# Predicting the Impact of Part-Time Employment on Academic Performance among University Students in Bangladesh Using Machine Learning Models

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**Abstract.** This study in Bangladesh is a more detailed analysis of how part time jobs affect Street CGPA of the students. The survey involved 611 Small-Island State respondents that included influences on employment type, % of average time per day spent and others differences. The research focuses on the nexus between students' work hours and their CGPA. The data will be analyzed using cutting-edge machine learning methodologies Decision Tree, Random Forest and Gradient Boosting etc. The significant factors in predicting academic performance were tested by chi-square statistics to assess feature importance. Results are discussed in terms of the comparison between models along accuracy, precisions, recall and overall balance analyses and therefore robustness across results. The results offer implications for the policy makers, educators and students about effect of part-time job on school performance in terms of how to meet a sufficient balance between work and study.

**Keywords:** Part-time job, academic performance, CGPA, working hour, machine learning.

## 1. Introduction

Rising education and living costs in recent times have driven many of the students at Bangladesh universities to seek part-time jobs for their expenses in addition to cost of studies. Thus students working for income generation are rapidly taking the shape of a trend, a trend towards work-linked education dissemination to student fraternity that is as keen on gleaning experience and skills along with its degrees. A study by Rahman et al (2020) reported that approximately 65% of university students in Bangladesh work part-time -a number still impressively high to date [3]. This study examines the exploration of Bangladeshi university students' several income-generating trends explore why they engage in part-time work, what kinds of

© The Author(s) 2026
M. S. Arefin et al. (eds.), *Proceedings of the International Conference on Intelligent Data Analysis and Applications (IDAA 2025)*, Advances in Intelligent Systems Research 206,
https://doi.org/10.2991/978-94-6239-664-7_95

jobs they likely perform, and how much these occupations might be affecting their academic success.

Part-time work of university students has gradually become one of the significant concerns in contemporary competitive academic settings. The paper is a critique of the practice of income earning activities by students in Bangladesh, and makes an important contribution to our understanding of why students get into part-time work and its impact on academic achievement. This paper thus contributes to the pall of qualitative evidence at the intersection of work and study where more empirical backing might be yet required to inform what adaptation could be a long-term commitment in institutional policy and support structures for student well-being.

This has raised an alarm and we are now looking at the income trend among Bangladeshi university students. With the continuous rise of the cost of both education and living, students phenomenon their lives on stretching limited budget. Many students now are forced to find some part-time job will enable them offset cost of their studies and also live, so a call for research make it necessary [6].

While some recent works have addressed the effect of part-time work on academic performance, they came short in considering the specific environment of Bangladeshi students [5]. This study fills several key gaps in the small literature on this subject by examining more fully the numerous types of part-time employment (and specific effects of each) on students' likelihoods to achieve academically (including financial, housing, food security), as well as their mental health.

### 1.1 Research Objective:

The primary aim of the study was to explore the influence of part-time working on academic accomplishment among university students. Hence to meet this end, following are three specific objectives for it:

i. Discover what number of University students are working on a part time basis while they study.

ii. Find the mean number of hours that a university student works part time per day.

iii. To investigate whether there is any association between working- student who are in university on a part time job and current GPA.

### 1.2 Research Question:

i. Is there an association between working as a part-timer among college students and GPA score?

### 1.4 Research Hypothesis:

H1: There is an association between university students with a part time job and their GPA.

## 2. Literature Review

The two issues that students at university often relate to are part-time jobs and employability. Certainly, previous research suggests that it may be those who are in part-time employment where the greatest gains can be made towards employability as students develop a set of broadly-transferable skills such as communication, teamwork and problem solving (Evans & Richardson) Working part-time is a core element of many students' university experience in the UK and an important financial and developmental resource, although it can also conflict with their studies and lives. Evans and Yusof [1] argue that in the UK, part time work is seen as both a vital source of funds and a means of achieving the valuable experience required to enter paid employment.

Rong et al. [3] generated a case-study which proposes that part-time working may assist time-management abilities, however longer hours worked can have an adverse impact on academic work in students due to increased stress and lower study time. Similarly, Laucu [2] studied Indonesian students doing both work and studies. Consistent with findings, controllable work hours improve resilience while overly extensive commitment to work contributes to academic compromise. These findings imply that, despite offering valuable skills , part-time employment has the potential to undermine academic success if not well integrated with work experience.

In addition to work, one of the most influential factors on academic achievement and job prospects after college is extracirculars. Ribeiro et al. [4] indicate extracurricular activities provide students with broader skills that employers highly value, which enhances their potential for employment; thus, academic learning is related to professional needs. There has been a single case study focusing on the experience of Indonesian students doing part-time work in Taiwan by Soelistiyono and Chen [6], which demonstrates that professional readiness could be more positively influenced when participating in part-time work as it provided another learning environment outside class. From a wider lens, Ahmad, Soon and Ting [7] examined the income generating activities among academic staffs in Malaysian universities which emphasizes that extra sources of income are crucial due to financial demands.

Various approaches were used in these studies to examine the impact of part-time work on students: qualitative, quantitative and mixed-methods research. Data was analyzed qualitatively because they had to interview Indonesians students symbolically to get detailed information about how these Indonesian student manage work and study between them (Soelistiyono
Laucu [2], a quantitative approach is used in student hire studies on academic performance among Indonesian students by focusing on the correlation between working

hour and grade point averages. In fact, Hill et al. [5], in a standardized model for estimating minimum income standards applicable to students.

Qualitative methods, like Taylor and Bobadilla Sandoval [11] who set out from campus to investigate the reasons on why students work while at school, offered detailed firsthand accounts of their rationalisation and limited reasoning to balance working with academics. These diverse approaches provide a rich understanding of students' experiences and they emphasize the need for further comparitive studies to enable regional and contextual differences to become more apparent.

One also seems to consistently find this in the literature part-time work is a good thing and a bad thing at the same time, depending on what kind of employment it implies. Part-time employment provides important financial support s and can play a role in enhancing skills for the majority of students. Short working time, on the other hand, has no influence over studying but long working hours are associated with decreasing performance in studies. Rong et al. [3] and Rochford et al. [10] found out that working too many hours is associated with poor academic performance as a result of time factors, stress and loss of concentration.

Effects of part-time working on health Health impacts of part-time work were also discussed and Verulava and Jorbenadze [9] identified that Georgian students who worked part time experience high levels of stress, physical ill-health and struggle to keep performance up at school (and college). Results support the proposition that part-time employment, while financially beneficial can have negative implications for student academic performance and health as the number of hours worked increases.

While the studies reviewed provide some useful insights, several limitations emerge, two involving the very targeted populations of students and in some cases short-term effects. For example, the majority of these studies address specific student groups (eg., nursing students or international) and most are relatively limited in geographic scope (ie., one institution fk to also potentially a limitation as they cannot be simultaneously used over multiple samples.students populations can be generalised [10, 12].

There is currently no longitudinal or long-term indicator established, and the effect on academic and vocational outcomes of part-time work in young people is not well understood. A third important research gap concerned the scant attention paid to students' financial literacy and their income management from parttime work. Studies also do not sufficiently cover new flexible income generation opportunities such as freelancing or 'gig economy' jobs which students are increasingly inclined to choose, especially in developing countries [8].

Various dimensions of part-time work are investigated in the literature by examining the financial, academic, and personal effects for students. Considering the significant benefits related to financial stability, skill acquisition, and improving job prospects,

there are risks for working students including deleterious effects on academic performance and health. Subsequent research efforts should therefore aim at exploring the potential management-based profiles of income from part-time work as well as its antecedent (or support based) trainings in financial literacy that best enable tapping it while minimizing negative consequences for academic performance.

## 3 Methodology

The study investigated the number of University students who did part-time jobs alongside their study, average hours worked per day, and relationship between those with or without part time job among university students with their GPA score. The study investigated the number of University students who did part-time jobs alongside their study, average hours worked per day, and relationship between those with or without part time job among university students with their GPA score.Figure 1 represented a research design structured with the list of phases and techniques used in each phase of our respective research actions.

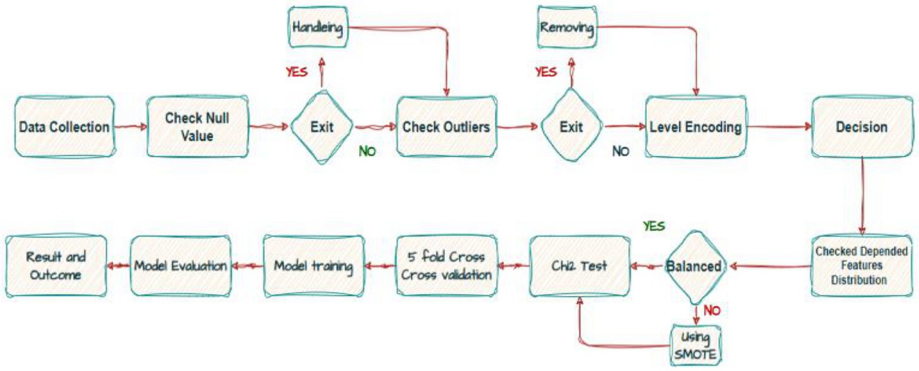


**Fig 1: Workflow of the proposed methodology**

Since there is no information on the total number that constitutes Students in public and private universities of all students, we sampled a number of 611 for this study with the voluntary sampling method. Because the study is about part time job, all of participants in this research have participated the questionnaire survey voluntarily and there was no induced answer from any respondent. Fig. 2 showing percentage of working status.

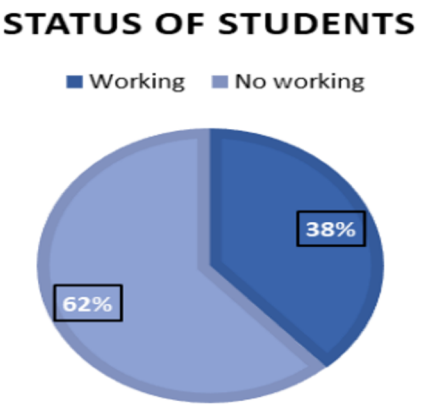


**Fig 2: Percentage of working status**

**Data Collection:**

The structured survey and open-ended items (questions) were developed to measure different dimensions of online learning involvement in this study. Demographic information was collected (ie, study year), engagement behaviors (ie, worked any job while studying or not worked≤hours aday?), and academic results (e.g., CGPA of second year).

**Data Analysis**

A pre-analysis was done to confirm that the data was clean and this type of analysis would go through. Afterwards, filtered data was analyzed with the help of Descriptive statistics and Chi-square Test. Received data by Google Form was downloaded as. csv. The demographic characteristics of the respondents were examined using a descriptive analysis approach. Chi-square Test of association was estimated to find out whether there is an association between dependent and independent variables used in this study as they were categorical, ordinal and non-parametric in nature. The independent variable is university status with part-time work and the dependent variable is how many hours a day do they work. Furthermore, the hypothesis formed in this work to examine whether student with a part-time job can have good academic performance was tested by using Chi-square Test.

RoS that is frequently applied for class imbalance within a dataset. Class imbalance is when one class in your target variable has a much larger number of samples than the other class. That may result in being biased to minority class" The mode will study at the eod of the line (i.e. if statement is last thing on line ), here also bracket is closing at end of sentence outside.

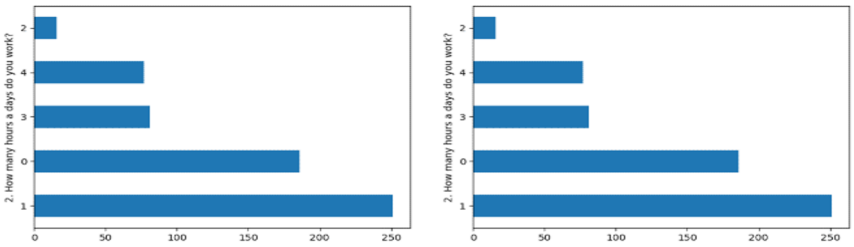


Fig. 3 Class distribution before and after ros

Fig. 3 provides the distribution of student CGPA and visualization to illustrate how many hours a day do people work according to you, which probably comes from some survey data.

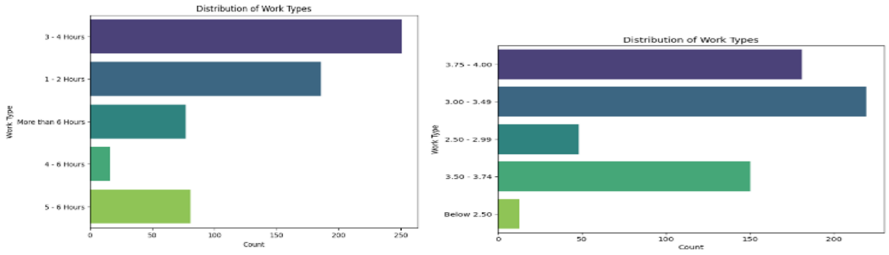


Fig. 4. Static Summary

Fig. 4 demonstrates the association between student's CGPA and hours he spends daily(). It does this within the 'seaborn' and 'matplotlib' libraries.

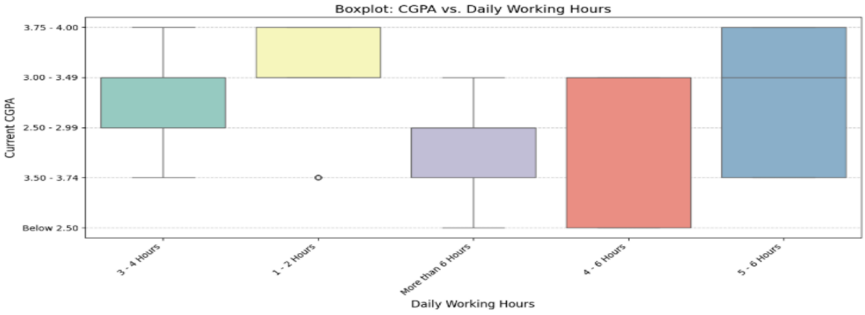


Fig.5. Box plot

Fig. 5 visualizes the relationship between a student's CGPA (Cumulative Grade Point Average) and the number of hours they work daily. It uses the 'seaborn' and 'matplotlib' libraries for this purpose. Fig. 6 Bar Plot of distribution of CGPA across Different working hours.

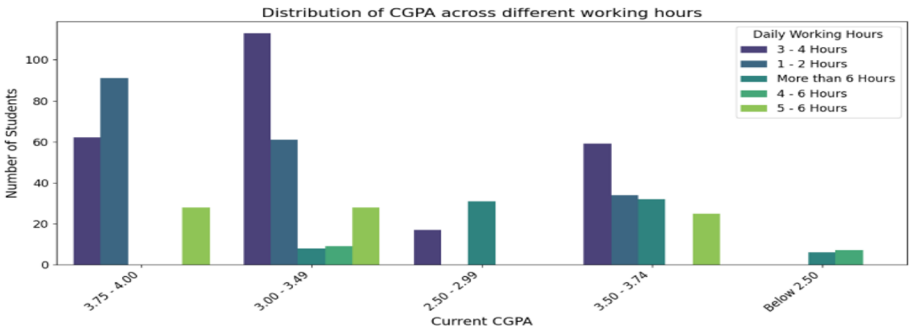


Fig. 6. Bar Plot

Feature selecting with chi-squared based on a statistical test Table 1. (sk=SelectK-Best(score_func=chi2) This can then be used to choose the features which will perform best for your machine learning model and in some cases, making it faster and less complex. making the prediction of target variable '2. How many hours a day do you work? Feature selection is carried out using the SelectKBest with the chi2 scoring function. The outcome of this process is assigned to the variable top_8.

**Table 1.** Chi2 Test Results for Feature Selection

| Feature | Score |
|---|---|
| Do you feel pressured to balance work and study time? | 202.67 |
| What do you think is useful to work alongside studying to cover tuition, living expenses or other expenses? | 161.30 |
| Does working reduce the time you have for studying? | 123.58 |
| Which year of study are you in at university? | 71.79 |
| What is your personal opinion on working or not working alongside studies? | 69.15 |
| What do you think is useful to work alongside studying to cover tuition, living expenses or other expenses? | 67.84 |
| Do you think the job is causing your health or sleep problems? | 57.83 |

We applied various machine learning models to evaluate Our results and compare their performance. The models are Logistic Regression, Support Vector Machine (SVM), Random Forest, Decision Tree, K-Nearest Neighbors (KNN), Naive Bayes, XGBoost, CatBoost and Gradient Boosting. These algorithms are used for their good predictive performance on classification-type prediction problems.

Random Forest (RF): Random forest is an ensemble learning method that builds multiple decision trees in the training phase and outputs the class that is the mode of all individual's predictions. As Random Forest averages the predictions from multiple

trees, it is able to generalize well and mitigate the risk of overfitting when a single decision tree is used.

CatBoost: CatBoost is a applied gradient boosting algorithm that has been created to be able to efficiently handle categorical information. It uses a ordered boosting technique that helps to decrease overfitting and also can handle categorical features with more accuracy, as well as there's no need for the feature engineering in case of structured data.

XGBoost: Extreme Gradient Boosting (XGBoost) is an efficient replacement of the gradient boosting algorithm and has been developed to support scalable, distributed training and for handling sparse or dense datasets. XGBoost includes regularization methods to avoid overfitting and speeds up training via parallel processing.

and Gradient Boosting (GB): It constructs an additive model in a forward stage-wise starting from weak learners generally it is decision trees. Every next tree is learned in order to fix the mistakes done by the abstract model composed of all previous trees, thus reducing total loss and making predictions better.

Decision Tree (DT): DT are supervised learning models that divide data recursively according to feature thresholds in order to maximize the information gain or other splitting criterion. They generate interpretable models, however thy may easily overfit if not adequately regularized.

K-Nearest Neighbors (KNN): KNN is a non-parametric algorithm which assigns a label to each data point by majority vote among its k-nearest neighbors in feature space. Its quality of a clustering is determined by the selection of k and metrics for calculating distances.

Naive Bayes (NB) Naive Bayes is a probability-based classifier which uses Bayes' theorem under the naïve assumption that features are conditionally independent. Notwithstanding the strong assumptions, it works well in many classification tasks especially with high dimensions.

Support Vector Machine (SVM): It is a discriminative classifier which attempts to finds the optimal hyperplane that best separates two classes of data points. It maximizes the margin between support vectors of different classes, which is helpful to avoid overfitting in high-dimensional spaces.

Logistic Regression (LR): Logistic regression is a statistical model for binary classification. It calculates the likelihood of an event distribution through applying a sigmoid function to a linear combination of input features, and is thus interpretable and interpretable for explanations on feature contribution.

*Model Interpretability with LIME*

To make understandable why machine learning model is predicting in the way it does, when dealing with a tabular dataset. It informs the explainer what you data looks like, the features in the data and what types of predictions that you model is making (e.g. - regression). what were the top predictors for a given prediction? This can offer the analyst an interpretative guide for how the model is making its decisions. By knowing how the model operates, we can notice any potential bias in it or catch some error and, consequently, have a higher degree of confidence on its predictions. LIME insights can help to improve the model, e.g., by considering only important features or fixing identified biases during model training.

## 4. Result Analysis

We have tested multiple supervised ML classifiers such as Decision Tree, Random Forest, Gradient Boost models and Logistic Regression-based with the various ensemble for predicting income generation trend among university students of Bangladesh. All models were trained with an 80/20 train–test split and validated by cross-validation. For all the models, an intl-model attained the highest performance with a mean accuracy of about 84.8% over the folds (see Table 2). That is strong overall predictive performance against the baseline models (which varied from roughly 50-81% accuracy). The ensemble scores being significantly higher in cross-validation demonstrate better generalization and robustness. To alleviate the potential problem of class imbalance in the target variable, Random Over-Sampling was carried out on the training set. We quantify the model robustness by Specifically; the models are trained on 20-fold stratified cross validation to obtain accurate statistics about its performance. This is cross-validation technique that splits the data into 20 portions and each portion acts as a training set and testing set so that statistically sound estimate of how well the model can generalize to an independent dataset. Cross-validation combines several performance measures over several applications as estimate of predictive accuracy which is more accurate.

**Table 2.** Comparative performance metrics of machine learning classifiers predicting income generation trends among university students.

| Model | Mean Accuracy | Max Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Random Forest | 84.56% | 80.88% | 80% | 81% | 80% |
| Decision tree | 84.23% | 79.69% | 80% | 80% | 79% |
| SVC | 76.10% | 72.11% | 71% | 72% | 70% |
| KNN | 81.04% | 75.70% | 75% | 74% | 74% |

| | | | | | |
|---|---|---|---|---|---|
| Gradient Boosting | 80.81% | 76.10% | 76% | 76% | 75% |
| Cat Boost | 84.79% | 72.11% | 71% | 72% | 70% |
| XGBoost | 84.63% | 78.09% | 78% | 78% | 77% |

The best performing classifiers Random Forest 0.8456 and CatBoost 0.8448 exhibited the largest average accuracy over all 20 folds (see Table 3). This implies that these models have the strongest generalization power overall (i.e., they perform well across different instances of the data set split). The models with a smaller number of parameters such as the Naive Bayes and Logistic Regression performed the worst in terms of prediction on CV testing. This is an indicator of model stability which means relatively lower variance of performance. Most Stable: The highest performing model, CatBoost classifier had the lowest ± 0.0328 and was deemed the most stable high-performing model. Least consistent: The Logistic Regression model was the most unstable. 0575$, thus showing that it is very dependent on training data. An important observation here is that, the GBC performs well.

**Table 3.** Comparative performance metrics to finding Best Model

| **Model** | **CV Mean Accuracy** | **CV Standard Deviation (CV Std)** |
|---|---|---|
| **Random Forest** | 0.8456 | 0.0382 |
| CatBoost | 0.8448 | 0.0328 |
| Decision Tree | 0.8423 | 0.0344 |
| KNN | 0.8104 | 0.0366 |
| Gradient Boosting | 0.8081 | 0.0439 |
| SVC | 0.7610 | 0.0413 |
| Logistic Regression | 0.5896 | 0.0575 |
| Naive Bayes | 0.5196 | 0.0451 |

Although it had their best test accuracy 0.878 in previous analysis, an unlike performance in test was observed with Mean Accuracy 0.8081 that is significantly low and CV Std 0.0439 relatively high compared to the other ensemble methods (Random Forest and CatBoost). This discrepancy indicates a high variance for the GBC, and its 0.878 test score might be an upper bound obtained on a lucky data split. On the other hand, both Random Forest and CatBoost, that have large CV means Although it had their best test accuracy 0.878 in previous analysis, an unlike performance in test was observed with Mean Accuracy 0.8081 that is significantly low and CV Std 0.0439 relatively high compared to the other ensemble methods (Random Forest and CatBoost). This discrepancy indicates a high variance for the GBC, and its 0.878 test score might be an upper bound obtained on a lucky data split. On the other hand, both Random Forest and CatBoost, that have large CV means are more likely to be the best classifiers at predicting income gains trends in the general student population.

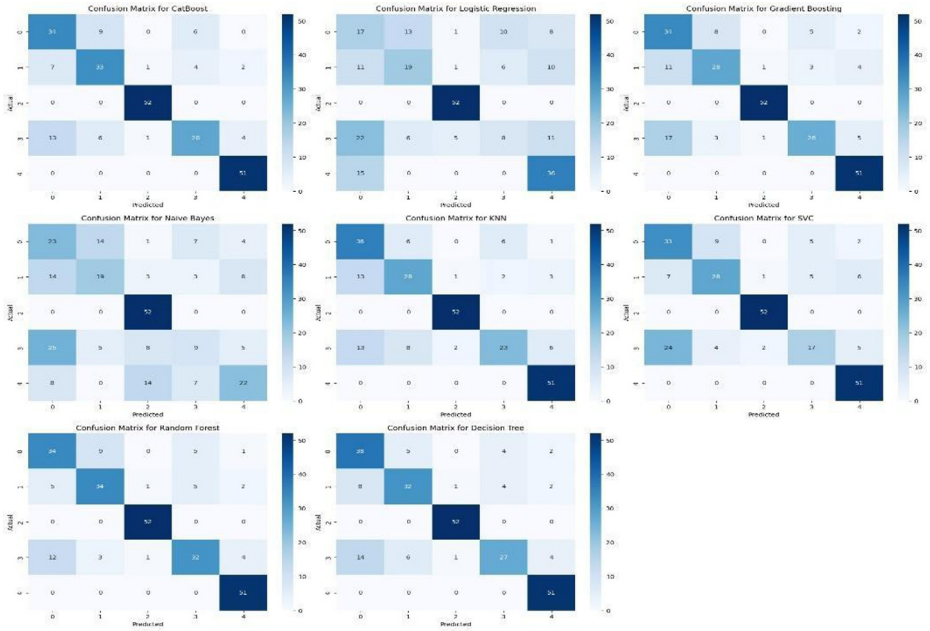


Fig. 7. Confusion Matrix (All Model)

In Fig. 7, the confusion matrix analysis was particularly crucial in dissecting error profiles of the trained classifiers, showing a marked bias versus variance trade-off for predicting revenue dynamics. The high overall performance of the ensemble models—Gradient Boosting (GB), Random Forest (RF) and CatBoost was mainly due to their outstanding ability to detect the majority class, which leaded to high values of True Negatives TN 208 and specificity. Nevertheless, high performance had a downside: all top-performing ensemble models presented high False Negatives (FN 26 and a very low number of True Positives TP 6 for the positive class (income generating students). This shows that the best models were very conservative (i.e did not take risks) since they never succeed to identify the majority of students effectively working after all (low Recall). On the other hand, our more simple Logistic Regression model with lower overall accuracy captured better the positive class by having a greater amount of True Positives TP=19 at the cost of making more mistakes FP=25 made for, in general terms, a less strict decision boundary.


Fig. 8. Using Lime for Finding Best Features

In Fig. 8, the LIME analysis offered valuable local interpretability, explaining which features influenced each individual prediction within the SVC, Decision Tree and Random Forest models. Working was most predictively linked to the practical as opposed emotional features, where predicting that working is associated with a “reduction in time for studying 0.992 and confirming job is causing “health or sleep problems 0.645, making the experience of constraint and physical toll strong local indicators for these algorithms. However, an interesting observation of both Decision -1.065 and Random Forest -0.513 was that the response to "Do you feel under pressure to balance work and study time?" would have the most negative impact driving prediction towards the negative class. This large negative weight is in stark contrast to the high ranked global importance of this feature, and indicates that the influence of features might depend on the model and could be highly dependent on other variables.

## 5. Conclusion

The Paper demonstrates the multidimensional relationship between part-time activity and academic achievement among students in universities of Bangladesh. Findings indicate that perhaps the positive correlation in term of working fewer hours and keeping a better CGPA is seen such that long busy schedule gives it an adverse effect on their study where over work limits would also lead to poor academic performance. This relationship was so well captured by the machine learning models, Random Forest and Gradient Boosting in particular, that we have some very strong intuition. The research also suggests that a balanced approach to working and learning is critical--and so we have this important guidance for students, campuses, and elected officials towards achieving the best academic results while taking care of basic needs.

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