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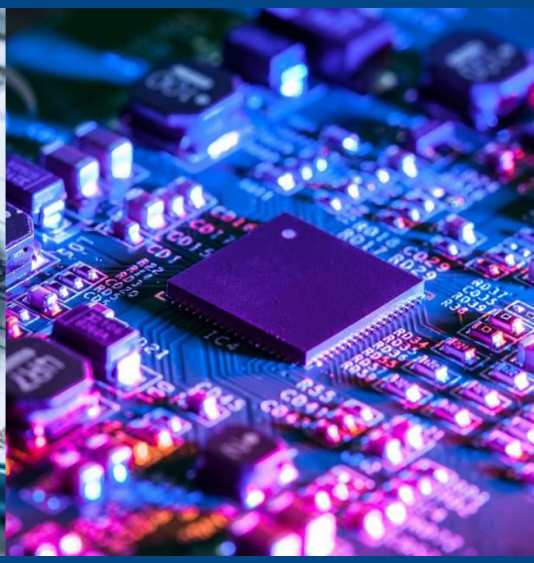

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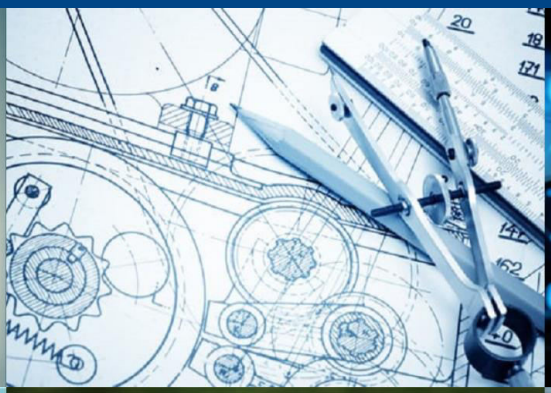

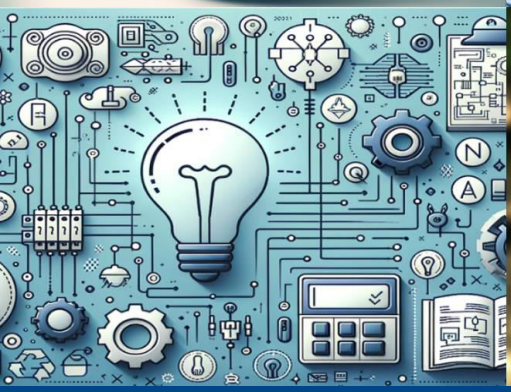

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Machine Learning-Based Employability Forecasting System for DCS Graduates at Nemsu–Cantilan

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ABSTRACT: This study developed and evaluated a Machine Learning-Based Employability Forecasting System for DCS graduates at NEMSU-Cantilan. The system addressed limitations of manual graduate tracer processes by integrating online tracer data collection, employability forecasting, and real-time visualization. The study employed a descriptive-developmental design and Agile Software Development Life Cycle. Linear Regression and Random Forest algorithms were implemented to analyze graduate data and generate employability predictions. Evaluation based on ISO/IEC 25010 showed a very great extent of quality, with an overall mean of 4.86. Findings indicate that the system supports graduate monitoring, curriculum evaluation, and evidence-based academic planning.

KEYWORDS: Machine Learning; Employability Forecasting; Graduate Tracer System; Random Forest; Agile SDLC

I. INTRODUCTION

Graduate tracer studies are essential mechanisms for monitoring employment outcomes, assessing curriculum relevance, and determining how academic programs prepare graduates for the labor market. From the perspective of Human Capital Theory, education, skills, training, and work experience are forms of human capital that improve productivity and employability (Schultz, 1961; Becker, 1964). In higher education institutions, graduate tracer data help administrators determine whether graduates are employed, whether their jobs are aligned with their specialization, and whether their acquired competencies match workplace expectations.

Traditional graduate tracer processes commonly rely on manual surveys, spreadsheet-based records, and fragmented data collection procedures. These methods often result in delayed reporting, incomplete employment records, and limited analytical value for institutional planning. Studies on employability prediction emphasize that graduate outcomes are shaped by academic, demographic, internship, skill-based, and behavioral factors, and that machine learning can reveal patterns that are difficult to identify using manual or purely descriptive approaches (Mezhoudi et al., 2023; Haque et al., 2024).

At North Eastern Mindanao State University-Cantilan Campus, the Department of Computer Studies requires an efficient and data-driven mechanism for monitoring the employability of its graduates. The uploaded full manuscript identifies persistent challenges in the existing tracer process, including slow data collection, inconsistent records, and absence of forecasting tools. These limitations affect the ability of the Program Coordinator and Research Office to generate timely reports, evaluate program outcomes, identify curriculum gaps, and support evidence-based decision-making.The increasing use of machine learning in educational analytics provides opportunities to strengthen graduate tracer systems. Random Forest, Logistic Regression, ensemble classifiers, and regression-based approaches have been applied in student employability prediction and have shown strong potential for identifying employment-related predictors (Baffa et al., 2023; Saidani et al., 2022; Abdulloh et al., 2022). In this study, Linear Regression was used to model employability trends over time, while Random Forest was implemented to capture more complex relationships among graduate-related variables.

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The system design is also supported by the Technology Acceptance Model and Diffusion of Innovations Theory. TAM explains that perceived usefulness and perceived ease of use influence users' acceptance of information systems (Davis, 1989). Diffusion of Innovations Theory further explains that adoption is affected by relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). These concepts are relevant because a graduate tracer and forecasting system must not only be technically functional but also acceptable, usable, and beneficial to graduates and institutional users. This study developed the Machine Learning-Based Employability Forecasting System for DCS Graduates at NEMSU-Cantilan. Specifically, it aimed to design an online tracer feature for graduate data submission; develop real-time graphical visualizations; implement Linear Regression and Random Forest algorithms for employability prediction; and evaluate the system using ISO/IEC 25010 software quality criteria. The study contributes to educational analytics and academic decision support by presenting a localized forecasting platform for graduate monitoring, curriculum evaluation, accreditation reporting, and evidence-based institutional planning.

II. LITERATURE SURVEY

Graduate Tracer Studies and Employability Monitoring

Graduate tracer studies provide evidence on employment status, job alignment, time to first job, industry placement, salary range, and competencies used in employment. Such information helps universities assess whether academic programs remain responsive to labor market needs. Basabe et al. (2023) emphasized the value of tracer studies in examining the employment outcomes and field alignment of information technology graduates in the Philippines. Similarly, employability studies indicate that tracer data can support curriculum evaluation, career services, and institutional quality assurance.

However, tracer studies become less useful when data collection remains manual, inconsistent, or difficult to update. Web-based tracer systems improve the speed, organization, and accessibility of graduate information. In this study, the system collects personal information, academic background, training and advanced studies, employment status, job alignment, salary range, time to first job, and competency-related data through an online survey instrument. This structure allows the institution to transform graduate responses into analyzable datasets for forecasting and decision support.

Machine Learning in Employability Prediction

Machine learning has become a significant approach in employability prediction because it can identify relationships among academic, demographic, skill-based, and employment-related variables. Mezhoudi et al. (2023) reviewed employability prediction studies and emphasized the importance of machine learning in skills mapping, curriculum restructuring, and employment insight generation. Baffa et al. (2023) found that Random Forest performed strongly in predicting student employability using academic and experiential attributes.

Saidani et al. (2022) showed that internship-related variables can be used to predict student employability through gradient boosting models, confirming that experiential learning data provide important signals for employment outcomes. Haque et al. (2024) also reported that graduate employability prediction can be supported by classification algorithms such as Logistic Regression, Random Forest, Naive Bayes, Support Vector Machine, Extreme Gradient Boosting, and Artificial Neural Networks. These studies justify the use of machine learning models in graduate tracer systems.

Linear Regression and Random Forest provide complementary strengths for forecasting. Linear Regression is useful for interpretable trend-based prediction, while Random Forest can capture nonlinear and interaction effects across multiple variables. Abdulloh et al. (2022) also highlighted the importance of handling imbalanced tracer data when predicting graduate employability, while Olipas (2026) demonstrated the relevance of explainable Random Forest models in the Philippine student employability context.

Data Visualization and Academic Decision Support

Data visualization strengthens institutional decision support by transforming large sets of tracer data into interpretable graphs and dashboards. Ramamurthy and Chandramauli (2024) emphasized that machine learning combined with data visualization can improve the interpretation of student employability patterns. In the proposed system, dashboards

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present employment status, average skills, graduates per year, industry placement, job alignment, time to first job, employment type, first job related to course, age demographics, and salary distribution.

Visualization allows Program Coordinators and Research Office personnel to review employment outcomes more efficiently than raw spreadsheets or paper-based reports. By presenting trends and summary indicators, the system supports curriculum review, accreditation preparation, institutional reporting, and career development planning. This aligns with educational analytics literature, which emphasizes that dashboards help decision-makers interpret patterns and make evidence-informed interventions.

Agile Development and Technology Acceptance

The Agile Software Development Life Cycle is appropriate for educational technology projects that require continuous feedback and incremental refinement. Agile development allows the system to evolve through sprints, with each cycle producing a functional module that can be reviewed and improved. This is relevant to the present system because requirements for graduate data, forecasting dashboards, and administrative reports may change during development.

User acceptance is equally important in the success of a web-based tracer system. Davis (1989) explained that perceived usefulness and perceived ease of use influence technology acceptance, while Rogers (2003) emphasized that adoption depends on an innovation's relative advantage, compatibility, complexity, trialability, and observability. These theories support the need for a system that is useful, simple, compatible with institutional workflows, and capable of demonstrating visible benefits to users.

ISO/IEC 25010 Software Quality Evaluation

ISO/IEC 25010 defines a product quality model applicable to ICT and software products. The model provides quality characteristics that may be used to specify, measure, and evaluate software quality throughout a product's life cycle (International Organization for Standardization, 2023). The software quality characteristics include functional suitability, performance efficiency, compatibility, usability, reliability, security, maintainability, and portability.

In the present study, the system was evaluated using selected ISO/IEC 25010 criteria: functionality, reliability, usability, performance efficiency, maintainability, and security. This is appropriate because a graduate tracer and forecasting system must not only generate useful predictions but also protect sensitive personal and employment data, process information efficiently, and remain easy to use for graduates and administrative stakeholders.

Synthesis

Table 1. Summary of key literature supporting the study

Author/s	Focus	Relevance to the Study
Baffa et al. (2023)	ML for student employability prediction	Supports use of Random Forest and academic/experiential variables.
Mezhoudi et al. (2023)	Survey of employability prediction approaches	Establishes employability prediction as a recognized ML research area.
Saidani et al. (2022)	Gradient boosting using internship context	Supports experiential and internship-related variables.
Haque et al. (2024)	Classification techniques for graduate employability	Supports classifier-based employability prediction.
Ramamurthy & Chandramauli (2024)	ML and visualization for employability analysis	Supports dashboard-based interpretation of graduate data.
ISO (2023)	Software product quality model	Supports standardized system evaluation.

The reviewed literature shows that employability monitoring requires more than manual tracer surveys. Higher education institutions need integrated platforms that collect graduate data, analyze employment outcomes, generate forecasts, and visualize results. Machine learning strengthens tracer studies by enabling predictive analytics, while dashboards improve the interpretation of graduate trends. Agile development ensures that the system evolves through user feedback, and ISO/IEC 25010 provides a structured basis for evaluating software quality. These insights support

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the development of the Machine Learning-Based Employability Forecasting System for DCS Graduates at NEMSU-Cantilan as a timely and relevant academic decision-support tool.

III. METHODOLOGY / APPROACH

Research Design

This study used a descriptive-developmental research design. The developmental component focused on the design and implementation of the Machine Learning-Based Employability Forecasting System, while the descriptive component involved the evaluation of system quality based on user responses. This design was appropriate because the study aimed to develop a functional system and evaluate its effectiveness using measurable software quality indicators.

System Development Methodology

The system was developed using the Agile Software Development Life Cycle. Agile allowed the researchers to develop the system in iterative cycles or sprints. Each sprint focused on a specific module, including data collection, system interface design, database development, machine learning integration, forecasting, visualization, testing, and refinement. This method enabled continuous improvement based on feedback from stakeholders.

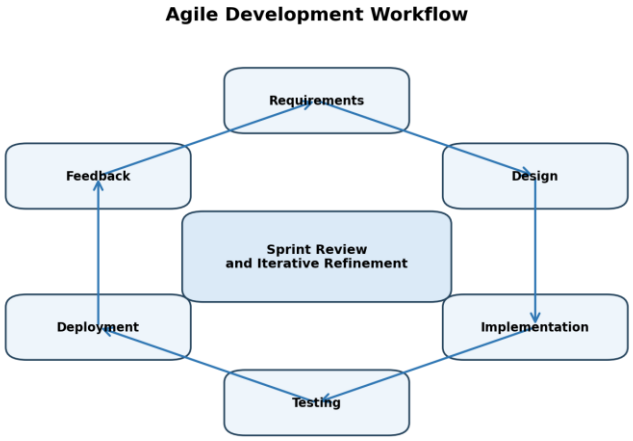

Figure 1. Agile development workflow adopted in the study.

The figure shows the Agile Development Workflow used in developing the Machine Learning-Based Employability Forecasting System. The process begins with identifying system requirements, followed by designing the interface, database, and forecasting modules. The system is then implemented, tested, deployed, and reviewed through user feedback. At the center, the Sprint Review and Iterative Refinement emphasizes that each development cycle produces a usable system component that is continuously improved based on stakeholder feedback.

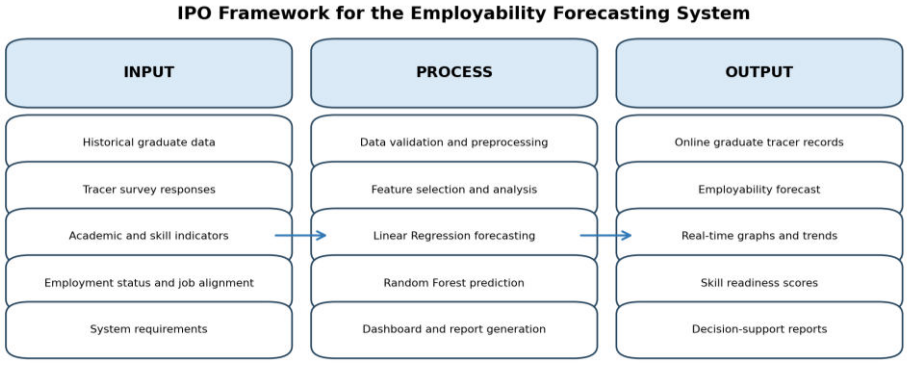

Figure 2. Input-Process-Output framework of the employability forecasting system.

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The figure presents the IPO Framework for the Employability Forecasting System. The input includes historical graduate data, tracer survey responses, academic and skill indicators, employment status, job alignment, and system requirements. These data are processed through validation, preprocessing, feature selection, Linear Regression forecasting, Random Forest prediction, and dashboard generation. The output includes online tracer records, employability forecasts, real-time graphs, skill readiness scores, and decision-support reports for academic planning and curriculum evaluation.

System Architecture and Features

The system was designed as a web-based platform that integrates graduate tracing, employability prediction, and data visualization. It includes an online graduate tracer survey, administrative dashboard, machine learning forecasting module, real-time visualization dashboard, and reporting and data management module. The system was implemented using Python for machine learning, PHP for backend logic, MySQL for database management, and HTML, CSS, JavaScript, and Bootstrap for frontend development.

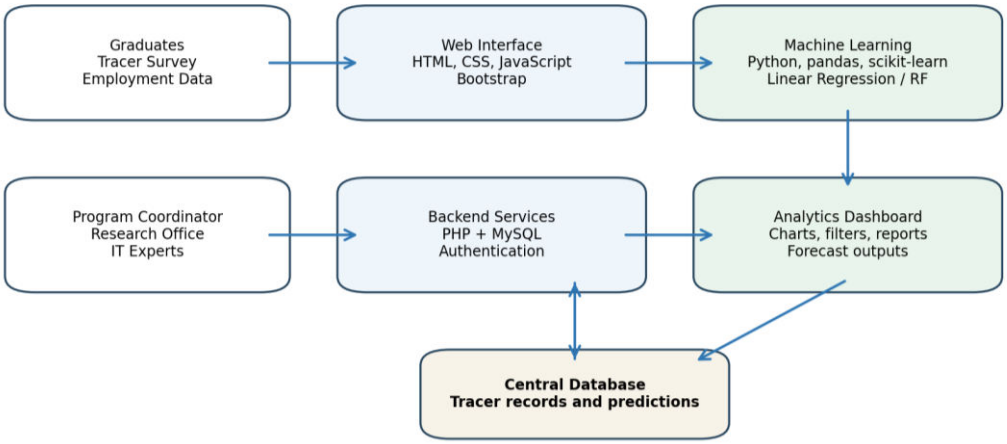

Figure 3. System architecture and data flow of the Graduate Tracer and Employability Forecasting System.

The figure shows the system architecture and data flow of the Machine Learning-Based Employability Forecasting System. Graduates submit tracer survey and employment data through the web interface, while the Program Coordinator, Research Office, and IT experts access the system through backend services with authentication. The submitted data are stored in the central database and processed using machine learning tools such as Python, pandas, scikit-learn, Linear Regression, and Random Forest. The processed results are then displayed in the analytics dashboard through charts, filters, reports, and forecast outputs for academic planning and decision-making.

Algorithms Used

Linear Regression was applied to model employability trends over time. It analyzes historical batch data and generates future employability projections. The model is useful because it provides interpretable trend-based forecasts that can support curriculum planning and institutional decision-making. The general equation is expressed as: $\hat{y} = b0 + b1x$.
Random Forest was implemented to generate robust employability predictions by constructing multiple decision trees and aggregating their outputs. For regression tasks, the final prediction is obtained by averaging the predictions of the individual trees: $\hat{y}(x) = (1/B)\ \Sigma Tb(x)$, where B represents the number of trees and Tb(x) represents the prediction of each tree.

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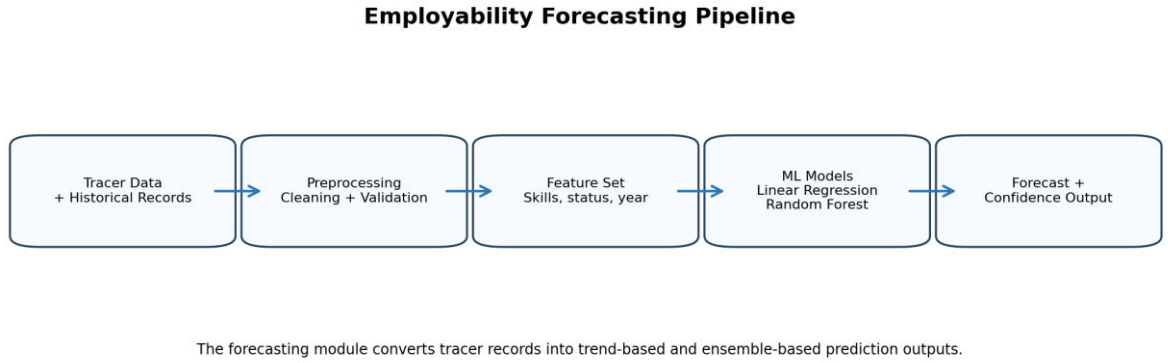

Figure 4. Employability forecasting pipeline using tracer records, preprocessing, and machine learning models.

The figure shows the Employability Forecasting Pipeline of the system. Tracer data and historical records are first collected, then cleaned and validated during preprocessing. Relevant features such as skills, employment status, and graduation year are selected for analysis. These data are processed using Linear Regression and Random Forest models to generate employability forecasts and confidence outputs for academic decision-making.

Respondents of the Study

The respondents included DCS graduates, Research Office personnel, Program Coordinators, and IT experts. A total of 90 respondents participated in the study. Purposive sampling was used because the respondents had direct relevance to the system: graduates provided employment and tracer data, Program Coordinators and Research Office personnel evaluated institutional usefulness, and IT experts assessed technical quality.

Table 2. Respondents of the study

Respondents	Frequency	Percentage
DCS Graduates	77	85.56%
Research Office Personnel	3	3.33%
Program Coordinator	3	3.30%
IT Experts	7	7.78%
Total	90	100%

The table shows that the study involved 90 respondents. Most of the respondents were DCS graduates, with 77 participants or 85.56%, since they are the primary users and data sources of the graduate tracer system. The remaining respondents included Research Office personnel, Program Coordinators, and IT experts, who evaluated the system based on data management, academic planning, and technical quality.

Research Instrument and Validation

The researchers used a structured software quality assessment questionnaire based on ISO/IEC 25010. The instrument measured functionality, reliability, usability, performance efficiency, maintainability, and security using a five-point Likert scale. The instrument was validated through content validity, face validity, and User Acceptance Testing to ensure that the items were relevant, clear, and aligned with the objectives of system evaluation.

Data Gathering and Analysis

Data gathering was conducted in three stages: pre-development, development, and post-development. The pre-development stage involved collecting requirements and identifying limitations of existing tracer practices. The development stage involved system prototyping, testing, and feedback collection during Agile sprints. The post-

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development stage involved system evaluation using the ISO/IEC 25010-based questionnaire after respondents interacted with the platform.

The collected data were analyzed using weighted mean, standard deviation, frequency, and percentage distribution. Weighted mean determined the level of system quality, standard deviation measured response consistency, and frequency and percentage distribution summarized respondent profiles and system-related data.

Ethical Considerations

The study observed data privacy and ethical standards. Respondents were informed about the purpose of the study, and participation was voluntary. Personal and employment data were treated with confidentiality. Access to the system was limited to authorized users, and role-based access control was implemented to protect sensitive records. The tracer survey included consent procedures before graduates submitted their information.

IV. RESULTS AND DISCUSSION

Online Graduate Tracer Feature

The system successfully provided an online graduate tracer feature that allowed DCS graduates to submit employment information and complete tracer surveys. The online survey included personal information, academic background, training and advanced studies, employment status, job alignment, salary range, industry, time to first job, co-curricular activities, and skills assessment. This feature addressed the limitations of manual tracer studies by improving accessibility, consistency, and data organization.

Real-Time Graphical Visualization

The system generated real-time graphical visualizations based on graduate tracer data. These visualizations included employment status, average skills radar, graduates per year, industry placement, job alignment, time to first job, employment type, first job related to course, age demographics, and salary distribution. The dashboard improved data interpretation by converting raw survey responses into clear and understandable graphs.

Machine Learning Employability Forecasting

The system implemented Linear Regression and Random Forest algorithms to analyze graduate data and generate employability predictions. Linear Regression provided trend-based forecasting, while Random Forest generated ensemble-based predictions. The forecasting feature strengthened the system by moving beyond descriptive tracer reporting and providing predictive insights that may guide academic planning, curriculum improvement, and career development interventions.

ISO/IEC 25010 Software Quality Evaluation

The system was evaluated using ISO/IEC 25010 software quality criteria. Results showed that the system achieved "Very Great Extent" ratings across all evaluated dimensions.

Table 3. ISO/IEC 25010 evaluation results

Software Quality Criterion	Mean	Standard Deviation	Description
Functional Suitability	4.86	0.34	Very Great Extent
Reliability	4.84	0.37	Very Great Extent
Usability	4.87	0.33	Very Great Extent
Performance Efficiency	4.83	0.40	Very Great Extent
Maintainability	4.85	0.39	Very Great Extent
Security	4.89	0.32	Very Great Extent
Overall Mean		4.86	Very Great Extent

The results show that the system obtained an overall mean of 4.86, interpreted as Very Great Extent. This indicates that the Machine Learning-Based Employability Forecasting System was highly rated by the respondents in terms of functionality, reliability, usability, performance efficiency, maintainability, and security. Among the criteria, security

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received the highest mean of 4.89, showing that users felt confident in the system's ability to protect personal and employment data. Performance efficiency received the lowest mean of 4.83, but it still falls under Very Great Extent, indicating that the system remained fast, responsive, and effective in processing data and generating outputs.

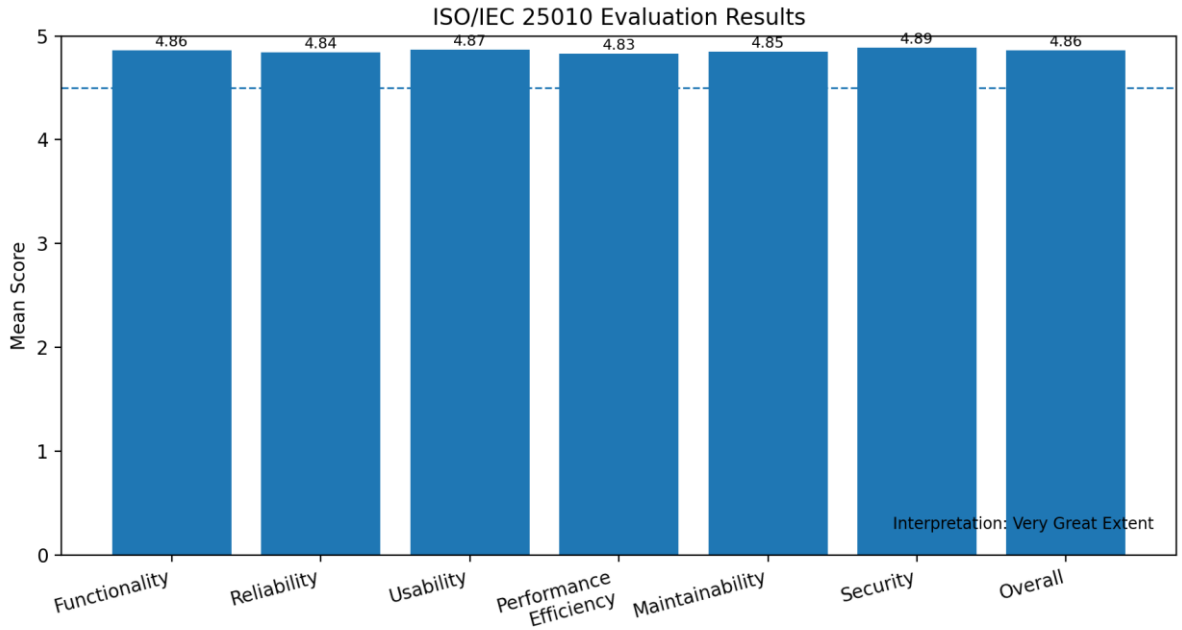

Figure 5. ISO/IEC 25010 software quality evaluation results of the developed system.

Security obtained the highest mean score of 4.89, indicating that users perceived the system as safe for entering and storing personal and employment information. This result is important because graduate tracer systems handle sensitive information that requires confidentiality and restricted access. Usability obtained a mean of 4.87, showing that users found the system easy to understand and navigate. Functional suitability obtained a mean of 4.86, indicating that the system performed its intended functions effectively, including tracer survey completion, data recording, skill readiness scoring, and employability feedback.

Reliability obtained a mean of 4.84, suggesting that the system consistently saved responses, loaded properly, and displayed results correctly. Performance efficiency obtained a mean of 4.83, showing that the system responded promptly and processed data efficiently. Maintainability obtained a mean of 4.85, indicating that the system was perceived as structured, flexible, and capable of future improvement. The overall mean of 4.86 confirms that the system was evaluated at a very great extent and is suitable for supporting graduate monitoring and employability forecasting.

Discussion of Findings

The findings demonstrate that the developed system effectively addressed limitations of manual graduate tracer processes. The online tracer feature improved data collection, while the visualization dashboard enhanced interpretation of graduate outcomes. The integration of Linear Regression and Random Forest added predictive capability, allowing the system to support future-oriented academic planning. These results align with prior studies showing that machine learning and visualization tools can improve employability analysis and support institutional decision-making (Baffa et al., 2023; Haque et al., 2024; Ramamurthy & Chandramauli, 2024).

V. CONCLUSION

This study developed and evaluated the Machine Learning-Based Employability Forecasting System for DCS Graduates at NEMSU-Cantilan. The system addressed the limitations of traditional graduate tracer processes by integrating online data collection, employability forecasting, and real-time visualization in a centralized web-based

platform. The implementation of Linear Regression and Random Forest algorithms allowed the system to generate employability predictions based on historical and self-reported graduate data. Evaluation results based on ISO/IEC 25010 showed that the system achieved a very great extent of quality, with an overall mean of 4.86. The system received strong ratings in security, usability, functionality, maintainability, reliability, and performance efficiency. The study contributes to educational analytics and academic planning by demonstrating how machine learning can enhance graduate tracer systems. It provides a practical tool for the Program Coordinator and Research Office to support curriculum evaluation, accreditation reporting, graduate monitoring, and evidence-based decision-making. Future studies may improve the system by integrating additional machine learning models, expanding the dataset to include other programs and campuses, incorporating labor market indicators, and developing a mobile application version for wider accessibility.

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