study years and also included diversity in social, academic and demographic background.

The data were collected by a structured, self-administered questionnaire. It included both academic and demographic data, including department, year of study, and self-reported academic performance and age, gender, socioeconomic status, and parental education. Questions were also included in order to assess social and psychological constructs known to influence self-esteem including peer support, family support and perceived stress.

Using machine learning methods on the data collected resulted in the most important predictors of self-esteem. Some of the preprocessing steps included scaling continuous variables where necessary, addressing missing values and coding categorical variables. The machine learning models used were Random Forest, Gradient Boosting, Support Vector Machines, and Logistic Regression. The performance of the model was evaluated using confusion matrices that provide information on the overall accuracy or about the true positive, true negative, false positive, and false negative rates. The discrimination ability of each model was assessed with the help of cross validation, Receiver Operating Characteristic (ROC) curves and the area under the curve (AUC), confusion matrix. Cross validation is used to measure the model performance, a five-fold cross-validation ($k = 5$) was carried out. Each iteration consisted of the dataset being divided into five folds, four of which were used to train the model and the remaining one was used to test the model. They repeated the procedure five times, and the mean accuracy over folds was provided in order to measure predictive performance.

Also, feature importance measures of tree-based models were used to rank the variables that had the greatest effect on self-esteem. All analyses were performed with R software with relevant machine learning and statistical analysis packages.

This methodological framework by integrating excellent sampling techniques and the use of the latest analytical procedures facilitated the comprehensive assessment of the prevalence and determinants of self-esteem, providing an in-depth insight into student well-being in the Malakand Division.

Result and Discussion

In this section, we present the study's findings, focusing on the key factors influencing self-esteem and its prevalence among undergraduate students.

Descriptive Analysis of important Variables

Table 1 shows grouped frequency distribution of four main variables, including Income, Locus of Control, Weight and GPA. The data was grouped into the right class intervals to realize the distribution and relative proportion of the different ranges.

Income of respondents (in thousand) is shown in Table 1. Most of the participants (83.99) are in the low income bracket of 9.11--188 units and this shows that most of the sample is made up of people with low incomes. A negligible portion of the participants earned more incomes and 0.38 percent of them earned the highest incomes of 722-901 units, which indicated a high level of income disparity among the sample.

The majority of the respondents (67.42) fell within the range of 1.6-2.4, which implies that they had a moderate internal locus of control. Extreme scores among the participants were lower and 2.07% had the lowest score (-0.004-0.8) and 5.65% the highest score (3.2-4), indicating that the perceptions of personal control are less extreme among this population.

Table 1: Frequencies of Important Variables

	Class	Frequency	Percentage
Income (in thousand)	9.11—188	446	83.99
	188—366	57	10.73
	366—544	20	3.77
	544—722	6	1.13
	722—901	2	0.38
Locus of control	-0.004—0.8	11	2.07
	0.8—1.6	30	5.65
	1.6—2.4	358	67.42
	2.4—3.2	102	19.21
	3.2—4	30	5.65
Weight	34.9—49.6	100	18.83
	49.6—64.2	327	61.58
	64.2—78.8	91	17.14
	78.8—93.4	9	1.69
	93.4—108	4	0.75
GPA	2.29—2.63	9	1.69
	2.63—2.97	34	6.4
	2.97—3.32	132	24.86
	3.32—3.66	179	33.71
	3.66—4	177	33.33

Most of the participants (61.58) are within the range of 49.6 to 64.2 units (only a small percentage (0.75) of the participants are in the highest range of 93.4 to 108 units). This distribution shows that the majority of the participants are within the normal or moderate range of weight with less people at the ends.

The academic performance of the participants is not that bad and distributed in the middle and upper ranges. In particular, 33.71 per cent have GPAs within 3.323.66 and 33.33 per cent have GPAs within 3.664. The lowest range (2.292.63) depicts only 1.69 percent of the participants, indicating that the majority of the participants have above-average academic accomplishments.

In general, these distributions give a detailed description of the sample features, with most of the variables being concentrated in the moderate ranges and the proportion at the extremes being smaller. These descriptive statistics play an important role in being able to comprehend the sample prior to making additional inferential analyses.

Cross Validation of Machine Learning Models

Table 2 shows the accuracy of cross validation of five machine learning models at a five-fold scale. Random Forest had the best accuracy of all folds (91.51, 97.17%), which means high and consistent predictive accuracy. The middle accuracy was 64.15, and 74.77% with SVM and the same with Logistic Regression and Gradient Boosting (56.60, 68.22%). On the whole, these findings suggest that ensemble approaches, especially Rand Forest, are the most efficient when working with this dataset.

Table 2: Cross Validation Score for k=5 for Five ML Models

Iteration	Logistic Regression	Random Forest	Gradient Boosting	SVM
1	56.60	91.51	56.60	67.92
2	66.36	93.46	68.22	74.77
3	61.32	97.17	63.21	71.70
4	58.49	91.51	58.49	64.15
5	64.15	95.28	65.09	72.64

Confusion matrix were used to assess the performance of four machine learning models: Random Forest, Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Logistic Regression. The result is presented in Table 3.

Table 3: Confusion matrix of ML Models

Model	TP	TN	FP	FN	Accuracy
Logistic Regression	76	7	45	4	0.6288
Random Forest	79	48	4	1	0.9621
GBM	76	31	21	4	0.8106
SVM	69	21	31	11	0.6818

The Table shows that Random Forest was the best model by the overall highest accuracy of 96.21, which is correct prediction of 79 positive and 48 negative cases with a few misclassifications. GBM was also performing well with an accuracy of 81.06 though it produced more false positives than random Forest. Logistic regression with moderate accuracy of 62.88 had the propensity of over predicting the positive class as indicated by large number of false positives. Similarly, SVM had higher misclassification scores on both positive and negative observations and an accuracy of 68.18, which can be summarized as the fact that Random Forest could be the most accurate in the desired prediction, whilst SVM and Logistic Regression may require some fine-tuning or feature adjustments to be more accurate.

Analysis of ROC Curves

The discriminative ability of the four machine learning models was tested on the Receiver Operating Characteristic (ROC) curve. In addition to simple accuracy measures, the ROC curve provides a comprehensive perspective on model performance since the True Positive Rate (sensitivity) and the False Positive Rate (1 -specificity) are plotted versus the threshold setting. The area under the ROC curve (AUC) is used to compare the performance of these different models; the greater the AUC, the better the model is capable of distinguishing between positive and negative cases.

Random Forest had the best AUC in this study and it had better sensitivity and specificity at a variety of thresholds. GBM also had a high discriminative power with a marginally lower AUC than Random Forest. The average values of SVM and logistic regression proved the poor ability of these methods to correctly classify the cases, particularly, the negative one. The confusion matrices results are backed up by the ROC analysis according to which Random Forest is the best model that can be used to predict the desired outcome since it provides the best balance between sensitivity and specificity.

The results of the ROC curves in general and specifically the applicability of ensemble based methods such as the Random Forest and GBM in predictive modeling to this data set are that these models are more effective than traditional models in that they provide both quantitative and graphical evidence of their superiority to the traditional models.

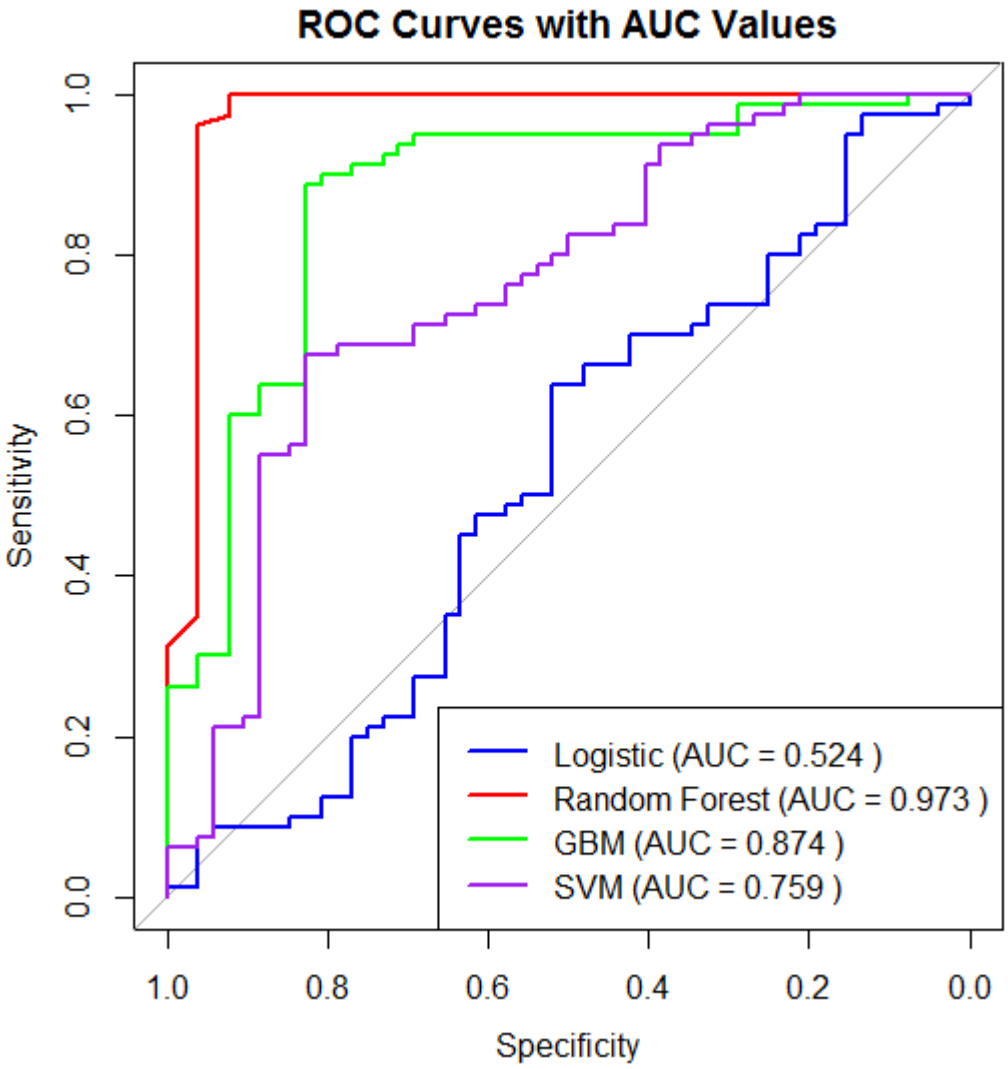


Figure 1: ROC Curve with AUC Values

Random Forest performed persistently better than all the other three machine learning models, namely, Logistic Regression, Gradient Boosting Machine (GBM) and Support Vector Machine (SVM) measuring in terms of all measures. It estimated most of the positive and negative cases correctly with the highest accuracy of 96.21 and lowest misclassification rates. Its ROC analysis showed that it has a powerful discriminative capacity further showing its highest AUC and excellent balance between sensitivity and specificity.

Overall Performance of the Model

Random Forest continuously outperformed the other three machine learning models, Logistic Regression, Gradient Boosting Machine (GBM), and Support Vector Machine (SVM) across all metrics. It accurately predicted the majority of positive and negative cases, achieving the highest accuracy (96.21%) and the lowest misclassification rates. With the highest AUC and a superb balance between sensitivity and specificity, its ROC analysis further demonstrated its potent discriminative ability.

Although GBM had a higher number of false positives than Random Forest, it still performed fairly well, with good accuracy (81.06%) and discriminative ability. With modest accuracy (62.88% and 68.18%, respectively) and higher misclassification rates, SVM and logistic regression performed worse, suggesting a propensity to either over predict or under predict the desired outcome.

Random Forest is the suggested option for real-world applications since it is, all things considered, the most robust and dependable model for forecasting the result in this dataset.

Analysis of Variable Importance

The relative significance of predictor variables in forecasting the desired outcome was assessed using the Random Forest model. The Mean Decrease in Gini index, which indicates how much each variable contributes to enhancing node purity in the decision trees, was used to quantify the importance of the variables. A greater influence on the model's predictions is indicated by a higher value.

According to the Figure 2, income had the greatest impact, closely followed by weight and GPA, indicating that these variables are crucial in determining the result. Variables like locus of control and level of knowledge about Islam demonstrated moderate importance, meaning they have some predictive value but are less significant than the top three variables.

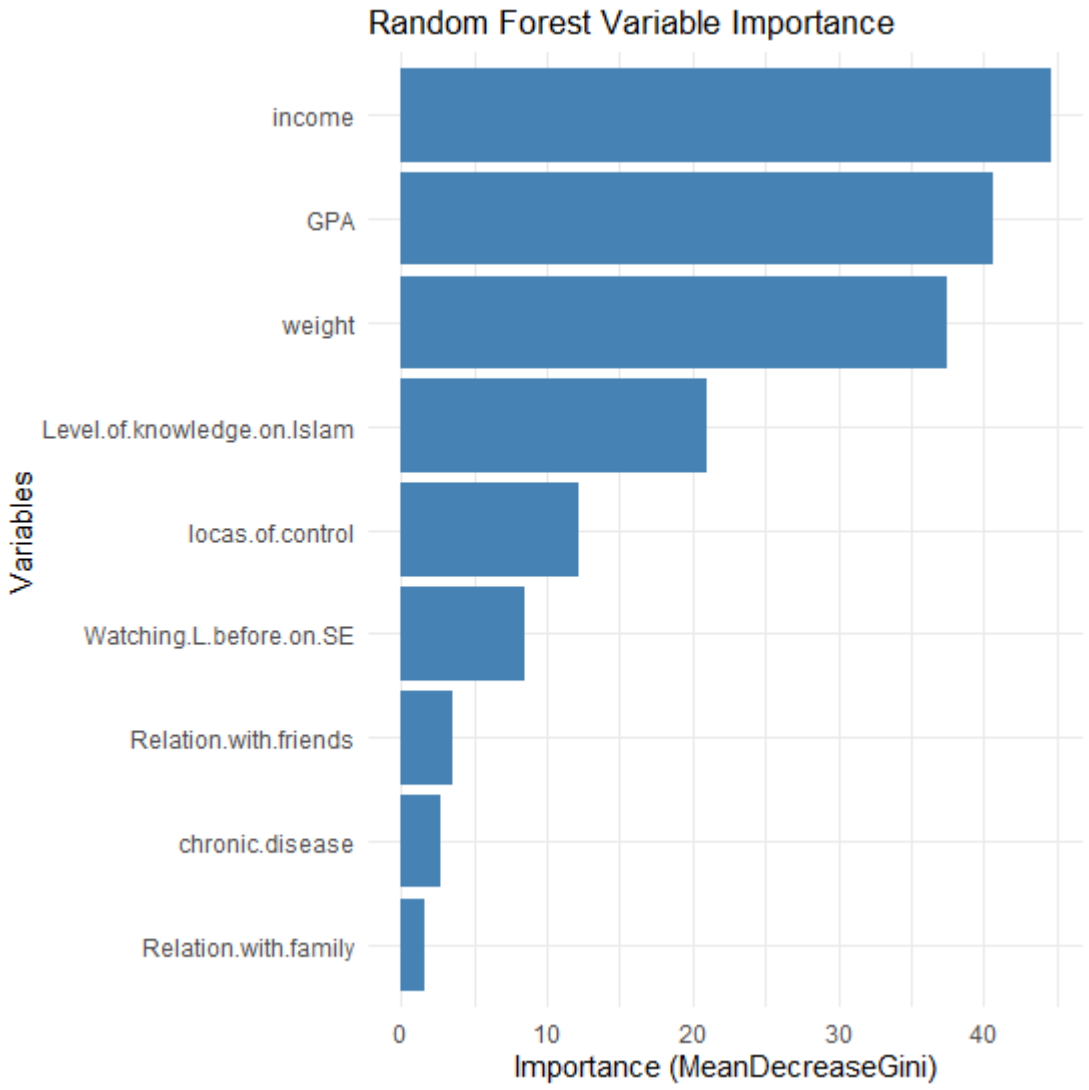


Figure 2: Important Variable of Self Esteem among Undergraduate Students

Overall, the findings show that academic and socioeconomic factors (weight, GPA, and income) are the main drivers in the model, with behavioral and social factors coming in second. Based on the most significant predictors, this insight can direct feature selection, additional analysis, and focused interventions.

Conclusion

This paper has analyzed the self-esteem prevalence among undergraduate students at Malakand Division universities and established the most important demographic, academic, social and psychological factors affecting self-esteem using machine learning models. In the results, it is emphasized that income and GPA is the most important factors for self-esteem.

Predictive accuracy of machine learning models such as Random Forest and Gradient Boosting had shown a high predictive accuracy in competition with traditional statistical methods to name the most influential factors. The presented methodological

novelty offers an evidence-based framework of identifying students at risk of low self-esteem and presents actionable recommendations to higher education administrators and mental health professionals.

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