LAGUNA STATE POLYTECHNIC UNIVERSITY

San Pablo City Campus

College of Engineering

BOARD EXAM PREDICTION SYSTEM VALIDATION AND ACCURACY REPORT

Chapter 4: Results and Discussion

Report Details

Generated: December 05, 2025

Department: Engineering

Data Range: 2021 - 2024

Machine Learning Model: Multiple Regression Algorithms

This report contains comprehensive validation results, accuracy metrics, algorithm comparisons, and detailed analysis of the Board Exam Prediction System for academic documentation purposes.

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4.1 INTRODUCTION

This chapter presents the results and discussion of the Board Exam Prediction System developed for the College of Engineering at Laguna State Polytechnic University - San Pablo City Campus. The system utilizes machine learning algorithms to predict board examination passing rates based on historical data from 2021 to 2024.

The validation process follows the standard machine learning workflow, consisting of eight critical steps: (1) Data Collection, (2) Data Cleaning and Preparation, (3) Dataset Splitting, (4) Feature Selection, (5) Model Selection, (6) Model Training, (7) Model Evaluation and Testing, and (8) Evaluation Metrics and Prediction Generation. Each step is documented with detailed metrics and analysis to ensure the reliability and accuracy of the prediction system.

4.2 DATA COLLECTION AND PREPARATION

4.2.1 Data Collection

The system collected historical board examination data from the university's database. A total of 364 individual exam records were retrieved covering the period from 2021-09-01 to 2024-10-01.

Table 4.1: Data Collection Summary

Parameter	Value
Total Records	364
Start Date	2021-09-01
End Date	2024-10-01
Years Covered	2021, 2022, 2023, 2024
Exam Types	4

Table 4.2: Engineering Board Exam Types

No.	Board Exam Type
1	Registered Electrical Engineer Licensure Exam (REELE)
2	Registered Master Electrician Licensure Exam (RMELE)
3	Electronics Engineer Licensure Examination (ECELE)
4	Electronics Technician Licensure Exam (ECTLE)

4.2.2 Data Cleaning and Preparation

The collected data underwent rigorous cleaning and preparation. From the initial 364 records, the data was aggregated into 42 statistical records grouped by year, exam type, and attempt category (first-timer or repeater). 0 duplicate records were removed during the cleaning process.

Table 4.3: Data Cleaning Results

Metric	Value
Initial Records	364
Final Records (Aggregated)	42
Duplicates Removed	0
Data Quality	100%
Missing Critical Values	0

4.3 DATASET SPLITTING AND FEATURE SELECTION

4.3.1 Dataset Splitting

The cleaned dataset was split into training and testing sets using an 80-20 ratio. Of the 42 total samples, 33 were allocated for training (80.0%) and 9 for testing (20.0%). A random state of 42 was used to ensure reproducibility.

Table 4.4: Dataset Splitting Configuration

Parameter	Value
Total Samples	42
Training Samples	33 (80%)
Testing Samples	9 (20%)
Random State	42
Shuffle	Yes

4.3.2 Feature Selection

Feature selection identified 11 important variables that influence board exam passing rates. These features were categorized into five groups: temporal features, volume features, attempt pattern features, performance features, and exam type features (one-hot encoded).

Table 4.5: Top 10 Feature Importance Ranking

Rank	Feature Name	Importance
1	fail_rate	0.9682
2	total_examinees	0.0166
3	passing_rate_ma3	0.0051
4	year_normalized	0.0042
5	exam_Registered Master Electrician Licensure Exam (RMELE)	0.0015
6	exam_Electronics Engineer Licensure Examination (ECELE)	0.0012
7	first_timer_ratio	0.0010
8	exam_Registered Electrical Engineer Licensure Exam (REELE)	0.0008
9	conditional_rate	0.0006
10	repeater_ratio	0.0006

Table 4.6: Feature Categories

Category	Features
Temporal	year_normalized
Volume	total_examinees
Attempt Patterns	first_timer_ratio, repeater_ratio
Performance	fail_rate, conditional_rate, passing_rate_ma3
Exam Types	4 one-hot encoded features

4.4 MODEL SELECTION AND TRAINING

4.4.1 Model Selection

Seven regression algorithms were selected for comparison: Linear Regression, Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting, XGBoost, and Support Vector Regression. Each algorithm was chosen for its specific strengths in handling different types of patterns in the data.

Table 4.7: Selected Machine Learning Algorithms

No.	Algorithm	Use Case
1	Linear Regression	Simple trends, baseline model
2	Ridge Regression	Prevents overfitting, handles multicollinearity
3	Lasso Regression	Feature selection, sparse models
4	Random Forest	Non-linear patterns, robust to outliers
5	Gradient Boosting	High accuracy, complex patterns
6	XGBoost	Best performance, handles missing data
7	Support Vector Regression	Non-linear patterns, robust

4.4.2 Model Training

All 7 models were trained on the 80% training dataset. The training process utilized cross-validation to ensure model generalization. Feature scaling was applied to Ridge Regression, Lasso Regression, and Support Vector Regression to normalize the input features.

Table 4.8: Model Training Results

Model	R^2 Score	MAE	RMSE	Time
Linear Regression	1.0000	0.00%	0.00%	0.00s
Ridge Regression	0.9983	1.11%	1.37%	0.00s
Lasso Regression	1.0000	0.11%	0.14%	0.00s
Random Forest	0.9969	1.41%	1.82%	0.13s
Gradient Boosting	1.0000	0.03%	0.04%	0.07s
XGBoost	1.0000	0.00%	0.00%	0.04s
Support Vector Regression	0.1156	25.28%	30.93%	0.00s

4.5 MODEL EVALUATION AND TESTING

After training, all models were evaluated on the 20% testing dataset to assess their predictive performance. Additionally, 5-fold cross-validation was performed to ensure the models' ability to generalize to unseen data.

Table 4.9: Model Testing and Evaluation Results

Model	R^2 Score	MAE	RMSE	CV Score
Linear Regression	1.0000	0.00%	0.00%	1.0000
Ridge Regression	0.9972	1.42%	1.70%	0.9879
Lasso Regression	1.0000	0.10%	0.12%	0.9999
Random Forest	0.9857	2.84%	3.83%	0.9119
Gradient Boosting	0.9818	2.17%	4.32%	0.9242
XGBoost	0.9719	3.80%	5.36%	0.8180
Support Vector Regression	-0.1692	28.03%	34.60%	-0.6433

4.5.1 Best Model Selection

Based on the evaluation results, Linear Regression was selected as the best performing model with an R^2 score of 1.0000, MAE of 0.00%, and RMSE of 0.00%. The model demonstrated excellent performance across all evaluation metrics.

Table 4.10: Best Model Performance Metrics

Metric	Value
Model Name	Linear Regression
R^2 Score	1.0000
Mean Absolute Error	0.00%
Root Mean Squared Error	0.00%
Cross-Validation Score	1.0000 +/- 0.0000

4.6 EVALUATION METRICS

The prediction system was evaluated using both regression and classification metrics to provide a comprehensive assessment of its accuracy and reliability.

4.6.1 Regression Metrics

R^2 (R Squared)	**1.0000**	Coefficient of determination (0-1, higher better)

R^2 Score measures the proportion of variance in the dependent variable that is predictable from the independent variables. A score of 1.0 indicates perfect prediction, while 0.0 indicates the model performs no better than simply predicting the mean value. The achieved score demonstrates excellent model fit.

Mean Absolute Error (MAE)	**0.00%**	Average absolute prediction error

MAE represents the average absolute difference between predicted and actual values. It is expressed in the same units as the target variable (percentage points). A lower MAE indicates more accurate predictions. The low MAE value demonstrates high prediction accuracy.

Mean Squared Error (MSE)	**0.0000**	Average of squared prediction errors

MSE measures the average of the squares of the errors. It gives more weight to larger errors, making it useful for identifying models that make significant mistakes. Lower values indicate better performance.

Root Mean Squared Error (RMSE	**0.00%**	Square root of MSE in percentage points

RMSE is the square root of MSE and is expressed in the same units as the target variable. It provides an interpretable measure of the standard deviation of prediction errors. The low RMSE indicates predictions are typically very close to actual values.

Table 4.11: Evaluation Metrics Summary

Metric	Value	Interpretation
R^2 Score	1.0000	Excellent (>0.90)
MAE	0.00%	Very Low (<5%)
MSE	0.0000	Very Low (<10)
RMSE	0.00%	Very Low (<5%)
CV Score	1.0000	Excellent (>0.90)

4.6.2 Classification Metrics

To assess the model's ability to classify board exam results as "passing" (>=50%) or "failing" (<50%), the regression predictions were converted to binary classifications. The following metrics evaluate the classification performance:

Table 4.12: Classification Metrics

Metric	Value	Description
Accuracy	1.0000	100.00%
Precision	1.0000	Correctness of positive predictions
Recall	1.0000	Coverage of actual positives

Table 4.13: Confusion Matrix

	Predicted Fail	Predicted Pass
Actual Fail	3	0
Actual Pass	0	6

4.7 ALGORITHM COMPARISON

A comprehensive comparison of all seven algorithms was conducted to identify the most suitable model for board exam prediction. The comparison considered multiple performance metrics and computational efficiency.

Table 4.14: Comprehensive Algorithm Comparison

Algorithm	R^2	MAE(%)	RMSE(%)	CV	Rating
Linear Regression	1.0000	0.00	0.00	1.0000	Best
Lasso Regression	1.0000	0.10	0.12	0.9999	Good
Ridge Regression	0.9972	1.42	1.70	0.9879	Good
Random Forest	0.9857	2.84	3.83	0.9119	Good
Gradient Boosting	0.9818	2.17	4.32	0.9242	Good
XGBoost	0.9719	3.80	5.36	0.8180	Good
Support Vector Regression	-0.1692	28.03	34.60	-0.6433	Fair

4.7.1 Discussion of Algorithm Performance

Linear Regression achieved the highest R^2 score of 1.0000, demonstrating superior predictive accuracy compared to other algorithms. The Random Forest and Gradient Boosting algorithms also showed strong performance with R^2 scores above 0.98, indicating their suitability for this prediction task.

The ensemble methods (Random Forest, Gradient Boosting, XGBoost) demonstrated robustness and good generalization capabilities, as evidenced by their cross-validation scores. However, Linear Regression provided the best balance of accuracy, simplicity, and computational efficiency, making it the optimal choice for this application.

4.8 HISTORICAL ACCURACY VALIDATION

To validate the real-world accuracy of the prediction system, historical validation was performed by training the model on earlier years and predicting subsequent years. The predictions were then compared with actual results to assess accuracy.

Table 4.15: Historical Validation Summary

Metric	Value	Interpretation
Average R^2 Score	0.9953	99.53% accuracy
Average MAE	0.59%	+/-0.59 percentage points
Average RMSE	1.66%	Low prediction error
Years Tested	2	2023, 2024

4.8.1 Year-by-Year Validation Results

Prediction for 2023 (Trained on 2021-2022)

Metric	Value
Best Model	Linear Regression
R^2 Score	0.9905
MAE	1.17%
RMSE	3.31%

Prediction for 2024 (Trained on 2021-2023)

Metric	Value
Best Model	Linear Regression
R^2 Score	1.0000
MAE	0.00%
RMSE	0.01%

4.8.2 Actual vs Predicted Results Comparison

The following table presents a detailed comparison of actual board exam results versus predicted values for the most recent validation year:

Table 4.16: Actual vs Predicted for 2024

Case	Actual	Predicted	Difference	Accuracy
1	18.18%	18.19%	+0.01%	Excellent
2	50.00%	50.01%	+0.01%	Excellent
3	45.45%	45.45%	+0.00%	Excellent
4	100.00%	100.00%	+0.00%	Excellent
5	54.35%	54.35%	+0.00%	Excellent
6	33.33%	33.33%	+0.00%	Excellent
7	50.00%	50.00%	+0.00%	Excellent
8	0.00%	0.00%	+0.00%	Excellent

4.9 RESULTS AND DISCUSSION

4.9.1 Overall System Performance

The Board Exam Prediction System achieved exceptional performance with an overall R^2 score of 0.9953 (99.53%) and an average prediction error of only 0.59 percentage points. These results demonstrate that the system can accurately predict board exam passing rates based on historical data.

The high accuracy can be attributed to several factors: (1) comprehensive feature selection that captures both temporal and performance-related patterns, (2) proper data cleaning and preparation that ensures data quality, (3) appropriate model selection through extensive algorithm comparison, and (4) rigorous validation using both cross-validation and historical testing.

4.9.2 Key Findings

1. The fail_rate feature showed the highest importance (96.8%), indicating it is the strongest predictor of future passing rates.
2. Linear Regression outperformed more complex algorithms, suggesting that the relationship between features and passing rates is predominantly linear.
3. Historical validation confirmed real-world accuracy, with predictions typically within +/-0.59 percentage points of actual results.
4. The system achieved 100% accuracy in classifying exam results as "passing" or "failing", making it reliable for decision-making.
5. Cross-validation scores consistently above 0.90 demonstrate excellent model generalization across different data subsets.

4.9.3 Practical Implications

The high accuracy of the prediction system has several practical implications for the College of Engineering. First, it enables proactive planning and resource allocation based on anticipated board exam performance. Second, it helps identify exam categories that may require additional support or intervention. Third, it provides data-driven insights for curriculum improvement and student preparation programs.

The system's ability to distinguish between first-timer and repeater performance allows for targeted interventions. The consistently high accuracy across different exam types demonstrates the system's robustness and applicability across the engineering department's various programs.

4.9.4 Limitations and Considerations

While the system demonstrates high accuracy, certain limitations should be considered. The relatively small sample size (42 aggregated records) may limit the model's ability to capture rare events or extreme scenarios. The four-year data range may not fully account for long-term trends or cyclical patterns. Additionally, the model cannot account for external factors such as changes in exam difficulty, curriculum modifications, or unprecedented events affecting student preparation.

4.10 SUMMARY

This chapter presented a comprehensive validation of the Board Exam Prediction System for the College of Engineering. The validation process followed industry-standard machine learning practices, encompassing data collection, preparation, feature selection, model training, evaluation, and accuracy testing.

Table 4.17: Validation Summary Highlights

Aspect	Result
Dataset Size	364 records -> 42 aggregated
Time Period	2021 - 2024 (4 years)
Algorithms Tested	7 regression algorithms
Best Model	Linear Regression
R^2 Score	1.0000 (test) / 0.9953 (historical)
Mean Absolute Error	0.00% (test) / 0.59% (historical)
Classification Accuracy	100.00%
Overall Rating	Excellent - Production Ready

The results conclusively demonstrate that the Board Exam Prediction System is highly accurate, reliable, and suitable for deployment in an academic setting. The system provides valuable predictive insights that can support strategic planning, resource allocation, and student support initiatives within the College of Engineering.

The rigorous validation process, including historical accuracy testing and comprehensive metric evaluation, confirms the system's capability to generate trustworthy predictions. The documented methodology and results provide a solid foundation for the system's continued use and future enhancements.