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Short Paper

Alumni Employability Prediction with Tracer and Feedback Systems Utilizing Classification and Sentiment Analysis Algorithms

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Abstract

Purpose – This study developed and evaluated a Graduate Tracer and Feedback System for Richwell Colleges, Inc. that integrates employability prediction and sentiment analysis in a unified web-based platform to support alumni monitoring, curriculum enhancement, and evidence-based institutional decision-making.

Method – The study used developmental and descriptive research designs guided by the Spiral Model and Knowledge Discovery in Databases process. Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting, and K-Nearest Neighbors were evaluated using 151 alumni responses for employability prediction. Sentiment analysis models using TF-IDF, machine learning, and deep learning techniques were tested on 83 alumni feedback responses. System acceptability was assessed using the ISO/IEC 25010:2023 Software Product Quality Model with 65 IT experts, administrators, and alumni users.

Results – Logistic Regression obtained the best employability prediction performance with 0.7419 accuracy, 0.8167 precision, 0.6125 recall, 0.6222 F1-score, and 0.5373 Cohen's Kappa. For sentiment analysis, Gradient Boosting achieved the highest overall performance with 0.706 accuracy, 0.468 precision, 0.497 recall, 0.481 F1-score, and 0.441 Cohen's Kappa. The system was rated Very Highly Acceptable (WM = 4.87). However, sentiment analysis results should be interpreted cautiously due to the small and imbalanced feedback dataset.

Conclusion – The findings show that integrating employability prediction and sentiment analysis in a graduate tracer platform can support alumni monitoring, curriculum improvement, and analytics-driven decision-making in higher education.

Recommendations – Future studies may use larger multi-institutional datasets, balanced sentiment data, and additional machine learning techniques.

Research Implications – The study contributes to educational data mining by demonstrating an integrated predictive and feedback analysis system for graduate tracer environments.

Keywords – Graduate Tracer System, Employability Classification, Sentiment Analysis, Machine Learning, ISO/IEC 25010:2023

INTRODUCTION

Producing employable graduates remains a primary objective of higher education institutions (HEIs), as graduate employability significantly influences institutional quality, workforce readiness, and national development. In response to rapidly evolving industry demands and technology-driven labor markets, HEIs increasingly adopt data-driven approaches to monitor graduate outcomes and evaluate the relevance of their curricula. Graduate tracer systems have therefore become essential institutional tools for tracking alumni employment and assessing the alignment between academic preparation and labor market needs (Victorino et al., 2022; Tayco et al., 2022; Saong et al., 2023; Andaya et al., 2024; Bustos, 2024). Recent studies further demonstrate that machine learning techniques, such as classification algorithms and sentiment analysis, can enhance educational decision-making by improving the interpretation of employability data and alumni feedback (Dalipi et al., 2021; Shaik et al., 2023; Dake & Gyimah, 2023; Sweta, 2024). Gonzales et al. (2024) revealed that integrated graduate tracer systems combine alumni tracking, program evaluation, and recommendation functionalities, although these systems primarily utilize rule-based decision support rather than machine learning-driven analytics. Similarly, Muhammad et al. (2023) demonstrated that Logistic Regression can be utilized in higher education to predict student employability using academic and experiential attributes such as academic performance, internship experience, and co-curricular involvement. Deshpande et al. (2025) further emphasized that sentiment analysis techniques can support curriculum enhancement by analyzing alumni and student feedback to identify institutional strengths and areas for improvement. In addition, analytics-driven educational decision-support systems have been shown to improve institutional monitoring and evidence-based decision-making through predictive analytics and behavioral data interpretation (Oyedotun et al., 2025). Comparative evaluations of machine learning algorithms also demonstrated the importance of identifying the most suitable predictive models for employability-related tasks using academic, technical, and experiential attributes (Kumar et al., 2025).

In the Philippine context, the Commission on Higher Education (CHED) continues to strengthen outcomes-based and typology-based quality assurance frameworks that emphasize graduate competencies and industry alignment. Despite these initiatives, many HEIs still rely on manual or fragmented graduate tracer processes that limit the accuracy, timeliness, and analytical value of collected alumni data. At Richwell Colleges, Inc., alumni monitoring and tracer-related processes were primarily managed through manual Excel-based tracking and decentralized records, resulting in delayed report generation, limited employability analytics, and the absence of a centralized mechanism for curriculum-related alumni feedback. Moreover, traditional tracer studies often focus on quantitative summaries while overlooking qualitative alumni feedback that may provide deeper insights into curriculum effectiveness and institutional responsiveness. Persistent concerns regarding graduate underemployment and job-skills mismatch further underscore the need for intelligent systems capable of transforming alumni data into evidence-based insights to support curriculum enhancement and academic planning (Melchor, 2024; Bustos, 2024; Ortiz, 2025). Despite these developments, existing studies commonly focus only on standalone graduate tracer systems, employability prediction models, or sentiment analysis applications independently rather than integrating these functionalities within a unified analytics-driven graduate tracer platform. Furthermore, many existing tracer implementations remain descriptive and administrative in nature, with limited predictive analytics, limited sentiment interpretation capabilities, and limited support for curriculum enhancement and institutional decision-making. These gaps highlight the need for an integrated graduate tracer system capable of combining employability prediction, alumni feedback analysis, and analytics-driven institutional support within a single platform.

To address these gaps, this study developed and evaluated a Graduate Tracer and Feedback System for Richwell Colleges, Inc., utilizing Classification and Sentiment Analysis Algorithms. The developed system integrates employability prediction, alumni feedback analysis, and tracer management functionalities within a unified web-based platform. Specifically, multiple machine learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine (SVM), Gradient Boosting, and K-Nearest Neighbors (KNN), were comparatively evaluated to determine the most effective employability prediction model using academic, demographic, and experiential alumni attributes. Logistic Regression emerged as the best-performing employability prediction component and was integrated into the system to support employability classification and analytics-assisted job matching functionalities. In addition, sentiment analysis techniques utilizing Gradient Boosting were applied to analyze alumni feedback and identify curriculum-related insights supporting institutional improvement and evidence-based academic planning. The study also evaluated the effectiveness of the classification and sentiment analysis algorithms and assessed the overall system acceptability using the ISO/IEC 25010:2023 Software Product Quality Model.

The study contributes to higher education practice and educational data mining research by demonstrating the integration of employability prediction and sentiment analysis within a unified graduate tracer platform. Unlike traditional tracer systems that primarily focus on alumni record management and descriptive reporting, the developed system provides analytics-driven functionalities such as employability prediction, sentiment-based feedback interpretation, skill-matching support, and institutional reporting to support curriculum enhancement and evidence-based decision-making in higher education institutions.

LITERATURE REVIEW

Graduate Tracer Systems in Higher Education

Graduate tracer systems have evolved from conventional survey-based monitoring tools into institutional mechanisms for evaluating graduate employability, curriculum relevance, and program responsiveness. Earlier tracer studies primarily emphasized descriptive profiling of graduates' employment status, job alignment, and curriculum usefulness (Dela Cruz, 2022; Handriyani, 2022; Burhan et al., 2022; Zen et al., 2024). While these studies contributed to graduate monitoring, their outputs were mostly limited to reporting employment outcomes rather than generating predictive or diagnostic insights for institutional planning.

Recent studies show a gradual shift toward digital and intelligent tracer systems. Abdulloh et al. (2022) and Hidayatullah & Samudera (2025) demonstrated the use of data mining and machine learning techniques in tracer-related employability prediction. Similarly, Gonzales et al. (2024) emphasized that integrated graduate tracer systems may combine alumni tracking, program evaluation, recommendation features, and decision-support mechanisms. However, many existing tracer systems remain largely rule-based or descriptive, with limited integration of predictive analytics and sentiment-based feedback interpretation. This suggests an unresolved gap in developing tracer systems that not only collect alumni data but also analyze employability status, interpret alumni feedback, and support evidence-based curriculum enhancement within a unified platform.

Machine Learning Applications in Education

Machine learning has become increasingly significant in education because of its capacity to identify patterns, generate predictions, and support data-driven decision-making. Earlier educational machine learning applications focused on predicting student performance, retention, and dropout risks using supervised learning algorithms (Alamri et al., 2019; Jeon & Park, 2020). More recent studies expanded machine learning applications into employability prediction, adaptive learning, intelligent educational systems, and natural language processing (Munir et al., 2022; Zheng et al., 2023).

Despite these developments, prior research shows methodological variation in the selection of algorithms, datasets, and evaluation objectives. Some studies prioritize interpretability through traditional machine learning approaches, while others emphasize higher predictive accuracy through ensemble or deep learning models. Mezhoudi et al. (2023) noted that employability prediction studies vary significantly in methodology and predictive approach, which indicates the absence of a universally superior model across educational contexts. This supports the need for comparative model evaluation rather than relying on a single predefined algorithm. In the present study, machine learning is applied not as a novel algorithmic invention but as an analytical component of the graduate tracer system to classify alumni employability status using institutional graduate data.

Employability Models Using Classification Algorithms

Employability prediction using classification algorithms has become a growing area in educational data mining. Classification models such as Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, Naïve Bayes, Gradient Boosting, and K-Nearest Neighbors have been applied to predict employability outcomes using academic, demographic, technical, and experiential attributes (ElSharkawy et al., 2022; Haque et al., 2024; Yusof et al., 2024). These studies demonstrate that employability prediction can help institutions identify patterns related to employment readiness, career preparedness, and job alignment.

In the Philippine computing education context, Arcalas et al. (2025) applied predictive analytics to assess BSIT internship performance and job readiness within a hybrid training framework. Their study demonstrated the usefulness of supervised learning models in analyzing student performance indicators and supporting evidence-based internship management, curriculum development, and employability preparation. This study is relevant to the present research because both works apply predictive analytics in computing education to support employability-related decision-making.

However, findings across studies vary depending on dataset characteristics, feature selection, institutional context, and evaluation metrics. Kumar et al. (2025) emphasized the importance of comparative evaluation because different algorithms provide different strengths, such as interpretability, variance reduction, nonlinear pattern recognition, and predictive optimization. Similarly, Arcalas et al. (2025) support the value of comparing multiple supervised learning models rather than assuming a universally superior algorithm for employability-related prediction tasks. Therefore, the selection of the final employability model should be data-driven rather than assumed in advance. In this study, several classification algorithms were evaluated using Richwell Colleges, Inc. graduate data, and the best-performing model was used as the employability prediction component of the system.

Sentiment Analysis in Alumni Feedback

Sentiment analysis has become an important method for transforming qualitative feedback into measurable insights for educational improvement. Earlier studies applied machine learning algorithms such as Naïve Bayes, Support Vector Machines, and Logistic Regression to analyze student and institutional feedback (Pacol & Palaoag, 2021; Dake & Gyimah, 2023). More recent studies have explored ensemble, hybrid, and deep learning approaches, including LSTM, CNN, and Gradient Boosting, to improve sentiment classification performance (Hossain & Logofătu, 2025; Chandrasekaran et al., 2025).

In educational contexts, sentiment analysis is useful because it enables institutions to interpret large volumes of feedback with less manual effort. Shaik et al. (2023) emphasized that sentiment analysis supports improvements in pedagogy, teaching practices, institutional decision-making, and quality assurance by converting feedback into actionable insights. Similarly, Deshpande et al. (2025) highlighted the role of sentiment analysis in identifying perceptions and improvement areas that may support curriculum enhancement. However, sentiment analysis is often applied separately from graduate tracer systems. This creates a gap in systems that can connect alumni employment data with alumni feedback interpretation. In the present study, sentiment analysis is integrated into the tracer system to classify alumni feedback as positive, negative, or neutral and to support curriculum-related institutional reflection.

System Evaluation Using ISO/IEC 25010:2023 Software Product Quality Model

The ISO/IEC 25010:2023 Software Product Quality Model provides a structured framework for evaluating software quality through characteristics such as functional suitability, reliability, performance efficiency, compatibility, interaction capability, security, maintainability, flexibility, and safety. Earlier system evaluation studies commonly focused on functionality and usability within educational or institutional systems (Manglapuz & Lacatan, 2019; Wenceslao, 2022). More recent studies emphasized the importance of evaluating technical quality, user acceptance, organizational usefulness, and system performance in integrated information systems (Adyaputra et al., 2025; Barzegar et al., 2025).

For intelligent and analytics-driven educational systems, software quality evaluation is important because the system not only stores information but also processes sensitive alumni data, generates analytical outputs, and supports institutional decision-making. Gobov & Zuieva (2025) and Doctor et al. (2024) emphasized the relevance of software quality attributes in systems requiring reliability, security, and safe operation. In this study, ISO/IEC 25010:2023 was used to evaluate whether the developed graduate tracer and feedback system was acceptable not only as a functional software product but also as an institutional decision-support platform.

Synthesis of Related Literature

The reviewed literature shows that graduate tracer systems, employability prediction, sentiment analysis, and software quality evaluation have each been studied in educational and institutional contexts. Graduate tracer systems support alumni monitoring and curriculum evaluation, while machine learning enables employability prediction based on graduate attributes. Sentiment analysis provides a way to interpret qualitative alumni feedback, and ISO/IEC 25010:2023 offers a framework for evaluating the quality of the developed system.

However, the literature also reveals important limitations. Many tracer studies remain descriptive and administrative, many employability prediction studies focus only on algorithmic performance, and many sentiment analysis studies are implemented independently from graduate monitoring platforms. As a result, there remains a need for a unified system that integrates alumni tracking, employability prediction, sentiment analysis, and system quality evaluation. The present study addresses this gap by developing and evaluating a graduate tracer and feedback system that combines predictive employability analytics and sentiment-based feedback interpretation within one platform.

Theoretical and Conceptual Framework

The study is anchored on Systems Theory, Machine Learning Theory, and Natural Language Processing (NLP) and Sentiment Analysis Theory, which collectively provide the theoretical and analytical foundation for the development of the proposed Graduate Tracer and Feedback System. Systems Theory explains how interconnected components interact through inputs, processes, outputs, and feedback mechanisms to support organizational functions and continuous improvement (Becvar et al., 2023; Münch et al., 2022). In the context of the study, the developed platform operates as an integrated system composed of alumni account management, administrator management, tracer data processing, employability prediction, job-matching support, feedback analysis, and institutional reporting modules. These interconnected components work together to support centralized alumni monitoring, evidence-based institutional decision-making, and continuous curriculum enhancement.

Machine Learning Theory supports the employability prediction component of the study by enabling the system to analyze structured alumni and academic data and identify employability-related patterns from graduate information (Mirtaheri & Shahbazian, 2022; Bach, 2024). Through supervised classification algorithms, the system classifies graduates as employed, underemployed, or unemployed based on attributes such as academic performance, skills, work experience, awards, and demographic information. This supports the institution in reducing manual employability categorization and generating predictive insights from alumni datasets.

Furthermore, Natural Language Processing (NLP) and Sentiment Analysis Theory provide the foundation for interpreting textual alumni feedback and transforming qualitative responses into measurable insights (Joseph, 2024; Li et al., 2022; Abdullah & Ahmet, 2022). In the study, sentiment analysis techniques are used to classify alumni feedback as positive, negative, or neutral, enabling the institution to identify curriculum-related concerns, institutional strengths, and areas requiring improvement. The integration of sentiment analysis within the graduate tracer system supports evidence-based curriculum planning and more responsive institutional evaluation processes.

Together, these theories establish the conceptual and analytical foundation of the study by integrating system interaction, predictive analytics, and feedback interpretation within a unified graduate tracer platform.

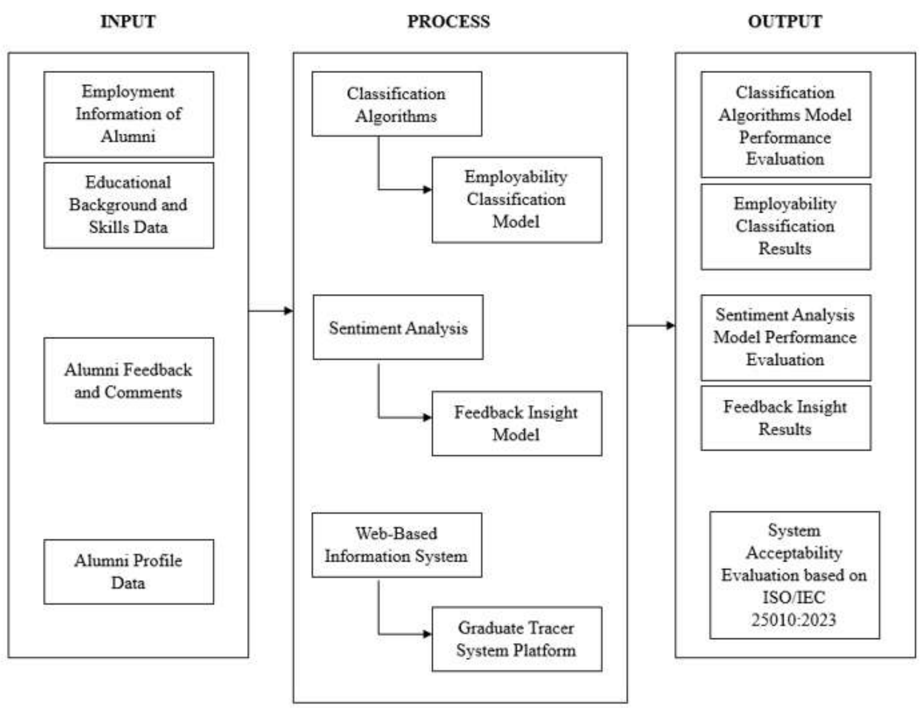

Figure 1. Conceptual Framework

Figure 1 presents the conceptual framework of the study using the Input–Process–Output (IPO) model to illustrate the flow of data and analytical processes within the proposed Graduate Tracer and Feedback System. The input component consists of

Alumni Profile Data, Employment Information, Educational Background and Skills Data, and Alumni Feedback and Comments. These inputs are processed within the web-based Graduate Tracer System using classification algorithms for employability prediction and sentiment analysis techniques for feedback interpretation. The process component also includes analytics-driven functionalities such as employability classification, job-matching support, feedback analysis, and institutional reporting. The output component generates Employability Classification Results, Feedback Insight Results, model performance evaluations, and System Acceptability Evaluation results based on the ISO/IEC 25010:2023 Software Product Quality Model. The framework demonstrates how integrated analytics, intelligent data processing, and system interaction collectively support employability assessment, curriculum enhancement, and evidence-based institutional decision-making in higher education institutions.

METHODOLOGY

This study employed developmental and descriptive research designs to develop and evaluate the Graduate Tracer and Feedback System for Richwell Colleges, Inc. The developmental research design guided the planning, design, development, implementation, and testing of the proposed system. Meanwhile, the descriptive research design was utilized to evaluate the overall quality and acceptability of the developed platform using the ISO/IEC 25010:2023 Software Product Quality Model.

Software Development Process

The study adopted the Spiral Model of Software Development, as shown in Figure 2, which emphasizes iterative phases of planning, risk analysis, development, testing, and evaluation throughout the software development lifecycle (Sari et al., 2022). The model guided the development and implementation of the Graduate Tracer and Feedback System by supporting continuous refinement, functional testing, and system improvement during each development iteration. The developed platform integrated five major functional components: Alumni Account Management, Administrator Account Management, Web Content Management, Employability Management, and Evaluation Management.

The system architecture and operational processes were represented using Functional Decomposition Diagrams (Figure 3) and Data Flow Diagrams (Figure 4), which illustrated the interactions among users, system modules, and data repositories. The Employability Management module served as the system's core analytical component by supporting employability prediction, job posting, job matching, qualified alumni identification, email notification, and employment alignment reporting functionalities. Meanwhile, the Evaluation Management module facilitated the collection, storage, and analysis of alumni feedback and evaluation responses for institutional assessment and curriculum improvement.

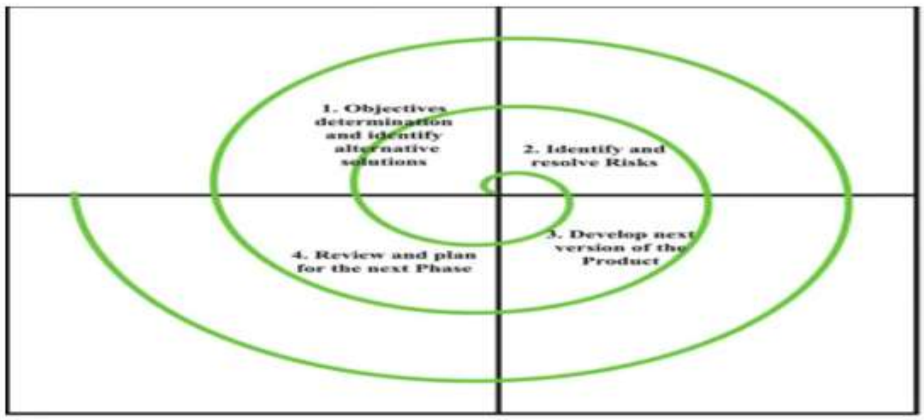

Figure 2. Spiral Model (Software Development)

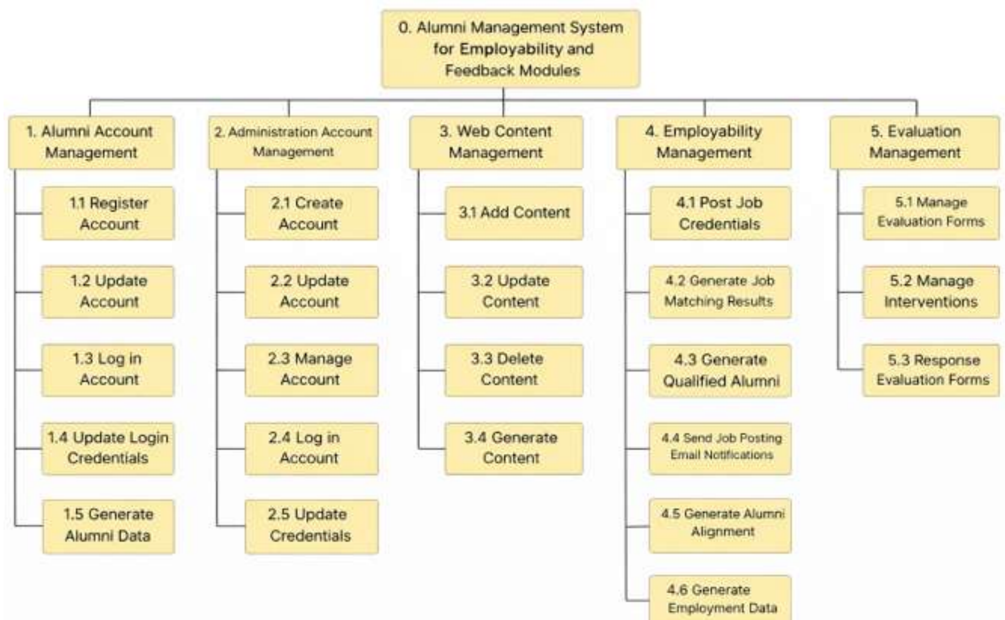

Figure 3. Functional Decomposition Diagram (FDD)

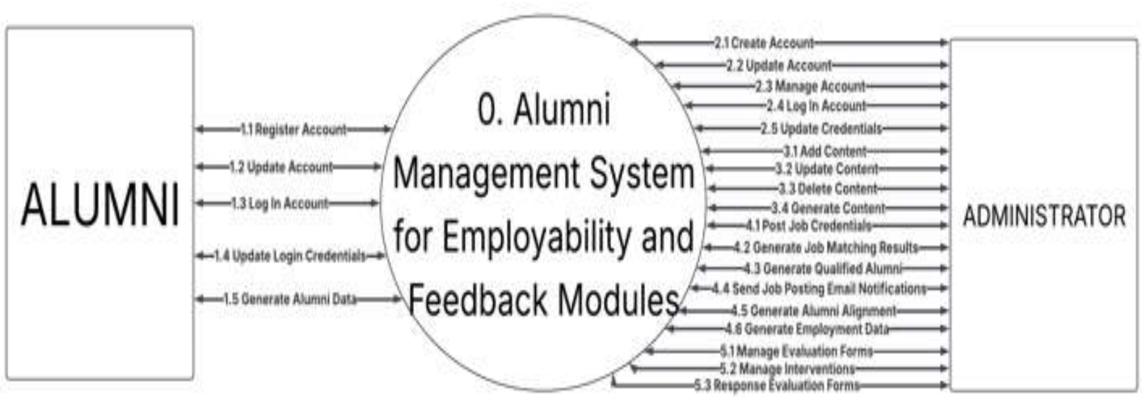

Figure 4. Data Flow Diagram (DFD)

Machine Learning and Knowledge Discovery Process

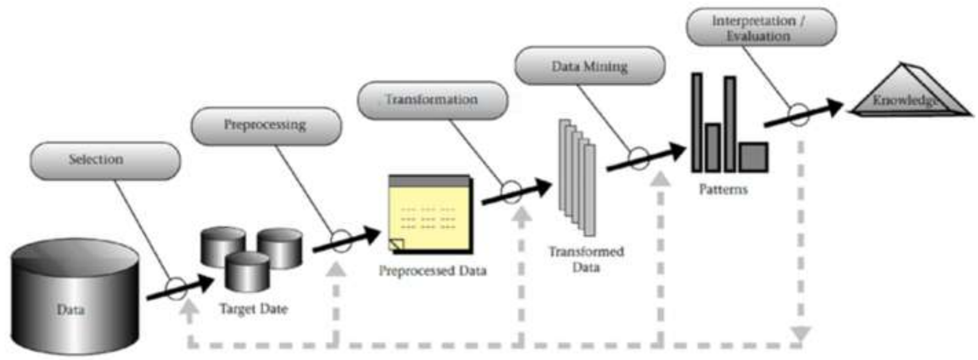

Figure 5. Knowledge Discovery in Databases (KDD)

As shown in Figure 5, the study utilized the Knowledge Discovery in Databases (KDD) process, which consists of data selection, preprocessing, transformation, data mining, and interpretation of results (Bold & Urschel, 2023). The KDD framework guided the implementation of the employability prediction and sentiment analysis components within the system. Similar applications of the KDD process in predictive analytics and machine learning implementation were demonstrated by Cenita et al. (2023).

Employability Prediction Dataset

The machine learning implementation was conducted using Google Colab and Python 3.x. The study utilized Scikit-learn for machine learning model implementation and evaluation, TensorFlow/Keras for deep learning implementation, and NLTK for text preprocessing and sentiment analysis. The employability prediction dataset consisted of 151 alumni responses gathered from the Graduate Tracer Study of Richwell Colleges, Inc. The dataset included academic, experiential, demographic, and employability-related attributes, specifically employment status, overall GPA, technical and hard skills GPA, soft and analytical skills GPA, work experience before graduation, academic honors, research awards, internship awards, and age. The employment status variable served as the target classification variable with three categories: employed (52.3%), underemployed (33.1%), and unemployed (14.6%).

Figure 6 presents the distribution of employability classification categories within the alumni dataset used in the study. The dataset consisted of employed, underemployed, and unemployed alumni classifications gathered from the Graduate Tracer Study of Richwell Colleges, Inc. The visualization was utilized to examine class distribution before model training and evaluation. Understanding the distribution of employment categories was important in assessing dataset balance and ensuring appropriate train-test splitting during machine learning implementation.

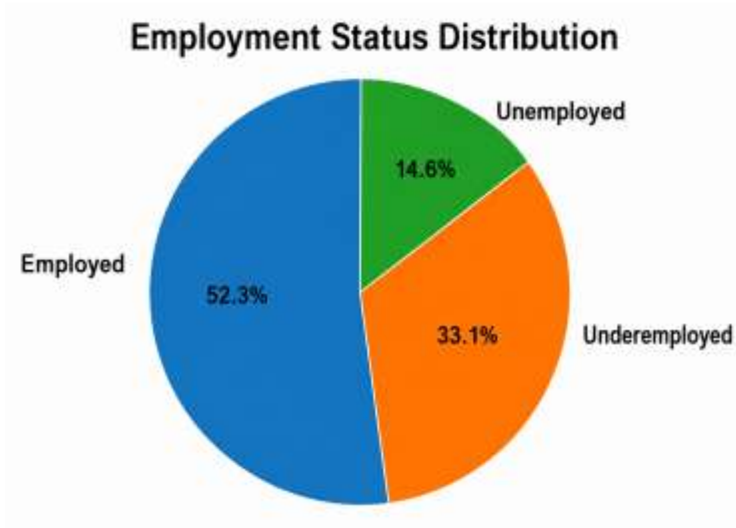

Figure 6. Employment Status Distribution

Data Preprocessing and Exploratory Analysis

Before model training, employment status labels were transformed using Label Encoding to convert categorical target labels into numerical representations. Exploratory Data Analysis (EDA) techniques, including class distribution analysis, pie chart visualization, and correlation heatmaps, were utilized to examine the distribution and relationships among variables. The dataset was divided using stratified train-test splitting with an 80/20 ratio and random_state=42 to preserve class distribution consistency during model evaluation.

Employability Classification Algorithms

The study comparatively evaluated multiple classification algorithms, including Logistic Regression, Random Forest, Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel, Gradient Boosting, and K-Nearest Neighbors (KNN), to determine the most suitable employability prediction model for the dataset. The Logistic Regression model utilized multinomial classification with the lbfgs solver and max_iter=1000. The Random Forest model utilized 100 estimators, while the KNN model used n_neighbors=5. Default Scikit-learn configurations were applied to the remaining models unless otherwise specified.

Sentiment Analysis Dataset

The sentiment analysis dataset consisted of 83 alumni feedback responses collected from the Graduate Tracer Study, where alumni voluntarily provided textual feedback regarding their educational experiences and institutional services. The feedback entries were written in English and underwent text preprocessing procedures, including lowercase transformation, URL removal, username removal, hashtag removal, punctuation filtering, whitespace normalization, and text cleaning. Since manually annotated sentiment labels were unavailable, the study utilized the VADER SentimentIntensityAnalyzer of NLTK to automatically generate sentiment labels based on compound polarity scores. Feedback with compound scores greater than or equal to 0.05 was classified as positive, scores less than or equal to -0.05 were classified as negative, and scores between the thresholds were classified as neutral.

The resulting sentiment distribution consisted of 46 neutral responses, 34 positive responses, and 3 negative responses. Due to the limited number of negative responses, the dataset exhibited class imbalance; however, no oversampling, undersampling, SMOTE, or class weighting techniques were applied. The dataset was divided using train-test splitting with random_state settings, while stratification was conditionally applied depending on class count availability.

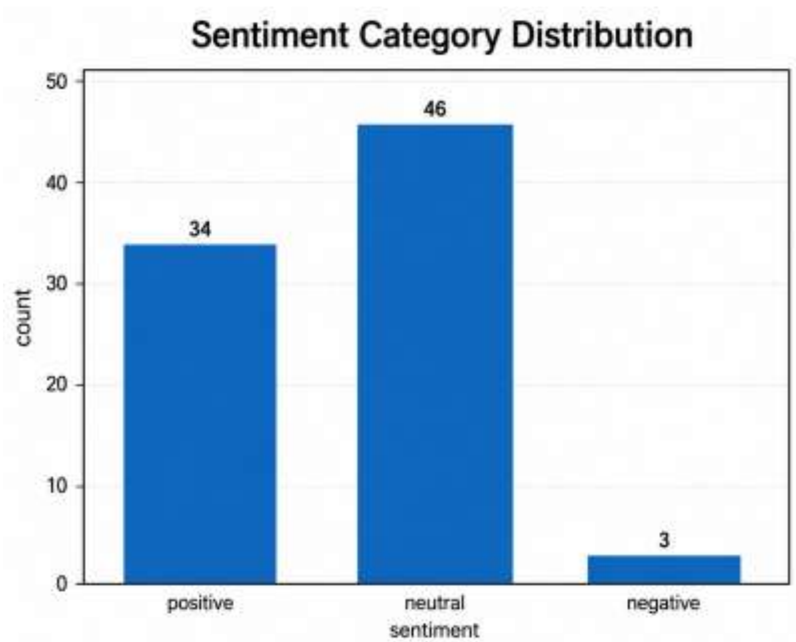

Figure 7. Sentiment Category Distribution

Figure 7 illustrates the distribution of sentiment categories generated from alumni feedback responses using the VADER SentimentIntensityAnalyzer. The sentiment analysis dataset consisted of 83 alumni feedback entries categorized into positive, neutral, and negative sentiments based on compound polarity score thresholds. The visualization highlights the imbalance within the dataset, particularly the limited number of negative feedback responses. This distribution was considered during model evaluation and interpretation of sentiment analysis results.

Text Preprocessing

For classical machine learning-based sentiment analysis, TF-IDF vectorization with max_features=30000, ngram_range=(1,2), and min_df=2 was utilized to transform textual feedback into numerical feature representations. Logistic Regression, Naïve Bayes, Random Forest, and Gradient Boosting models were comparatively evaluated using TF-IDF features. Logistic Regression utilized max_iter=2000, while Random Forest used 300 estimators with parallel processing enabled through n_jobs=-1. Gradient Boosting was implemented using dense TF-IDF arrays due to Scikit-learn requirements.

Sentiment Analysis Algorithms

The study comparatively evaluated multiple sentiment analysis algorithms, including Logistic Regression, Naïve Bayes, Random Forest, and Gradient Boosting, to determine the most suitable sentiment classification model for alumni feedback responses. These models were implemented using TF-IDF feature representations generated from the preprocessed textual feedback dataset. Logistic Regression utilized max_iter=2000, while the Random Forest model utilized 300 estimators with parallel processing enabled through n_jobs=-1. Gradient Boosting was implemented using dense TF-IDF arrays due to Scikit-learn requirements. Default Scikit-learn configurations were applied to the remaining models unless otherwise specified.

Deep Learning Implementation

For deep learning implementation, the study utilized a Bidirectional Long Short-Term Memory (BiLSTM) model implemented in TensorFlow/Keras. Tokenization and sequence padding were applied exclusively for the LSTM implementation using a maximum vocabulary size of 30000 and a maximum sequence length of 100. The LSTM architecture utilized an embedding layer, a Bidirectional LSTM layer, dropout regularization, and softmax output activation. The model was trained using the Adam optimizer, categorical cross-entropy loss function, batch size of 64, validation split of 0.1, and early stopping with patience=2 to minimize overfitting.

Model Evaluation Metrics

The performance of the employability prediction and sentiment analysis models was evaluated using multiple classification metrics to ensure comprehensive model assessment. Accuracy was utilized to measure the overall proportion of correctly classified instances. Precision, recall, and F1-score were computed using macro averaging to evaluate classification performance across multiple classes while minimizing bias toward majority class categories.

Cohen's Kappa was also utilized to assess the agreement between predicted and actual classifications beyond chance agreement. In this study, Cohen's kappa was interpreted as a chance-corrected agreement metric rather than merely an additional performance score. This means that the metric considers whether the agreement between predicted and actual classifications is better than what may occur by chance. Therefore, low Cohen's kappa values indicate limited agreement beyond chance, while a kappa value of zero indicates that the model did not demonstrate agreement beyond chance-level classification (Li & Yu, 2022). This interpretation was considered important because the employability and sentiment analysis datasets involved relatively small sample sizes and imbalanced class distributions, which may affect the reliability of accuracy-based performance interpretation.

Confusion matrices and classification reports were generated to analyze class-level prediction performance, including correctly classified and misclassified instances. These evaluation metrics collectively supported the comparative assessment of the machine learning and deep learning models utilized in the study.

Respondents and System Evaluation

The study's respondents consisted of 65 participants selected using non-probability purposive sampling. The respondents included 15 IT experts and school administrators (23.08%) and 50 alumni from batches 2021–2023 (76.92%). IT experts and administrators evaluated the technical and functional quality of the system, while alumni respondents evaluated the usability, interaction capability, and overall acceptability of the platform based on actual system utilization.

The system evaluation instrument was adapted from the ISO/IEC 25010:2023 Software Product Quality Model. The instrument assessed nine software quality characteristics: Functional Suitability, Reliability, Flexibility, Interaction Capability, Performance Efficiency, Security, Compatibility, Maintainability, and Safety. Each quality characteristic contained multiple evaluation indicators measured using a five-point Likert scale. The weighted mean interpretation used in the study consisted of the following ranges: 4.21–5.00 (Very Highly Acceptable), 3.41–4.20 (Highly Acceptable), 2.61–3.40 (Acceptable), 1.81–2.60 (Less Acceptable), and 1.00–1.80 (Not Acceptable).

The updated ISO/IEC 25010:2023 framework was selected to align with contemporary software quality evaluation practices, particularly the inclusion of safety as an additional software quality characteristic. Previous studies have demonstrated the applicability of ISO/IEC 25010 in evaluating software systems within educational and institutional environments (Adyaputra et al., 2025; Gobov & Zuieva, 2025). Descriptive statistical methods, particularly weighted mean, were utilized to analyze and interpret the evaluation results.

RESULTS

Graduate Tracer System

The developed Graduate Tracer and Feedback System demonstrated integrated functionalities supporting alumni profiling, employment tracking, employability prediction, job matching, feedback analysis, and institutional reporting (Figure 8). The system allowed alumni to create and manage personal accounts containing academic, experiential, and employability-related information, which also functioned as a virtual resume profile within the platform. Through the employability management component, alumni were able to view available job postings, determine whether their current qualifications matched posted job requirements, and identify missing qualifications or skill gaps related to specific employment opportunities. The system also enabled alumni to submit institutional feedback and evaluation comments through digital tracer and evaluation forms.

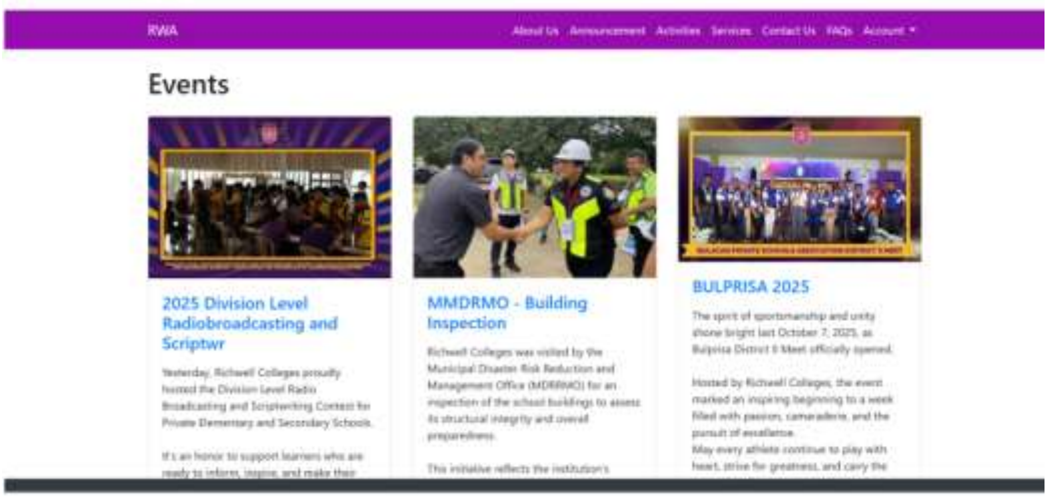

Figure 8. Graduate Tracer System

Meanwhile, administrators were provided with functionalities for managing alumni records, posting job vacancies, generating graduate tracer reports, monitoring employability results, viewing and analyzing alumni feedback, sending alumni notifications regarding job postings, and managing website content through the integrated content management module. The Employability Management module additionally supported qualified alumni identification and employment alignment reporting, while the Evaluation Management module facilitated analytics-driven interpretation of alumni feedback for curriculum enhancement and institutional assessment.

The development process involved consultation and content validation with school administrators to ensure that the implemented tracer functionalities aligned with institutional graduate tracer requirements and alumni monitoring practices. Following development, the system underwent evaluation using the ISO/IEC 25010:2023 Software Product Quality Model involving 65 respondents composed of IT experts, school administrators, and alumni users. The integration of employability prediction and sentiment analysis functionalities further enhanced the system by supporting analytics-driven institutional decision-making, employability monitoring, and curriculum improvement within a unified tracer platform.

Employability Classification Model

Table 1 presents the comparative performance evaluation of the employability classification algorithms tested in the study.

Table 1. Employability Classification Model Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score	Cohen's Kappa
Logistic Regression	0.7419	0.8167	0.6125	0.6222	0.5373
Random Forest	0.6452	0.4333	0.4917	0.4593	0.4593
SVM (RBF)	0.5161	0.1720	0.3333	0.2270	0.2270
Gradient Boosting	0.6774	0.4714	0.5250	0.4967	0.4967
KNN	0.6129	0.4074	0.4583	0.4277	0.4277

Among the evaluated models, Logistic Regression achieved the highest overall predictive performance with an accuracy of 0.7419, precision of 0.8167, recall of 0.6125, F1-score of 0.6222, and Cohen's Kappa of 0.5373. The findings indicate that Logistic Regression demonstrated stronger predictive consistency and class discrimination capability compared to Random Forest, SVM, Gradient Boosting, and KNN models within the structured alumni dataset used in the study. The results suggest that the employability attributes contained sufficiently linear and interpretable relationships that were effectively captured by Logistic Regression despite the relatively limited dataset size and class imbalance conditions. These findings support previous studies highlighting the effectiveness and interpretability of Logistic Regression in educational employability prediction tasks.

The correlation heatmap presented in Figure 9 further explained the relationships among employability-related variables used in the classification process. The strongest correlation was observed between Overall GPA and Technical and Hard Skills GPA ($r = 0.73$), indicating that graduates with higher overall academic performance also tended to demonstrate stronger technical competency performance. Meanwhile, Work Experience Before Graduation demonstrated the highest relationship with employment status (r =

0.52), suggesting that prior work exposure may significantly contribute to graduate employability outcomes. Soft and Analytical Skills GPA also demonstrated a moderate relationship with employment status (r = 0.30), while academic honors, internship awards, research awards, and age demonstrated relatively weaker correlations with employment classification. These findings indicate that employability outcomes were influenced more strongly by practical experience and skills-related factors than by awards or demographic characteristics alone.

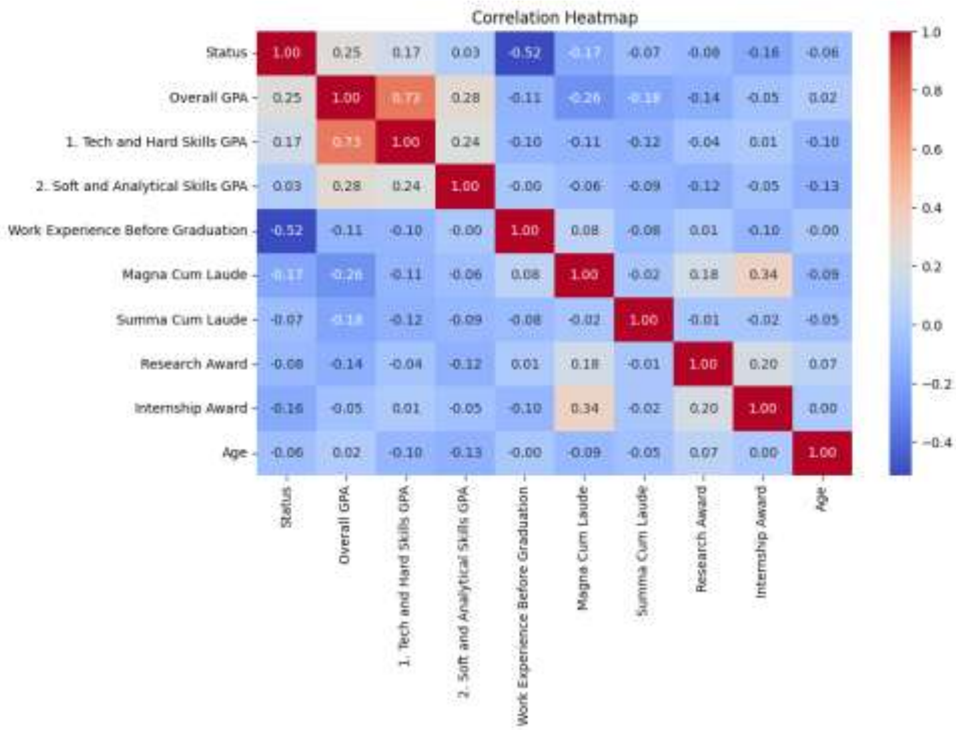

Figure 9. Correlation heatmap

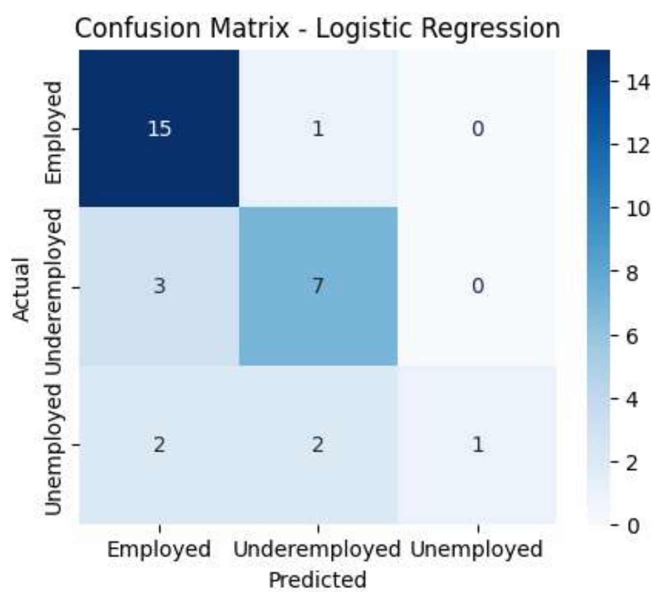

Figure 10. Logistic regression confusion matrix

The confusion matrix in Figure 10 further illustrates the predictive behavior of the Logistic Regression model across employment categories. The model demonstrated strong predictive performance in identifying employed graduates, correctly classifying 15 employed cases with only one misclassification as underemployed. The model also demonstrated moderate performance in classifying underemployed graduates, correctly identifying 7 cases while misclassifying 3 cases as employed. However, weaker predictive performance was observed in the unemployed category, where only one case was correctly classified, while the remaining unemployed instances were misclassified as employed or underemployed. These findings indicate that the class imbalance within the dataset affected minority class detection, particularly for unemployed graduates, while the model remained more effective in identifying majority employment categories.

Sentiment Analysis Algorithms

Table 2 presents the comparative performance results of the evaluated sentiment analysis models.

Table 2. Sentiment Analysis Model Performance Comparison

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Cohen's Kappa**
Gradient Boosting	0.706	0.468	0.497	0.481	0.441
Random Forest	0.706	0.548	0.476	0.461	0.401
Naïve Bayes	0.647	0.455	0.439	0.424	0.292
Logistic Regression	0.529	0.346	0.354	0.333	0.056
LSTM	0.529	0.176	0.333	0.231	0.000

Among the evaluated sentiment analysis models, Gradient Boosting achieved the highest observed performance with an accuracy of 0.706, precision of 0.468, recall of 0.497, F1-score of 0.481, and Cohen's kappa of 0.441. Although Random Forest achieved identical accuracy, Gradient Boosting demonstrated slightly higher recall, F1-score, and chance-corrected agreement performance. The model performance was evaluated using multiple classification metrics, including accuracy, precision, recall, F1-score, Cohen's kappa, confusion matrices, and classification reports, which are commonly utilized in evaluating machine learning classification performance (Pilare et al., 2024). Similar sentiment analysis studies also emphasized the importance of classification evaluation metrics and optimization techniques in improving sentiment classification assessment (Cruz et al., 2024).

However, Cohen's kappa values indicate that the sentiment analysis findings should be interpreted cautiously. While Gradient Boosting obtained the highest performance among the evaluated sentiment models, its kappa value does not establish strong sentiment classification reliability. The very low kappa value of Logistic Regression and the zero kappa value of LSTM indicate weak or no agreement beyond chance. In particular, the LSTM result suggests that the model did not learn a reliable classification pattern from the available feedback dataset.

These findings may be attributed to the relatively small sentiment dataset, the limited number of negative responses, and the absence of balancing techniques such as oversampling, undersampling, SMOTE, or class weighting. Therefore, the sentiment analysis results should not be interpreted as evidence of strong predictive robustness across all models. Instead, the findings indicate that Gradient Boosting showed the most practical potential among the evaluated sentiment models under the existing dataset conditions. This cautious interpretation is consistent with methodological discussions emphasizing that Cohen's kappa should be interpreted as agreement beyond chance and that low or zero kappa values require careful reporting to avoid overstating classification performance (Li & Yu, 2022; Pontius Jr. et al., 2025). The observed performance of Gradient Boosting may still be viewed as consistent with studies highlighting the usefulness of boosting-based approaches in predictive and sentiment-related classification tasks, although such a comparison should be understood within the limitations of the present dataset (Villones & Mababa, 2026).

Figure 11 shows that the Gradient Boosting model demonstrated strong predictive performance in identifying neutral sentiments, correctly classifying 7 neutral responses with only 2 misclassifications as positive sentiments. The model also demonstrated moderate performance in identifying positive sentiments, correctly classifying 5 responses, while 2 positive responses were incorrectly predicted as neutral. However, the model failed to correctly classify the single negative sentiment instance, which was instead predicted as positive. These findings indicate that the model performed effectively on the majority sentiment categories but struggled to recognize minority sentiment classes because of severe dataset imbalance. The sentiment dataset consisted of only three negative responses, which limited the model's ability to effectively learn minority class patterns despite acceptable overall predictive performance.

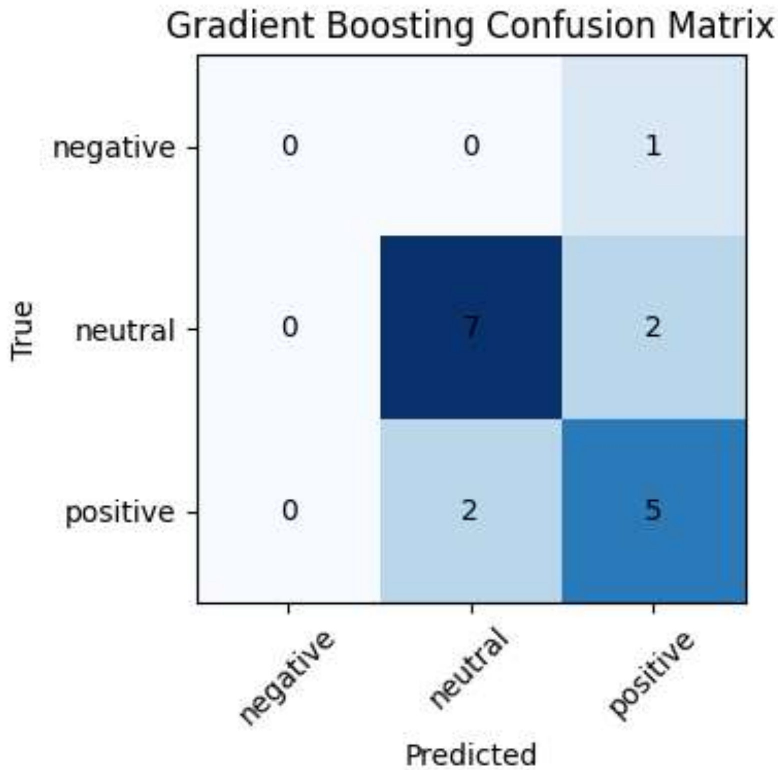

Figure 11. Gradient boosting confusion matrix

System Acceptability Evaluation

The evaluation results revealed that the developed system achieved an overall rating of Very Highly Acceptable (WM = 4.87) based on the ISO/IEC 25010:2023 Software Product Quality Model. All evaluated quality characteristics, including Functional Suitability, Reliability, Flexibility, Interaction Capability, Performance Efficiency, Security, Compatibility, Maintainability, and Safety, received ratings within the Very Highly Acceptable range. Functional Suitability obtained the highest rating (WM = 4.92), followed by Performance Efficiency (WM = 4.89) and Security (WM = 4.88), indicating that the system effectively delivered accurate functionalities, efficient operations, and secure handling of alumni information.

The findings also suggest strong user satisfaction and technical acceptability among both alumni users and expert evaluators. Alumni respondents provided slightly higher ratings (WM = 4.88) compared to IT Experts and School Administrators (WM = 4.84), indicating positive user experience while maintaining compliance with technical software quality standards. These findings align with previous studies emphasizing the importance of usability, system efficiency, security, and reliability in successful graduate tracer systems and intelligent educational platforms (Hapsari & Putra, 2022; Guiling et al., 2024; Fahmy et al., 2025).

Table 3. Overall summary of system acceptability based on ISO/IEC 25010:2023

Software Quality Characteristics	Alumni	VI	Admin	VI	Overall WM	VI
Functional Suitability (ISO/IEC 25010:2023)	4.95	VHA	4.89	VHA	4.92	VHA
Reliability (ISO/IEC 25010:2023)	4.88	VHA	4.77	VHA	4.82	VHA
Flexibility (formerly Portability) – ISO/IEC 25010:2023	4.81	VHA	4.79	VHA	4.8	VHA
Interaction Capability (formerly Usability) – ISO/IEC 25010:2023	4.87	VHA	4.88	VHA	4.87	VHA
Performance Efficiency (ISO/IEC 25010:2023)	4.92	VHA	4.87	VHA	4.89	VHA
Security (ISO/IEC 25010:2023)	4.85	VHA	4.92	VHA	4.88	VHA
Compatibility (ISO/IEC 25010:2023)	4.89	VHA	4.83	VHA	4.86	VHA
Maintainability (ISO/IEC 25010:2023)	4.89	VHA	4.8	VHA	4.84	VHA
Safety (ISO/IEC 25010:2023)	4.87	VHA	4.85	VHA	4.86	VHA
Overall Weighted Mean	**4.88**	**VHA**	**4.84**	**VHA**	**4.87**	**VHA**

DISCUSSION

The findings of the study demonstrate that the developed Graduate Tracer and Feedback System provide an effective analytics-driven platform for alumni monitoring, employability assessment, feedback interpretation, and institutional reporting. The integration of employability prediction and sentiment analysis within a unified tracer platform enhanced the system's capability to generate predictive and interpretive insights from both structured alumni records and textual feedback responses. Unlike traditional graduate tracer systems that primarily focus on descriptive reporting and alumni record management, the developed platform integrated predictive employability analytics, feedback interpretation, job-matching support, and institutional evaluation functionalities within a single system environment. These findings support previous studies emphasizing the importance of integrated graduate tracer systems and analytics-driven institutional decision-support platforms in higher education environments (Gonzales et al., 2024; Oyedotun et al., 2025).

Among the evaluated employability classification algorithms, Logistic Regression obtained the highest observed performance in the present study, achieving the highest accuracy, precision, recall, F1-score, and Cohen’s kappa among the tested classifiers. This result suggests that the structured alumni dataset contained relatively interpretable relationships among employability-related variables such as work experience before graduation, overall GPA, technical and hard skills GPA, and soft and analytical skills GPA. The correlation heatmap further supported this interpretation, particularly the observed relationship between work experience before graduation and employment status, indicating that practical experience contributed to employability outcomes. These findings align with previous studies emphasizing the effectiveness and interpretability of Logistic Regression in employability prediction and educational analytics tasks (Muhammad et al., 2023; Kumar et al., 2025).

This finding may also be compared with the study of Arcalas et al. (2025), which applied predictive analytics to assess BSIT internship performance and job readiness within a hybrid training framework. Their study evaluated Logistic Regression, Random Forest, SVM, and KNN and identified Random Forest as the best-performing model. In contrast, the present study identified Logistic Regression as the best-performing model for alumni employability classification. This difference suggests that the most suitable predictive algorithm may vary depending on dataset structure, feature composition, target outcome, and institutional context. While Arcalas et al. (2025) focused on internship performance and job readiness using internship evaluation indicators, the present study focused on alumni employability status using tracer-based academic, demographic, and experiential attributes. The comparison supports the need for data-driven model selection rather than assuming a universally superior algorithm for employability-related prediction tasks.

The confusion matrix analysis further revealed that the Logistic Regression model performed effectively in identifying employed graduates while demonstrating weaker performance in detecting unemployed cases. This behavior was influenced by class imbalance within the dataset, where employed graduates represented the majority class while unemployed graduates comprised the smallest category. The findings indicate that the model demonstrated stronger predictive sensitivity toward the majority employment classes while struggling to accurately classify minority employment outcomes. Similar observations were emphasized in machine learning classification studies, where class imbalance significantly affects predictive sensitivity and minority class detection performance (Adao, 2026). Despite this limitation, Logistic Regression still showed the highest agreement among the evaluated employability models; however, its predictive use should be limited to institutional monitoring and exploratory analytics rather than generalized or definitive employability prediction.

For sentiment analysis, Gradient Boosting achieved the strongest overall performance among the evaluated models. The findings suggest that boosting-based ensemble methods were more effective in handling sparse TF-IDF textual feature representations generated from alumni feedback responses. Although Random Forest achieved similar accuracy performance, Gradient Boosting demonstrated stronger balance in recall, F1-score, and Cohen's Kappa metrics. In contrast, the lower performance of Logistic Regression and LSTM may have been influenced by the limited dataset size, severe class imbalance, and insufficient training data for deep learning-based sentiment modeling. The sentiment analysis dataset consisted of only 83 feedback entries, with only three negative responses, which significantly affected minority class recognition performance. This limitation was evident in the confusion matrix results, where the model failed to correctly classify the negative sentiment instance. These findings indicate that the sentiment analysis component should be interpreted as an exploratory institutional analytics mechanism rather than a high-performance natural language processing system. Nevertheless, the developed sentiment analysis component still demonstrated practical usefulness in identifying general alumni sentiment patterns and supporting curriculum-related institutional reflection. These findings are consistent with previous studies emphasizing the effectiveness of boosting-based approaches and sentiment analytics in educational feedback interpretation and institutional decision-support systems (Deshpande et al., 2025; Villones & Mababa, 2026).

The findings also demonstrated that the developed system achieved an overall evaluation of Very Highly Acceptable based on the ISO/IEC 25010:2023 Software Product Quality Model. High ratings across Functional Suitability, Performance Efficiency, Security, Interaction Capability, and Reliability indicate that the developed platform was able to effectively support alumni monitoring, feedback collection, employability analytics, and institutional reporting functionalities while maintaining usability and technical quality standards. The positive evaluation results suggest that integrating predictive analytics and feedback interpretation within graduate tracer systems may enhance institutional capability in supporting evidence-based planning, employability monitoring, curriculum enhancement, and CHED-related reporting processes. In addition, the developed system provided practical benefits for alumni users through centralized employment opportunities, employability awareness, and skills-gap identification functionalities.

From a theoretical perspective, the findings support Systems Theory by demonstrating how interconnected system modules, data flows, and feedback mechanisms collectively contributed to institutional monitoring and decision-support processes. The findings also support Machine Learning Theory through the successful implementation of predictive analytics for employability classification using structured alumni datasets. Furthermore, the study supports Natural Language Processing and Sentiment Analysis Theory by demonstrating how textual alumni feedback may be transformed into interpretable institutional insights supporting curriculum enhancement and institutional evaluation.

Despite these contributions, the study has several limitations. The employability and sentiment analysis models were trained using datasets obtained from a single higher education institution, which may limit the generalizability of the findings across other institutional contexts. The sentiment analysis dataset was particularly limited due to the small number of feedback responses and severe class imbalance, especially the minimal number of negative sentiment entries. Additionally, the study did not implement balancing techniques such as SMOTE, oversampling, undersampling, or class weighting during model training.

The low and zero Cohen’s kappa values observed in some models further indicate that not all evaluated algorithms demonstrated reliable agreement beyond chance. Therefore, the predictive findings should be interpreted as preliminary, context-specific, and limited by the characteristics of the available datasets. The results support the practical feasibility of integrating employability prediction and sentiment analysis within the graduate tracer system, but they should not be interpreted as evidence of strong predictive robustness across all evaluated algorithms. Future studies may improve model reliability by utilizing larger multi-institutional datasets, balanced sentiment corpora, additional feature engineering techniques, cross-validation procedures, and more advanced model optimization approaches. Future research may also explore hybrid deep learning architectures and explainable artificial intelligence techniques to further enhance predictive interpretability and institutional applicability.

CONCLUSIONS AND RECOMMENDATIONS

The study concludes that the developed Graduate Tracer and Feedback System demonstrated practical institutional applicability for alumni monitoring, employability assessment, and feedback analysis within the context of Richwell Colleges, Inc. The integration of employability classification and sentiment analysis enabled the system to generate predictive and interpretive insights from structured alumni information and textual feedback responses. Among the evaluated employability classification algorithms, Logistic Regression achieved the strongest overall predictive performance for the structured alumni dataset, while Gradient Boosting demonstrated the most balanced performance for sentiment analysis under the existing dataset conditions. In addition, the developed system achieved a Very Highly Acceptable evaluation based on the ISO/IEC 25010:2023 Software Product Quality Model, indicating positive evaluation results in terms of functionality, reliability, interaction capability, performance efficiency, security, and overall software quality.

The findings further suggest that integrating predictive analytics and sentiment analysis within a unified graduate tracer platform may support evidence-based institutional planning, curriculum enhancement, employability monitoring, and alumni engagement initiatives in higher education institutions. However, the findings should be interpreted within the limitations of the study. The employability and sentiment analysis models were trained using datasets obtained from a single institution, while the sentiment analysis dataset consisted of only 83 alumni feedback entries with severe class imbalance, particularly the limited number of negative sentiment responses. These conditions may limit the generalizability and predictive robustness of the developed models across broader educational contexts. Furthermore, the sentiment analysis component should be interpreted as an exploratory institutional analytics mechanism rather than a high-performance natural language processing system.

Based on the findings, higher education institutions may consider implementing integrated graduate tracer platforms that support centralized alumni monitoring, employability analytics, and institutional feedback interpretation to strengthen curriculum alignment and evidence-based decision-making processes. Institutions are also encouraged to promote regular alumni data updating and sustained alumni participation in tracer-related activities to improve data quality and analytical reliability. Continuous retraining and refinement of the employability classification and sentiment analysis models are likewise recommended to improve predictive consistency and responsiveness to changing labor market conditions.

Future studies may further strengthen predictive performance and institutional applicability by utilizing larger multi-institutional datasets, more balanced sentiment datasets, and additional machine learning and deep learning techniques. Future researchers may also explore advanced feature engineering approaches, explainable artificial intelligence methods, and enhanced natural language processing models to improve analytical interpretability and sentiment classification performance in educational tracer systems.

IMPLICATIONS

The findings of the study present several practical implications for higher education institutions, particularly in the areas of graduate monitoring, curriculum responsiveness, and institutional decision-making. The successful implementation of the developed

Graduate Tracer and Feedback System demonstrates that analytics-driven tracer platforms may support institutions in automating traditional alumni tracking processes while improving the organization, accessibility, and interpretation of graduate employability data. The integration of employability prediction and sentiment analysis functionalities further suggests that institutions can utilize intelligent tracer systems not only for descriptive alumni reporting but also for predictive employability assessment and feedback interpretation. Through tracer automation, alumni engagement mechanisms, and employability analytics, institutions may strengthen evidence-based curriculum planning, monitor graduate outcomes more effectively, and support data-informed academic and administrative decision-making processes.

The study also presents theoretical implications in the fields of educational data mining, intelligent educational systems, and machine learning integration in higher education. The findings demonstrate the applicability of Machine Learning Theory and Natural Language Processing within graduate tracer environments by showing how structured alumni data and textual feedback may be transformed into predictive and interpretive institutional insights. The successful integration of classification algorithms and sentiment analysis within a unified tracer platform further contributes to the growing body of literature on analytics-driven educational systems and intelligent institutional support mechanisms. In addition, the findings support Systems Theory by demonstrating how interconnected system components, feedback mechanisms, and analytical modules collectively contribute to institutional monitoring and continuous improvement processes.

From an institutional perspective, the findings reinforce the applicability of ISO/IEC 25010:2023 as a comprehensive framework for evaluating intelligent educational systems that manage sensitive alumni and institutional data. The high acceptability ratings obtained by the developed system suggest that educational institutions may utilize software quality evaluation frameworks not only for traditional information systems but also for analytics-capable platforms integrating machine learning and feedback interpretation functionalities. The findings also imply that centralized tracer platforms may improve institutional capability in conducting graduate tracer studies, generating employability reports, supporting CHED-related quality assurance initiatives, and maintaining updated alumni information repositories for long-term institutional planning.

The study likewise presents social implications related to graduate employability, workforce preparedness, and labor market alignment within the Philippine higher education context. The integration of employability analytics and feedback interpretation may help institutions identify employability gaps, monitor underemployment patterns, and recognize skills mismatches among graduates more effectively. By identifying employment-related trends and curriculum concerns from alumni data and feedback, institutions may become more responsive to industry demands and workforce expectations. Therefore, the findings suggest that analytics-driven graduate tracer systems may contribute to broader educational and workforce development initiatives by supporting curriculum alignment, employability awareness, and graduate preparedness in rapidly changing labor market environments.

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DECLARATIONS

Conflict of Interest

The researcher declares no conflict of interest regarding the publication of this study.

Informed Consent

Informed consent was obtained from all respondents who voluntarily participated in the conduct of the study and evaluation of the developed system.

Ethics Approval

The study adhered to ethical research standards in the collection, processing, and management of alumni data and feedback. All collected information was utilized solely for academic and research purposes, and appropriate measures were implemented to ensure data privacy, confidentiality, and responsible use of information.

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