Research Paper

Comparative analysis of supervised machine learning algorithms for predicting student programming anxiety levels

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ABSTRACT

Computer programming anxiety is a widespread problem in students taking computing-related degrees, which normally impacts their grades and confidence in programming activities. As much as the psychological and academic effects of programming anxiety have been researched, there still exists a gap in research in using supervised machine learning methodologies in predicting anxiety within these varied computing fields. This study demonstrated a comparative analysis of supervised machine learning classification techniques for predicting student programming anxiety levels. A cross-sectional data set comprised of student self-reported answers were analyzed using feature selection methods to determine the most relevant attributes. The five classification algorithms utilized in the study were J48 Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, and Naive Bayes. All the algorithms were applied to create a respective prediction model, and the models were implemented and tested with the help of the WEKA software tool. The performance of the models was evaluated based on accuracy, F-measure, precision, recall, and Cohen's kappa. Among all the resulting prediction models, the one created from Logistic Regression performed the best in overall performance and showed excellent predictive ability. The results illustrated that machine learning models can be used effectively to build predictive systems for facilitating early identification and intervention for programming anxiety students, thus improving academic support approaches.

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1. INTRODUCTION

Increased numbers of mental illness such as stress, anxiety, and depression have become a public issue worldwide with anxiety disorders considered one of the most prevalent disorders [1]. Depressive disorders are the leading mental problem in the Philippines, but anxiety contributes significantly too many others, mainly manifested through behavioral issues like being easily irritated, being restless, or having difficulties in concentrating [2]. In the context of computer education, anxiety often occurs while performing programming activities [3]. This phenomenon, referred to as programming anxiety, has a negative impact on students' learning results, usually caused by self-doubt, fear of failure, or insufficient confidence in problem-solving.

Programming anxiety stands as one of the challenges that computing-related degree students face. To measure programming anxiety psychometrically, some instruments such as the Programming Anxiety Scale (PAS), which uses standardized self-reporting, have been established [4]. The method, effective enough at measuring one's own ratings about programming anxiety scores, does not come without compromises, as the method can be time consuming and applied only at discrete intervals. As a result, its practical use for timely intervention within academic settings remains limited. This study aimed to perform a comparative analysis on the accuracy percentage of five classification algorithms, namely J48 Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and Naive Bayes (NB) using WEKA (Waikato Environment for Knowledge Analysis), an open-source Machine Learning (ML) software to predict student's programming anxiety level, and further evaluate their performance using machine learning validation metrics such as F-measure, precision, recall, , and Cohen's kappa.

This study contributes to the understanding of programming anxiety by providing a machine learning framework for predicting students' risk. Using cross-sectional data from students alongside feature selection and model assessment, this work contributes evidence to the notion of predictive modeling in mental health education, supporting the argument for prioritizing mental health. Predictive modeling illustrates the potential of immediate academic intervention driven by data. This research also offers practical recommendations to assist education researchers, educators, and school administrators in enhancing student performance and fostering more positive computing learning experiences and environments.

2. RELATED WORKS

Recent studies have affirmed the capability of classification algorithms in forecasting mental health conditions among student populations. One investigation, for example, applied DT to predict stress, SVM for depression detection, and both LR and NN for identifying anxiety, with reported accuracy ranging from 68% to 88% [5]. Similarly, another study further highlighted the potential of machine learning to help mental health diagnosis and early intervention efforts by building predicting models for major depressive disorder and generalized anxiety disorder in student cohorts [6]. To further focus, a number of research have looked at risk factors for depression and anxiety in educational settings. After determining significant factors such as academic performance, financial status, bullying, abuse at home, and school violence, SVM was determined to be the best classifier [7]. These results were backed by a systematic study, which identified SVM and LR as the most frequently employed algorithms to predict anxiety and stress in college students [8].

With the aim to predict anxiety, stress, and depression in college students, [9] assessed DT, RF, SVM, and NN, emphasizing the importance of demographic and lifestyle data. Meanwhile, Katiyar et al. [10]

compared RF, Gradient Boosting (GB), Artificial Neural Networks (ANN), and a proposed Deep Recurrent Neural Network (DRNN) to investigate mental health issues among women. According to their findings, the DRNN performed better than expected, indicating that it can be useful for early detection.
Using behavioral and physiological data, [11] evaluated LR, RF, Forest, SVM, and Gradient Boost Classifier, offering standards for applications in mental health.

This investigation was further refined [12], who examined LR, RF, SVM, NB, Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN). The results demonstrated that RF and SVM were the most effective in classifying anxiety and depression. Some research has concentrated on identifying a variety of conditions related to anxiety. To predict different anxiety subtypes, [13] used datasets from educational and hospital organizations. Their results demonstrated how machine learning, in particular RF and SVM, may be used to differentiate between various anxieties subtypes. New methods have further improved the accuracy of predictions. [14] Incorporated physiological data into machine learning for the detection of anxiety in real-time virtual reality therapy, proving the importance of multimodal data. [15] Used Decision Trees to evaluate the mental health of college students with methodological care, controlling for confounding variables in the prediction of anxiety, depression, and suicidal thoughts.

Even with these developments, minimal is known about programming anxiety, a unique type of academic anxiety that is common in computer education. Studies that have already been done mostly deal with generalized anxiety and contribute less attention to programming anxiety-related to a specific discipline. The study work evaluates supervised machine learning methods for programming anxiety prediction to overcome this limitation. This aids in the development of focused treatments in computing education and advances research on digital mental health. Table 1 complied the additional pertinent studies on anxiety in educational and other settings. Numerous gaps in recent research were found. Interestingly, there aren't many thorough studies that employ classification algorithms to predict students' programming anxiety levels. Furthermore, several studies failed to take into consideration the Philippines' distinct cultural and educational backgrounds.

Table 1. Matrix of Related Studies in Anxiety Prediction Using Machine Learning

Research	Attributes	Datasets	Classification Algorithms	Best
Sau & Bhakta (2017) [16]	Demographic, Recent Bereavement, Employment and Socio-Economic Status, Medical Records, HADS scale	250	RF, LR, NB, J48 DT, and 4 more	Random Forest
Priya et al. (2020) [17]	DASS-21 Questionnaire	348	RF, NB, DT, SVM, KNN	Random Forest
Mutalib (2021) [5]	Demographic, Program, Part, CGPA, Financial Support, WHOQOL, Spirituality/ Religion/Personal Beliefs, DASS-21	629	DT, SVM, NB, LR	Decision Tree
Farooq et al. (2023) [18]	8 Anxiety Symptoms Questionaries	107	NB, LR, RF, SVM, DT, and 9 more	Naive Bayes

3. METHODOLOGY

This study employed a developmental research approach [19], which entailed examining and detailing the development of a prediction model through machine learning techniques, as shown in Figure 1. Each step in this process is explained in the following paragraph.

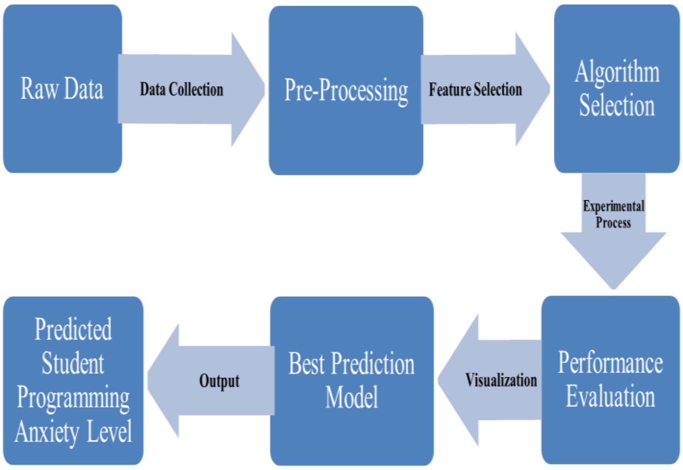

Figure 1. Prediction Model Development Pipeline.

1. Data Collection

The dataset used in this study was acquired during the first semester of the 2023–2024 academic year from the Computer Studies Department (CSD) of a public higher education institution in the Philippines. It includes 1,732 student record instances, incorporating self-reported scores from a validated programming anxiety scale [4], current academic achievement data, and other pertinent characteristics. By adhering to ethical standards, the data gathering procedure, protected personal data in accordance with the Philippine Data Privacy Act of 2012 (Republic Act No. 10173). To safeguard the participants' rights and privacy, all information was collected with their consent and managed in a strictly confidential manner.

2. Data Pre-Processing

To guarantee that the data was suitable for machine learning, it underwent extensive preparation. This involves the process of standardizing, normalizing, and fixing errors, contradictions, and missing numbers. Python libraries were used to carry out real preprocessing. The target variable was labeled after the initial Programming Anxiety Scores, which varied from 11 to 55 and higher scores indicated higher anxiety, were divided into two categories: "Low" (scores between 11 and 33) and "High" (scores between 34 and 55). One hot encoding was used to transform other attributes to satisfy the requirements of the machine learning algorithms. One hot encoding was used to transform other attributes to satisfy the requirements of the machine learning algorithms. The Synthetic Minority Oversampling Technique, or SMOTE, was used to create synthetic samples for the minority class to rectify the dataset's unequal class distribution. [20]. The nine significant features were identified using feature selection techniques such Greedy Stepwise, Attribute Ranking, and Best Fit.

3. Algorithm Selection

Classification algorithms were chosen for this study because they are effective with categorical binary class problems. In this study, students' programming anxiety levels were predicted to be "Low" or "High". The ability of these algorithms to identify patterns and correlations in labeled data indicates that they are effective for categorical prediction tasks. Five different algorithms were used in this study: J48 DT, RF, SVM, LR, and NB. They were chosen based on their proven utility in previous anxiety and mental health prediction research. Each algorithm exhibits a unique modeling approach, allowing for a thorough evaluation of expected performance.

1. J48 Decision Tree: The J48 algorithm is a variant of the C4.5 decision tree algorithm, which generates decision trees through recursive data partitioning. It does so by selecting attributes that maximize information gain to divide the data into subsets. The selection of attributes for splitting is typically based on metrics like Information Gain (IG). It constructs a tree by selecting the attribute that minimizes uncertainty, thus ensuring an efficient structure for classification. This method is known for

its transparency and ease of interpretation, producing decision-making rules that are intuitive, while being capable of handling both categorical and continuous data with efficiency [21].

2. Random Forest: This algorithm, based on ensemble learning, constructs multiple decision trees by using random subsets of features and bootstrap sampling. The predictions of these individual trees are aggregated through majority voting (for classification tasks) to enhance overall accuracy and minimize overfitting. Random Forest is known for its robustness against noise and outliers, and it reduces the high variance that typically affects single decision trees. Its ability to perform well on datasets with missing values or high dimensionality makes it a preferred choice across various machine learning domains [22].
3. Support Vector Machine (SVM): SVM seeks to identify the hyperplane that separates two classes by maximizing the margin between them in a multi-dimensional space. For datasets that are linearly separable, this is accomplished by solving the following optimization problem. SVM is highly effective in dealing with data that is both high-dimensional and not linearly separable by employing kernel functions, which transform the input features into a higher-dimensional space. Due to its precision and resilience, SVM is extensively utilized in classification problems, especially when handling complex decision boundaries and large-scale datasets [23].
4. Logistic Regression: Logistic Regression is a statistical technique commonly used for binary classification problems. It estimates the likelihood that a given input belongs to a class by applying the logistic (sigmoid) function to a linear combination of input features, which results in an output between 0 and 1. Logistic Regression is particularly valued for its simplicity and effectiveness in binary classification, offering clear interpretability and computational efficiency [24].
5. Naive Bayes: The Naive Bayes classifier is a probabilistic model grounded in Bayes' Theorem, which operates under the assumption that the features used for classification are conditionally independent given the class label. Although Naive Bayes assumes that all features used for classification are conditionally independent given the class label, which may not always hold, it has demonstrated strong performance in real-world applications such as spam filtering, text classification, and scenarios involving high-dimensional data. Its effectiveness is attributed to its simplicity, resilience to noisy data, and scalability [25].

4. Performance Evaluation

To ensure the robustness and validity of the classification model in predicting students' programming anxiety levels, a comprehensive set of performance evaluation metrics was employed. These include accuracy, F1-measure, precision, recall, and Cohen's kappa. Each metric captures a unique aspect of model performance, providing a multidimensional assessment that supports the reliability and interpretability of the results:

Accuracy is measured as the ratio of correctly classified instances to the total number of predictions. Despite being widely used due to its simplicity, this statistic can prove deceptive in situations when there is a class imbalance, since the dominance of one class may skew the actual performance of a model. To prevent overestimating performance, [26] emphasized that accuracy should be regarded cautiously in these situations.

Formula:

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

Precision is the ratio of true positive predictions to all positive instances. Since it shows the model's capacity to produce correct positive classifications without overestimating, it is particularly important in situations where the cost of false positives is large. The significance of precision in assessing classification models that handle sensitive outcomes was emphasized by [27].

Formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall, also known as sensitivity, measures the model's ability to detect true positive cases among the whole pool of actual positives. In applications where ignoring positive cases could have serious consequences, this metric is essential. High recall values are crucial for creating models to identify possibly at-risk individuals, [28] showed.
Formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F-measure (or F1 Score) represents the harmonic average of precision and recall, providing a single metric that balances both. This measure is particularly useful in situations where there is a need to consider the trade-off between false positives and false negatives equally [29].
Formula:

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Cohen's Kappa is a statistical measure that evaluates the agreement between predicted and actual classifications while accounting for the possibility of chance agreement [30]. This metric guarantees that evaluation results reflect actual predictive performance rather than coincidental alignment when it comes to estimating student programming anxiety levels. Its use increases the model evaluates' reliability and aids in the creation of strong, data-driven techniques for identifying students who are at risk and providing focused intervention plans [31].
Formula:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

Where P_o is the observed agreement and P_e is the expected agreement by chance.

4. RESULTS AND DISCUSSION

The findings are presented in the following discussions, which include the results of feature selection techniques, performance evaluation of classification algorithms for predicting students' programming anxiety levels.

A) Feature Selection Techniques

The most predictive features of programming anxiety level were found using these feature selection techniques. The model's overall predicted accuracy was improved by the relevant and statistically significant features that were chosen. These chosen features helped to increase the success rate and overall predicted accuracy of the classification algorithms by reducing dimensionality while getting eliminated of less useful attributes.

Table 2. Results of Feature Selection Techniques

Feature Selection Technique	Attribute Evaluator	Best Attribute Selected
Best First	CFS Subset Evaluator	1. Working Status 2. Course 3. Current Year Level 4. Prev. Sem. GWA 5. Computer Prog. 1 Grade 6. Senior High School Track 7. ICT Equipment 8. Preferred Learning Style 9. Avg. Sleep Hours
Greedy Stepwise	CFS Subset Evaluator	
Attribute Ranking	Information Gain Ranking Filter	

Table 2 summarizes the feature selection techniques, attribute evaluators, and top attributes identified. Using WEKA, nine significant attributes were selected from an initial set of eighteen. The Best First and Greedy Stepwise methods, both with the Correlation based Feature Selection (CFS) Subset Evaluator, identified the same nine attributes, confirming their importance. The Information Gain Ranking Filter ranked them according to its significance.

B) Performance of Classification Algorithms for Predicting Student Programming Anxiety Levels

A comparative analysis of five classification algorithms was visualized to identify the best model for predicting students' programming anxiety level.

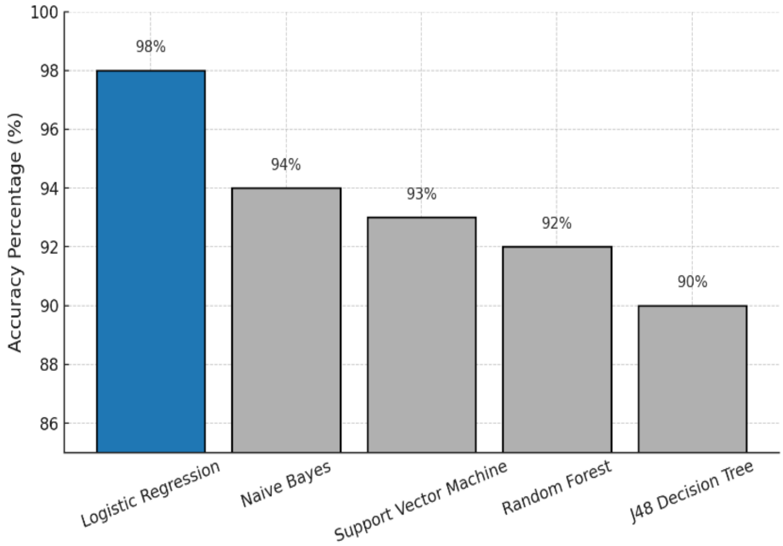

Figure 2. Accuracy-Based Bar Chart of Classification Algorithms.

Figure 2 revealed that Logistic Regression was the most accurate of the five classification algorithms evaluated, with a prediction accuracy of 98% in classifying student programming anxiety levels. RF and SVM came next, both of which demonstrated great overall performance and comparatively high accuracy ratings. Among the models, NB had the lowest accuracy, whereas J48 DT showed an acceptable degree of accuracy. Based on the provided dataset, these results demonstrated that Logistic Regression generated the best model for this classification and supported its choice as the best model for predicting programming anxiety.

Table 3. Results of Feature Selection Techniques

Model	Precision	Recall	F Measure	Cohen's kappa
Logistic Regression	98%	99%	98%	0.96
Naive Bayes	92%	98%	95%	0.86
Support Vector Machine	92%	98%	95%	0.85
Random Forest	93%	95%	94%	0.82
J48 Decision Tree	92%	93%	92%	0.78

Table 3 shows the comparison results of the five classification algorithms that include four critical validation metrics: precision, recall, F-measure, and Cohen's kappa. Logistic Regression consistently outperforms the other models, with the greatest results in all metrics—98 percent precision, 99 percent recall, 98 percent F-measure, and a Cohen's kappa of 0.96. It is the most effective algorithm for predicting students' programming anxiety levels because of its robust and well-rounded performance. Other algorithms, such as NB and SVM performed similarly, notably in Recall and F-measure, but fall somewhat short in overall consistency and agreement when compared to Logistic Regression.

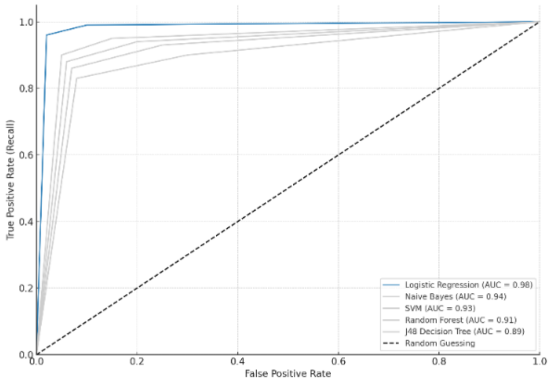

Figure 3. ROC Curve Comparison of Classification Algorithms

Figure 3 illustrates five classification models' Receiver Operating Characteristic (ROC) curves to predict levels of programming anxiety. Logistic Regression, blue, recorded the best AUC of 0.98, reflecting better classification accuracy. The grey models performed reasonably well, solidifying Logistic Regression as the best option for this study.

5. CONCLUSION

This study evaluated the prediction of student programming anxiety levels using supervised machine learning algorithms and identified key predictors such as working status, previous semester GWA, preferred VARK learning style, available ICT equipment, average sleep hours, final grade in Computer Programming 1, senior high school track, course, and year level. Among the algorithms tested, Logistic Regression demonstrated the highest predictive performance with 98% accuracy, supporting its potential integration into educational systems for early identification of students at risk of high programming anxiety. These findings offer valuable insights for developing targeted interventions aimed at reducing anxiety and enhancing academic performance and well-being among students in computing-related programs. To further improve the model's performance and applicability, it is recommended to use a larger dataset for more robust analysis, adopt a Machine Learning Development Life Cycle for scalable implementation, and integrate the top-performing model into an intelligent system with real-time monitoring capabilities to support universities in proactively addressing programming anxiety.

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Ethical Approval

The researchers obtained local approvals to ensure ethical and institutional compliance. Data collection followed the Philippine Data Privacy Act of 2012, with strict measures to protect participant privacy.

Data Availability

The data supporting the results of this study are available from the corresponding author upon reasonable request and subject to institutional approval and compliance with the Philippine Data Privacy Act of 2012.

Authors Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Eduardo R. Yu II	✓	✓	✓		✓	✓	✓		✓		✓	✓	✓	✓
Elmerito D. Pineda	✓	✓								✓		✓		
Isagani M. Tano	✓			✓	✓					✓	✓			
Ace C. Lagman	✓			✓						✓				
Jayson M. Victoriano	✓		✓	✓				✓		✓				

C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su	:	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P	:	**P**roject administration
Va	:	**Va**lidation	O	:	**O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal Analysis	E	:	**E**diting & Review			

Conflict of Interest

The authors declare no conflicts of interest.

Informed Consent

All participants were informed of the study's purpose, procedures, and their right to voluntary participation.

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