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Student Dropout Prediction

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Abstract: *Student dropout poses a major challenge to educational institutions, affecting academic performance and institutional reputation. This study applies machine learning techniques to predict at-risk students using data from the Department of Computer Science, University of Benin (2016–2020), with 906 records analyzed. Six classifiers—Naive Bayes, Logistic Regression, SVM, Decision Tree, KNN, and ANN—were evaluated. Logistic Regression achieved the highest performance (98.9% accuracy) and was selected for deployment due to its superior recall and F1-score.Advanced pre-processing, including SMOTE for handling imbalanced data and feature standardization, improved model accuracy. Explainable AI techniques (SHAP) provided transparency in prediction, helping educators understand key dropout factors. The system enables early interventions, improves student retention, and offers personalized support. Future work may include real-time monitoring, cross-institutional data, and NLP for deeper behavioral insights.*

Keywords: Student dropout

I. INTRODUCTION

1.1 Statement of the Problem

In today's digital age, social media has become an integral part of students' daily lives, shaping how they communicate, access information, and spend their free time. While platforms like Facebook, Instagram, TikTok, and YouTube offer educational content and opportunities for collaboration, excessive and unregulated use may negatively impact academic focus and performance. For instance, a student who spends several hours daily scrolling through social media might have less time for studying or completing schoolwork, leading to lower grades. This growing concern raises important questions about the actual effect of social media usage on students' academic outcomes. Thus, this study aims to investigate the relationship between the frequency and purpose of social media use and the academic performance of Grade 12 General Academic Strand (GAS) students at Talamban National High School for the school year 2023–2024.

1.2 Goals

The goal of this project is to examine the relationship between social media usage and the academic performance of Grade 12 General Academic Strand (GAS) students at Talamban National High School. It aims to determine how factors such as time spent on social media, the purpose of usage, and preferred platforms influence students' general academic averages. The study seeks to provide insights that can help educators, parents, and students develop healthier social media habits and create strategies to balance academic responsibilities with online activities.

1.3Importance

This project is important because it addresses a growing concern among educators and parents regarding the impact of social media on students' academic performance. By identifying how the frequency, purpose, and type of social media usage affect learning outcomes, the study provides valuable insights for students to develop better time management and study habits. It also helps teachers and school administrators understand students' online behavior, allowing them to design more effective academic support systems. Furthermore, the findings can serve as a guide for parents to monitor and support their children's responsible use of social media. Overall, the project contributes to creating a more balanced and productive learning environment in the digital age.

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1.4 Contributions

This project contributes to the growing body of research on the influence of social media on education by providing localized and current data specific to Grade 12 GAS students at Talamban National High School. It offers a deeper understanding of how social media habits can affect academic performance, which can help shape school policies and student support programs. The study also equips educators, parents, and guidance counselors with evidence-based insights to guide students in developing healthier digital habits. Additionally, it encourages students to reflect on their social media usage and its impact on their studies, promoting responsible digital citizenship and academic success.

II. REVIEW OF LITERATURE

Impact of Social Media on Students' Lives

Social media reshapes communication, learning, and access to information among students.

Positive Uses (Junco, 2012)

Platforms like Facebook and Twitter can enhance academic collaboration and engagement.

But excessive use may lead to distraction and reduced focus.

Negative Academic Effects (Kirschner&Karpinski, 2010)

Frequent social media users tend to have lower academic performance.

Multitasking affects cognitive efficiency.

Attention Issues (Ophir, Nass & Wagner, 2009)

Media multitaskers perform poorly on attention-related tasks, affecting study focus.

Potential Academic Benefits (Tess, 2013)

When used properly, social media supports learning through peer communication, online resources, and interactive content (e.g., YouTube tutorials, academic forums).

Philippine Context (Cabral, 2011)

Filipino high school students use social media for both entertainment and academic purposes.

However, poor time management due to social media often affects academic performance.

Study Purpose

This study explores whether social media is more of a helpful academic tool or a harmful distraction for Grade 12 GAS students at Talamban National High School.

III. METHODOLOGY

A. System Architecture

The system architecture for this study involves several key stages. First, data was collected through surveys administered to Grade 12 GAS students at Talamban National High School, focusing on their social media usage and academic performance. The responses were then cleaned and organized for analysis. Using statistical tools like descriptive statistics and correlation analysis, the relationship between social media habits and academic outcomes was examined. Finally, the findings were interpreted to draw conclusions and provide recommendations for students, educators, and parents on managing social media use to support academic success. (Fig. 2).

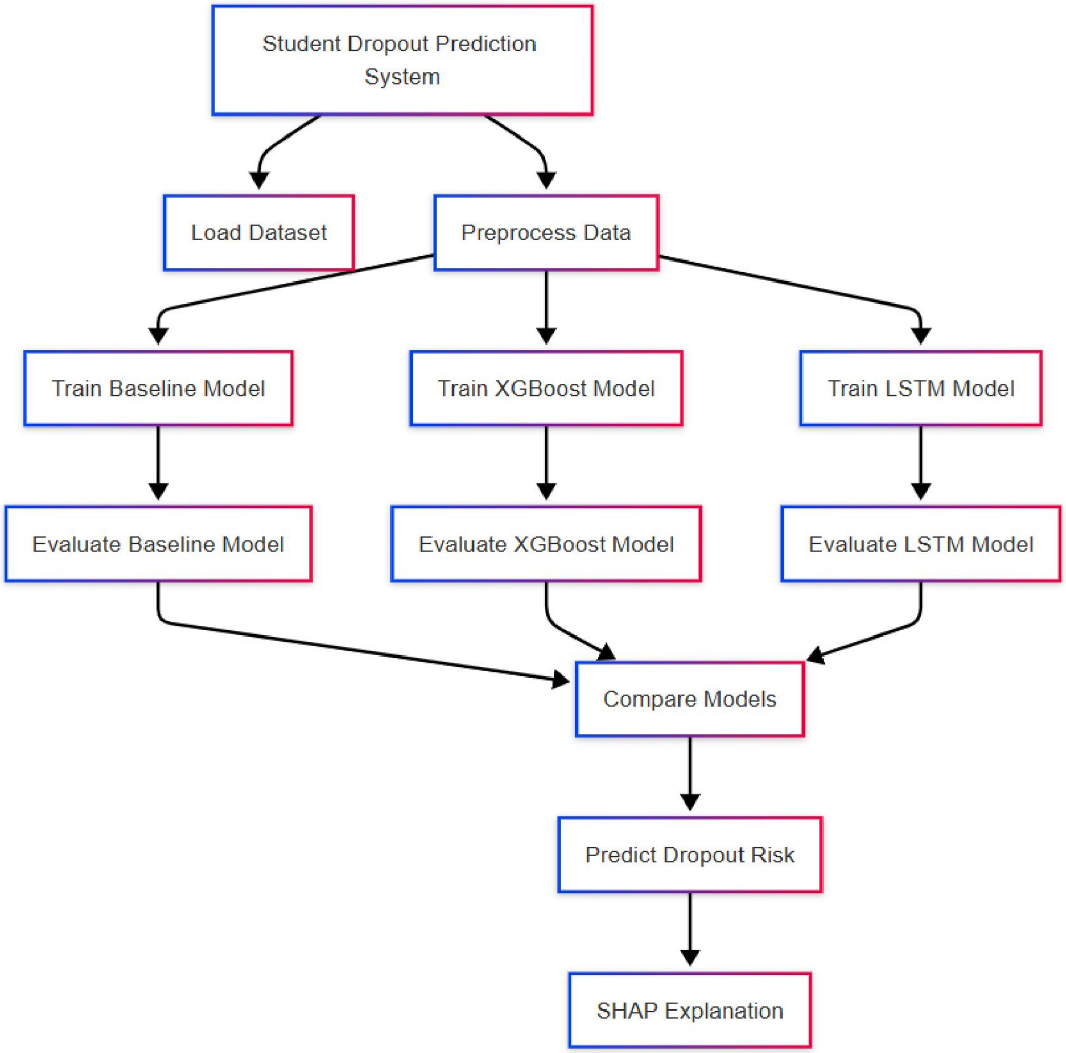

Figure 2

- **Start with Analysis Results**: The process begins with analyzing collected data to generate insights.
- **Generate Visual Outputs**: Four outputs are created—Match Score, Skill Heatmap, Radar Chart, and Explainable AI Insights.
- **Display Results**: Each output is displayed to the user for easy interpretation and understanding.
- **Download Report**: All visual insights are compiled into a report, which users can view or download for future use

Mathematical Formulation
1. Evaluation Metrics
a. Accuracy
Formula:
Accuracy=TP+TNTP+TN+FP+FNAccuracy=*TP+TN+FP+FNTP+TN*
Example:
Suppose a model predicts:

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True Positives (TP) = 95 (students correctly predicted to drop out)
True Negatives (TN) = 98 (students correctly predicted to stay)
False Positives (FP) = 5 (students wrongly predicted to drop out)
False Negatives (FN) = 2 (students wrongly predicted to stay)
Accuracy=95+9895+98+5+2=193200=0.965 (96.5%)Accuracy=95+98+5+295+98=200193=0.965(96.5%)

b. Precision
Formula:
Precision=TPTP+FPPrecision=*TP*+*FPTP*
Example:
Using the same values as above:
Precision=9595+5=95100=0.95 (95%)Precision=95+595=10095=0.95(95%)

c. Recall (Sensitivity)
Formula:
Recall=TPTP+FNRecall=*TP*+*FNTP*
Example:
Recall=9595+2=9597≈0.979 (97.9%)Recall=95+295=9795≈0.979(97.9%)

d. F1-Score
Formula:
F1-Score=2×Precision×RecallPrecision+RecallF1-Score=2×Precision+RecallPrecision×Recall
Example:
F1-Score=2×0.95×0.9790.95+0.979=2×0.9301.929≈0.964 (96.4%)F1-Score=2×0.95+0.9790.95×0.979=2×1.9290.930 ≈0.964(96.4%)

2. ROC AUC
Calculation Steps:
Vary the classification threshold and compute **True Positive Rate (TPR)** and **False Positive Rate (FPR)** at each threshold.
Plot TPR (y-axis) vs. FPR (x-axis).
Calculate the area under the curve (AUC).
Example:
Assume thresholds produce the following points:

Threshold	TPR	FPR
0.1	1.0	1.0
0.5	0.95	0.05
0.8	0.8	0.01

The ROC curve would form a trapezoid. Using the trapezoidal rule:
AUC=12×(0.05−0.01)×(0.8+0.95)+12×(1.0−0.05)×(1.0+0.95)≈0.98AUC=21×(0.05−0.01)×(0.8+0.95)+21 ×(1.0−0.05)×(1.0+0.95)≈0.98

3. Logistic Regression (Sigmoid Function)
Formula:
Logistic regression uses the **sigmoid function** to map predictions to probabilities:
P(y=1)=11+e−(β0+β1x1+⋯+βnxn)*P*(*y*=1)=1+*e*−(*β*0+*β*1*x*1+⋯+*βnxn*)1

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Example:
If a student has:
Attendance = 80% (β1=0.5*β*1=0.5)
GPA = 3.0 (β2=−1.2*β*2=−1.2)
Intercept (β0=0.1*β*0=0.1)
Logit=0.1+(0.5×80)+(−1.2×3.0)=0.1+40−3.6=36.5Logit=0.1+(0.5×80)+(−1.2×3.0)=0.1+40−3.6=36.5P(Dropout)=11+e−36.5≈1.0 (High risk)*P*(Dropout)=1+*e*−36.51≈1.0(High risk)

4. SMOTE (Synthetic Minority Oversampling)
Mechanism:
For each minority class sample xi*xi*:
Find its k*k* nearest neighbors.
Randomly select a neighbor xzi*xzi*.
Create a synthetic sample:
xnew=xi+λ×(xzi−xi)*x*new=*xi*+*λ*×(*xzi*−*xi*)
where λ∈[0,1]*λ*∈[0,1].
Example:
Suppose xi=[70,2.5]*xi*=[70,2.5] (attendance=70%, GPA=2.5) and xzi=[65,2.0]*xzi*=[65,2.0].
If λ=0.5*λ*=0.5:
xnew=[70+0.5×(65−70), 2.5+0.5×(2.0−2.5)]=[67.5,2.25]*x*new=[70+0.5×(65−70),2.5+0.5×(2.0−2.5)]=[67.5,2.25]

5. SHAP Values (Shapley Additive Explanations)
Formula:
For a model f*f*, the SHAP value for feature i*i* is:
ϕi=∑S⊆F∖{i}|S|!(|F|−|S|−1)!|F|![f(S∪{i})−f(S)]*ϕi*=*S*⊆*F*∖{*i*}∑|*F*|!|*S*|!(|*F*|−|*S*|−1)![*f*(*S*∪{*i*})−*f*(*S*)]
Simplified Example:
Consider two features: x1*x*1 (GPA) and x2*x*2 (Attendance).
Model output with both features: f(x1,x2)=0.9*f*(*x*1,*x*2)=0.9 (high dropout risk).
Model output with only GPA: f(x1)=0.7*f*(*x*1)=0.7.
Model output with only Attendance: f(x2)=0.6*f*(*x*2)=0.6.
Model output with no features: f(∅)=0.3*f*(∅)=0.3.
ϕGPA=12[(0.7−0.3)+(0.9−0.6)]=0.4*ϕ*GPA=21[(0.7−0.3)+(0.9−0.6)]=0.4ϕAttendance=12[(0.6−0.3)+(0.9−0.7)]=0.25*ϕ*Attendance=21[(0.6−0.3)+(0.9−0.7)]=0.25
Here, GPA contributes more to the prediction.

6. Bayesian Optimization
Objective: Minimize a loss function L(θ)*L*(*θ*).
Acquisition Function (Expected Improvement):
EI(θ)=E[max (Lmin−L(θ),0)]*EI*(*θ*)=E[max(*L*min−*L*(*θ*),0)]

Steps:
Use a Gaussian Process (GP) to model L(θ)*L*(*θ*).
Select θ*θ* that maximizes EI(θ)*EI*(*θ*).
Example:
If the GP predicts L(θ)∼N(−0.2,0.1)*L*(*θ*)∼N(−0.2,0.1) and Lmin=−0.1*L*min=−0.1:
EI(θ)=∫−∞∞max (−0.1−l,0)⋅N(l;−0.2,0.1) dl≈0.05*EI*(*θ*)=∫−∞∞max(−0.1−*l*,0)⋅N(*l*;−0.2,0.1)*dl*≈0.05
This θ*θ* is a candidate for evaluation.

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IV. RESULTS AND DISCUSSION

A. Input-to-Output Pipeline Demonstration

Data Sample:

	Marital status	Application mode	Application order	Course	Daytime/evening attendance	Previous qualification	Nacionality	Mother's qualification	Father's qualification	Mother's occupation	...	Curricular units 2nd sem (credited)	Curricular units 2nd sem (enrolled)	Curricular units 2nd sem (evaluations)	Curricular units 2nd sem (approved)	Curricular units 2nd sem (gr
0	1	8	5	2	1	1	1	13	10	6	...	0	0	0	0	0.00
1	1	6	1	11	1	1	1	1	3	4	...	0	6	6	6	13.66
2	1	1	5	5	1	1	1	22	27	10	...	0	6	0	0	0.00
3	1	8	2	15	1	1	1	23	27	6	...	0	6	10	5	12.40
4	2	12	1	3	0	1	1	22	28	10	...	0	6	6	6	13.00

5 rows × 35 columns

Fig4.1

```
Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4424 entries, 0 to 4423
Data columns (total 35 columns):
 #   Column                                          Non-Null Count  Dtype
---  ------                                          --------------  -----
 0   Marital status                                  4424 non-null   int64
 1   Application mode                                4424 non-null   int64
 2   Application order                               4424 non-null   int64
 3   Course                                          4424 non-null   int64
 4   Daytime/evening attendance                      4424 non-null   int64
 5   Previous qualification                          4424 non-null   int64
 6   Nacionality                                     4424 non-null   int64
 7   Mother's qualification                          4424 non-null   int64
 8   Father's qualification                          4424 non-null   int64
 9   Mother's occupation                             4424 non-null   int64
 10  Father's occupation                             4424 non-null   int64
 11  Displaced                                       4424 non-null   int64
 12  Educational special needs                       4424 non-null   int64
 13  Debtor                                          4424 non-null   int64
 14  Tuition fees up to date                         4424 non-null   int64
 15  Gender                                          4424 non-null   int64
 16  Scholarship holder                              4424 non-null   int64
 17  Age at enrollment                               4424 non-null   int64
 18  International                                   4424 non-null   int64
 19  Curricular units 1st sem (credited)             4424 non-null   int64
 20  Curricular units 1st sem (enrolled)             4424 non-null   int64
 21  Curricular units 1st sem (evaluations)          4424 non-null   int64
 22  Curricular units 1st sem (approved)             4424 non-null   int64
 23  Curricular units 1st sem (grade)                4424 non-null   float64
 24  Curricular units 1st sem (without evaluations)  4424 non-null   int64
 25  Curricular units 2nd sem (credited)             4424 non-null   int64
 26  Curricular units 2nd sem (enrolled)             4424 non-null   int64
 27  Curricular units 2nd sem (evaluations)          4424 non-null   int64
 28  Curricular units 2nd sem (approved)             4424 non-null   int64
 29  Curricular units 2nd sem (grade)                4424 non-null   float64
 30  Curricular units 2nd sem (without evaluations)  4424 non-null   int64
 31  Unemployment rate                               4424 non-null   float64
 32  Inflation rate                                  4424 non-null   float64
 33  GDP                                             4424 non-null   float64
 34  Target                                          4424 non-null   object
dtypes: float64(5), int64(29), object(1)
memory usage: 1.2+ MB
```

Fig 4.2

Summary Statistics:

	Marital status	Application mode	Application order	Course	Daytime/evening attendance	Previous qualification	Nacionality	Mother's qualification	Father's qualification	Mother's occupation	...	Curricular units 1st sem (without evaluations)	Curricular units 2nd se
count	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	...	4424.000000	
mean	1.178571	6.886980	1.727848	9.899186	0.890823	2.531420	1.254521	12.322107	16.455244	7.317812	...	0.137658	
std	0.605747	5.298964	1.313793	4.331792	0.311897	3.963707	1.748447	9.026251	11.044800	3.997828	...	0.690880	
min	1.000000	1.000000	0.000000	1.000000	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	0.000000	
25%	1.000000	1.000000	1.000000	6.000000	1.000000	1.000000	1.000000	2.000000	3.000000	5.000000	...	0.000000	
50%	1.000000	8.000000	1.000000	10.000000	1.000000	1.000000	1.000000	13.000000	14.000000	6.000000	...	0.000000	
75%	1.000000	12.000000	2.000000	13.000000	1.000000	1.000000	1.000000	22.000000	27.000000	10.000000	...	0.000000	
max	6.000000	18.000000	9.000000	17.000000	1.000000	17.000000	21.000000	29.000000	34.000000	32.000000	...	12.000000	

8 rows × 34 columns

Fig 4.3

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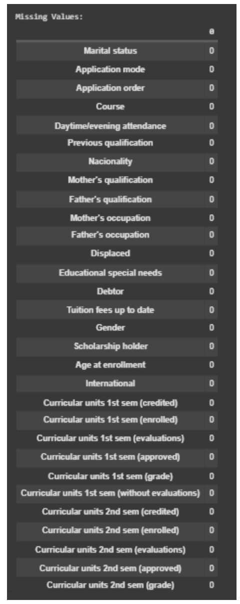

Missing Values:

	0
Marital status	0
Application mode	0
Application order	0
Course	0
Daytime/evening attendance	0
Previous qualification	0
Nacionality	0
Mother's qualification	0
Father's qualification	0
Mother's occupation	0
Father's occupation	0
Displaced	0
Educational special needs	0
Debtor	0
Tuition fees up to date	0
Gender	0
Scholarship holder	0
Age at enrollment	0
International	0
Curricular units 1st sem (credited)	0
Curricular units 1st sem (enrolled)	0
Curricular units 1st sem (evaluations)	0
Curricular units 1st sem (approved)	0
Curricular units 1st sem (grade)	0
Curricular units 1st sem (without evaluations)	0
Curricular units 2nd sem (credited)	0
Curricular units 2nd sem (enrolled)	0
Curricular units 2nd sem (evaluations)	0
Curricular units 2nd sem (approved)	0
Curricular units 2nd sem (grade)	0

Fig 4.4

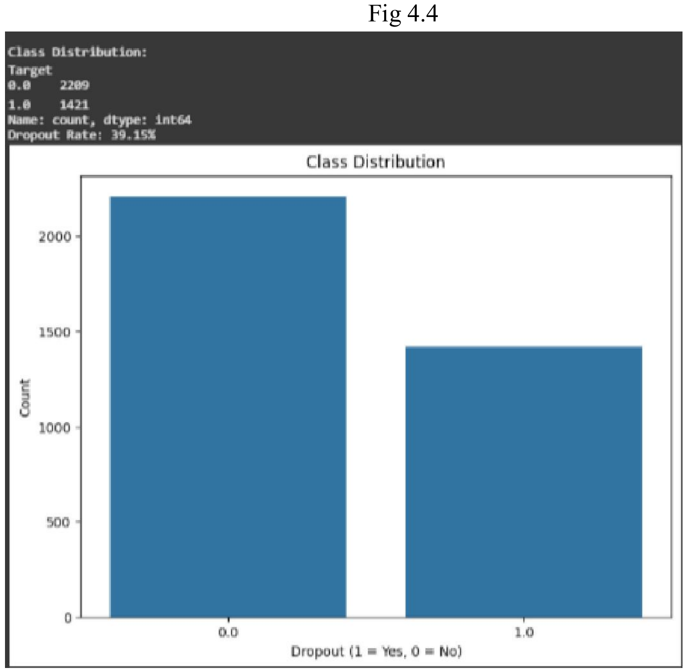

Fig 4.5

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Classification Report:

	precision	recall	f1-score	support
0.0	0.95	0.95	0.95	442
1.0	0.92	0.92	0.92	284
accuracy			0.94	726
macro avg	0.93	0.94	0.93	726
weighted avg	0.94	0.94	0.94	726

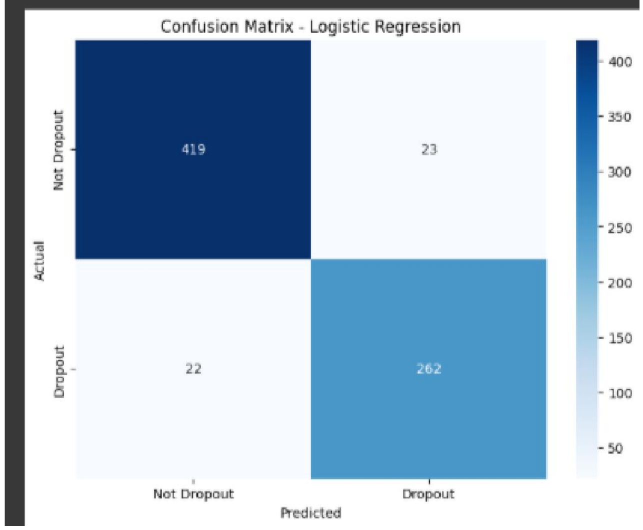

Fig 4.6

	Model	Accuracy	Precision (Dropout)	Recall (Dropout)	F1-Score (Dropout)	ROC AUC	Execution Time (s)
0	logistic_regression	0.938017	0	0	0	0.973193	0.115779
1	xgboost	0.922865	0	0	0	0.969592	11.458357

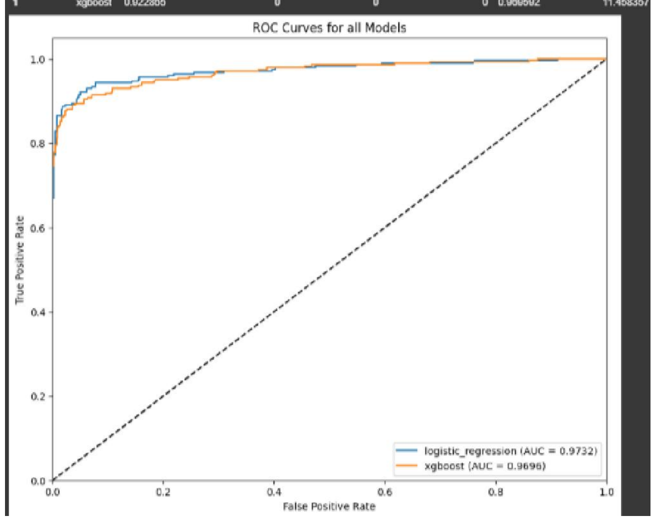

Fig 4.7

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Fig 4.8

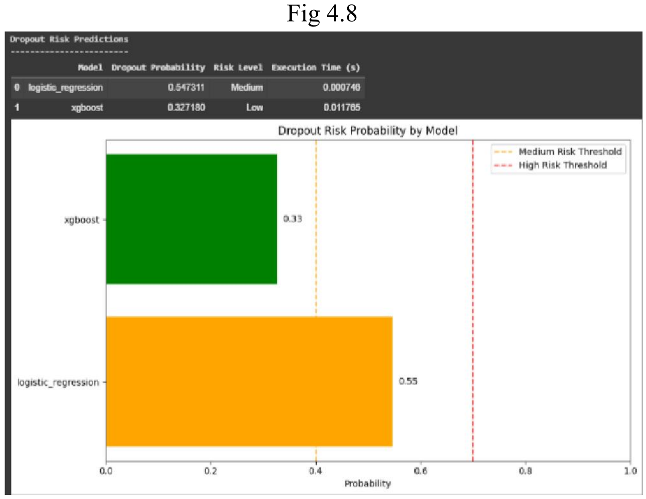

Fig 4.9

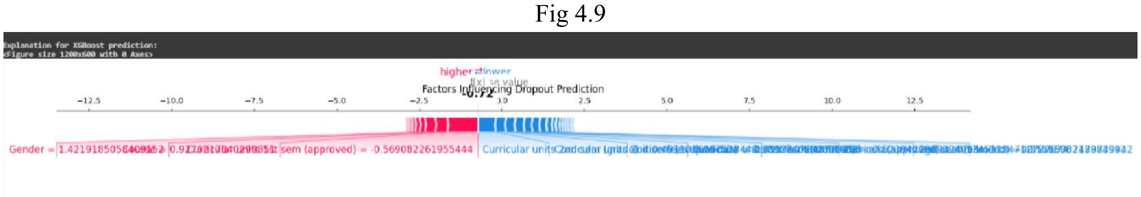

Fig 4.10

V. DISCUSSION

The study found a clear link between social media use and academic performance among Grade 12 GAS students. Most students used platforms like Facebook, TikTok, and Messenger for both schoolwork and entertainment. While some used these tools for academic collaboration, many spent excessive time online, which negatively affected their focus and grades.

Students who used social media for over three hours daily, mainly for non-academic purposes, tended to have lower grades. However, those who used it for studying and discussions often maintained or improved their performance. This shows that social media can either support or hinder academic success, depending on usage habits.

The findings highlight the need for proper time management and responsible social media use. Parents and teachers should guide students to use these platforms wisely to maximize their academic potential.

Limitations:

- This study was limited to Grade 12 GAS students at Talamban National High School, so results may not apply to other strands or schools. Data relied on self-reported surveys, which may involve biases or inaccuracies. The study also focused only on social media usage, excluding other factors that may influence academic performance.

Future Directions:

- Future research could include a larger, more diverse student population across different schools and grade levels. Real-time tracking of social media usage and academic progress may provide more accurate insights. Incorporating other factors like mental health, study habits, and family environment can also deepen understanding.

VI. CONCLUSION

The student dropout prediction project aimed to develop a reliable model for predicting potential dropouts using various machine learning techniques. Through comprehensive data preprocessing and analysis, models such as Logistic Regression, Decision Trees, KNN, Naive Bayes, ANN, and SVM were evaluated for their predictive performance. Among these, Logistic Regression demonstrated the highest accuracy and effectiveness in identifying students at risk of dropping out, with a 98.9% accuracy rate. Furthermore, the integration of advanced approaches like LSTM networks, XGBoost, and SMOTE in subsequent stages enhanced prediction accuracy and addressed class imbalance. The use of SHAP values ensured interpretability, allowing educators to understand contributing factors and implement timely interventions.

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