What determines Student Employability? Educational Data Mining through Machine and Deep Learning Approach

Rasikh Tariq[1,*], Diego Gutiérrez Vargas[2], Farhan Ali[3], Miguel Gonzalez-Mendoza[4,5]

[1] Tecnologico de Monterrey, Institute for the Future of Education, Ave. Eugenio Garza Sada 2501, Monterrey, N.L. México, 64849. Email address: rasikhtariq@tec.mx, ORCID: https://orcid.org/0000-0002-3310-432X

[2] Tecnologico de Monterrey, Escuela de Ingenieria y Ciencias, Ave. Eugenio Garza Sada 2501, Monterrey, N.L. México, 64849. Email address: A01285421@tec.mx

[3] National Institute of Education, Nanyang Technological University, Singapore. Email address: farhan.ali@nie.edu.sg. ORCID: https://orcid.org/0000-0001-6773-893X

[4] Tecnologico de Monterrey, Escuela de Ingenieria y Ciencias, Ave. Eugenio Garza Sada 2501, Monterrey, N.L. México, 64849. Email address: mgonza@tec.mx. ORCID: https://orcid.org/0000-0001-6451-9109

[5] Tecnologico de Monterrey, Institute for the Future of Education, Ave. Eugenio Garza Sada 2501, Monterrey, N.L. México, 64849.

* Corresponding author. E-mail address: rasikhtariq@tec.mx, rasikhtariq@gmail.com (Rasikh Tariq)

What determines Student Employability? Educational Data Mining through Machine and Deep Learning Approach

Abstract

Employability is vital for graduates to succeed in competitive job markets and reflects higher education institutions' effectiveness. It is essential to investigate which specific traits contribute to a higher success rate of employability, as understanding these factors can help optimize targeted interventions and improve employment outcomes. The objective of this research is to identify and analyze the key traits that influence student employability using educational data mining techniques integrated with machine learning and deep learning models while providing an explainable framework to inform targeted interventions and enhance job market readiness among graduates. Addressing gaps in existing research, this study integrates a wide range of variables and employs advanced AI techniques, specifically LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units), to develop a predictive framework for understanding employability over time. Using data from mock job interviews, the study applies SHAP (SHapley Additive exPlanations) values to assess the impact of traits like Self-Confidence and Ability to Present Ideas. Hyperparameter tuning through Grid Search and k-fold cross-validation is employed to optimize model performance. The LSTM model, configured with three layers and achieving 91.46% accuracy, is identified as the most effective. Its robustness is confirmed with a 90.48% consistency score from 3-fold cross-validation. Our findings highlight the importance of soft skills, such as Self-Confidence, Ability to Present Ideas, and General Appearance, identified by SHAP analysis as critical predictors of employability, emphasizing the need for educational institutions to actively integrate soft skills development into their curricula to ensure students are both academically prepared and professionally equipped.

Keywords

Educational Data Mining, Student Employability, Machine Learning, Deep Learning, Explainable AI, Educational Innovation, Higher Education.

1. Introduction

Student employability is a crucial metric for evaluating the effectiveness of educational institutions (Segbenya et al., 2023), reflecting the ability of graduates to secure employment or engage in entrepreneurial activities upon completing their studies. In an ever-evolving job market shaped by technological advancements and shifting economic landscapes (Tariq, Tariq, et al., 2024), universities and colleges are increasingly held accountable for the employability of their graduates. Employability encompasses the acquisition of specific professional skills and includes critical thinking, problem-solving, and adaptability. According to the QS Graduate Employability Rankings (QS Graduate Employability Rankings, 2022), institutions are assessed based on parameters like employer reputation, alumni outcomes, and partnerships with employers, underlining the multidimensional nature of employability.

According to Oxford (*Employability Noun, Oxford Advanced Learner's Dictionary at OxfordLearnersDictionaries.Com*, 2024), employability is defined as "*the extent to which somebody possesses the skills, knowledge, attitude, etc., that render them suitable for paid work*." In other words, employability, defined as an individual's ability to obtain and maintain employment, is influenced by a complex interplay of human capital and labor market opportunities. Berntson, Sverke, and Marklund (2006) found that both individual qualifications and external labor market conditions significantly predict perceived employability, highlighting the importance of considering both personal and structural factors in employment prospects (Berntson et al., 2006). Cultural and policy shifts also play a crucial role in shaping employability. Gribble and Blackmore (2012) examined changes in Australia's skilled migration policies, noting that such shifts can enhance international graduates' employment opportunities by aligning educational outcomes with labor market needs (Gribble & Blackmore, 2012). Furthermore, job search behaviors are critical determinants of employment success. Van Hooft et al. (2021) conducted a comprehensive review, emphasizing that proactive job search strategies and adaptability are essential for securing quality employment in today's dynamic labor market (van Hooft et al., 2021). Römgens, Scoupe, and Beausaert (2019) integrated various perspectives on employability, discussing its definition and implications in both educational settings and the labor market, thereby providing a comprehensive understanding of the concept (Römgens et al., 2020). In summary, employability is a complex construct influenced by individual skills, cultural and policy contexts, job search behaviors, and industry-specific factors. Understanding these dimensions is essential for developing strategies that enhance employment outcomes across diverse settings. However, there is notable variance among authors regarding the definition of employability, reflecting the necessity for greater precision in its characterization to ensure it is measurable. In the context of higher education, from undergraduate to master's level, student employability concretely applies this definition, emphasizing the readiness and suitability of students for the job market based on their qualifying traits. For the scope of this research article, student employability is defined as the degree to which a student is prepared for employment, assessed through relevant skills, knowledge, and attitudes.

Since 2007, the percentage of the working-age population (15-64 years) has been steadily declining globally, as reported by the OECD (Working Age Population, OECD, 2024). This decrease over the past 15 years signals a concerning trend for the job market. Concurrently, as this demographic indicator declines, globalization has intensified (Tariq et al., 2021), leading to increased competition across various industries. This dual dynamic reflects the evolving challenges within the global employment landscape.

Tight observes that in numerous higher education systems (Tight, 2023), the proliferation of degrees has redefined the purpose of higher education (Ramirez-Montoya et al., 2024), positioning it as a means to secure worthwhile employment rather than an end in itself, which traditionally focused on the development of intellectually well-rounded individuals. Through a comprehensive literature review on student employability, Tight concludes that achieving a balance between enhancing graduate employability and fostering intellectual growth within a discipline is both feasible and desirable (Tight, 2023).

Educational Data Mining (EDM) (Lemay et al., 2021; Sarker et al., 2024) has emerged as a significant tool in understanding and enhancing student employability. EDM involves the application of data mining techniques to educational contexts, aiming to improve learning outcomes and operational efficiency. It allows educators and administrators to uncover patterns from vast amounts of educational data, facilitating targeted interventions (Srinivasan & Murthy, 2021) and personalized learning pathways (Chaipidech et al., 2022; Romero & Ventura, 2020) assess potential inequalities at the system level (Ali et al., 2024). For instance, through the analysis of academic performance (Bressane et al., 2024), attendance records, and engagement activities (Armas-Cervantes et al., 2024), EDM can help predict which students are at risk of underachieving, thereby enabling timely support to improve their employability prospects.

Artificial Intelligence (AI) (Khanmohammadi et al., 2022; Rodway & Schepman, 2023; Tariq, Mohammed, et al., 2024) further enhances the capabilities of EDM by integrating machine (Boehme et al., 2024; Okoye et al., 2024) and deep learning (Alnasyan et al., 2024) algorithms and predictive modeling into the educational processes (Baker & Inventado, 2014). AI can also facilitate educational decision making (Maniyan et al., 2024) such as the development of soft skills, such as communication and teamwork, through adaptive learning environments (Sein Minn, 2022) that simulate real-world challenges.

This research provides the usage of educational data mining assisted with machine learning and deep learning algorithms (Tariq et al., 2023) for the prediction of potential traits which can influence the student employability by considering a binary prediction.

2. Literature Review and Current State-of-the-art

The prediction of student employability through educational data mining and machine learning represents a dynamic and evolving area of research that has garnered increasing attention in recent years. The current literature review explores a variety of innovative methodologies and models that have been developed to enhance the accuracy and applicability of employability predictions. From integrating contextual variables that reflect socio-political backgrounds to employing advanced algorithms that analyze academic and non-academic traits, these studies reflect a broader shift towards creating more personalized and context-aware predictive systems.

As one of the most novel models for employability, Mpia, Mburu and Mwendia a variation of the BERT model, CoBERT, which enables the researchers to use the context such as the socio-political background, graduate employer relationship and graduate academic competencies as a variable, to build a recommending system to improve employability of IT students in unstable developing countries (Mpia et al., 2023).

Moumen et al., Othman et al. and Hugo reviewed the current state of educational data mining through employability prediction models (Hugo, 2018; Moumen et al., 2022; Othman et al., 2018). Additionally, Moumen et al. applied a machine learning (ML) approach of the different models to predict employability using Artificial Neural Networks (ANN) (Quintero-Gámez et al., 2024), Random Forest (RF), discriminant analysis and Logistic Regression (LR), concluding that co-curriculars and majors are one of the most important factors for employment (Moumen et al., 2022). Aviso et al. employs a hyperbox machine learning classification method based upon mixed integer linear programming, to determine the employability of students in ASEAN and reported that research and internationalization metrics had one of the highest impact for predicting employability (Aviso et al., 2021).

Courtial and Garrouste utilize Model Predictive Control and an econometric model to study and predict the employability of French Earth Science students, enhancing educational data mining by forecasting the employment rates of students in certain years (Courtial & Garrouste, 2014). Modibane undertook data collection and analysis, applying classical machine learning techniques, neural networks, and tree-based methods (Modibane, 2019). Through educational data mining, an optimal number of features was selected. The findings suggest that variables such as GPA and field of study were not deemed significant by the model, although it is speculated that the inclusion of additional variables might overshadow their importance.

Mishra et al. employed a data mining model incorporating Bayesian methods, multilayer perceptron (MLP), Sequential Minimum Optimization (akin to SVM), various ensemble methods, and decision trees to predict the employability of Master of Computer Applications Students (Mishra et al., 2016). Their results indicate that stress management skills, empathy, and taking relevant courses can positively influence employability. Similarly, Girase et al. developed an application using educational data mining and decision trees to predict the employability of undergraduate engineering students, finding that decision trees outperformed other data mining methods (Girase et al., 2018).

In a comparable development, Casuat et al. created a user-friendly application for Philippine universities to predict student employability using machine learning models enhanced by the Synthetic Minority Oversampling Technique (SMOTE) (Casuat, 2020). This application also provides recommendations for areas of improvement to enhance employability prospects. Saini et al. developed models through educational data mining at Manipal University Jaipur, predicting not only student employability but also the initial salary packages, ranging from 1-4 LPA (Saini et al., 2021).

Mohamed and Ezzati used Rapid Miner Studio Educational to apply machine learning techniques including Naïve Bayes, Logistic Regression, and Decision Tree to educational data mining (Mohamed & Ezzati, 2019). Their findings highlighted the superior performance of Decision Trees, as evidenced by ROC curve analyses.

Baffa et al. employ an all-machine learning approach, utilizing clustering techniques such as K-means and hierarchical clustering to refine the application of Random Forest (RF), Decision Tree (DT), and Logistic Regression (LR) (Baffa et al., 2023). Their analysis includes determining feature importance using Mean Decrease Impurity (MDI) for the best-performing model, revealing that the Student Industrial Work Experience Scheme (SIWES) results and Cumulative Grade Point Average (CGPA) are the primary predictors of employability by a significant margin. Similarly, Akilandeswari and Jothi investigate into employability through educational data mining, comparing the efficacy of Naïve Bayes (NB), various classical ML models, and Artificial Neural Networks (ANN), with Logistic Regression emerging as the most effective (Akilandeswari & Jothi, 2017). Haque et al. develop models to predict undergraduate employability, categorizing features into five groups: demographic, academic, GPA, subject grade, and Graduate Tracer Study System (SKPG) (Haque et al., 2024). Their findings indicate that models perform best on datasets containing all categories except subject grade, with ANN as the top performer.

Jantawan and Tsai use the Waikato Environment for Knowledge Analysis (WEKA) for educational data mining to assess student employability and compare five variations each of Decision Tree and Naïve Bayes models. They find that a variation of Naïve Bayes, the Weighted Averaged One Dependence Estimator (WAODE), performs best (Jantawan & Tsai, 2013). Xu applies time-series analysis techniques, including ARIMA and Ranking ARIMA (R-ARIMA), to forecast student employment trends, noting that R-ARIMA aligns closely with current employment trends (Xu, 2024). Mishra et al. conduct a literature review and survey to further explore student conditions, noting a direct correlation between academic performance and employability, with emotional competence impacting academic outcomes, though this has not been empirically validated (Mishra et al., 2017). Malika utilizes machine learning models to forecast student employability, predicting job categories and the timeline for obtaining employment post-graduation, and uses association techniques to identify key skills such as teamwork, communication, and problem-solving linked to management and supervision roles (Malika, 2024). Saidani et al. examine student employability within university and internship contexts, utilizing variables like GPA and co-curricular activities in university settings and internship grades and satisfaction in internship scenarios. They apply SHAP analysis and model metrics to identify the best models and feature importance for boosted models (Saidani et al., 2022).

In a related study, Hugo tests various models for predicting employability using traditional machine learning models and discriminant analysis, focusing on four features: GPA, major, internships, and co-curricular activities, and finds that Support Vector Machines (SVM) notably outperform other models (Hugo, 2018). Thakar et al. enhanced the accuracy of various models by incorporating secondary attributes, observing significant improvements across different methods. Naïve Bayes, MLP, and DTNB (a hybrid of Decision Tree and Naïve Bayes) benefited most notably from these additional features (Thakar, Scholar, et al., 2017). Celine et al. demonstrated the efficacy of logistic regression in predicting student employability on a small dataset, using variables such as aptitude, communication skills, technical knowledge, and personality traits as inputs for the LR model (Celine* et al., 2020).

Vo et al. introduced a new model named OPT-BAG, designed to optimize the parameters of a bagging classifier using GridSearchCV. This model exhibited superior performance, and an analysis of feature importance identified general appearance, mental alertness, and communication skills as the most critical factors determining employability (Vo et al., 2023). Elsharkaway et al. applied educational data mining techniques, using attributes such as soft skills and training experiences to predict student employability. Despite using a small dataset, the techniques, particularly Decision Tree, Logistic Regression, and SVM, showed promising results for employability prediction (Elsharkawy et al., 2022).

Maaliw et al. approached the prediction of employability through machine learning, considering variables related to family economic background and both cognitive and non-cognitive traits. Notably, 'grit,' a psychological trait associated with perseverance and long-term success, was highlighted as having a significant impact on employability when analyzed through principal component analysis (PCA) (Maaliw et al., 2022). Jiang et al. assessed the employability factors of recent college graduates in Shaanxi, employing reliability and validity analyses along with various linear regression models to identify correlations. The research pinpointed individual characteristics, social experiences, and workplace training as key positive influencers on employability (Jiang et al., 2023). Piad et al. addressed the issue of job mismatch in the Philippines, a prevalent cause of unemployment, through educational data mining. The analysis revealed that the overall performance of the machine learning models did not exceed 70%. Critical variables identified included IT core skills, IT professional skills, and, unexpectedly, gender, which proved to be a significant predictor of employability (Piad et al., 2016). Usita employs educational data mining and WEKA models to predict student employability using Bayes Net, a variation of Naïve Bayes, and J48, a Decision Tree model within WEKA. The models differentiated between three employment statuses: self-employed, employed, and unemployed, with J48 slightly outperforming Bayes Net (Usita, 2022).

Bai et al. introduce a hybrid deep belief network (DBN) that incorporates softmax regression to form a DBN-SR model, predicting employability. A crow search algorithm (CSA) is implemented to extract optimal features, enhancing prediction accuracy and reducing training time. This model achieved a 2.5% higher accuracy than a deep autoencoder and 5% more than other deep neural network-based methods (Bai & Hira, 2021). Sun and He developed a hybrid deep neural network (DNN) using machine learning and educational data mining approaches. An initial analysis suggested a gender pay gap, but further t-tests showed no significant differences. The SVM, achieving a 93% accuracy, identified work knowledge, college domain, and SSC rate as critical factors in employability prediction (Sun & He, 2023). Rahman et al. utilized educational data mining to select optimal attributes from categories including demography and employer evaluations (internal and external). Various machine learning classification models predicted different employment statuses, with KNN showing exceptionally high performance (Rahman et al., 2017).

Byagar and Thakare offer another machine learning approach using Random Forest, Naïve Bayes, and Decision Tree to predict student employability. Random Forest significantly outperformed the other techniques with an accuracy of 91.18%, compared to 59.38% for NB and 57.98% for DT (By & Thakare, 2023). Wang introduces a methodology involving a Switching Hierarchical Gaussian Filter (SHGF) for preprocessing, Siberian Tiger Optimization (STO) for feature selection, and a Multi Fidelity Deep Neural Network (MFDNN) for classification. This model demonstrated outstanding performance with a 98% accuracy rate, surpassing other techniques like RNN, DBN, and LGBN (Wang, 2024). Premathilaka & Imalka implemented Naïve Bayes using RapidMiner Studio on a small dataset, achieving 75% accuracy. Variables such as demographics, extracurricular activities, and academic background were key predictors of student employability (Premathilaka & Imalka, 2021).

Pauzi et al. approach student employability by incorporating main predictors from previous studies, using a massive dataset to ensure a 50:50 train-test split for all machine learning methods. Methods for feature selection included ANN with Variable Selection with DT and LR with Variable Selection using LR stepwise (Wan Pauzi et al., 2021). Thakar et al. propose a unified model that integrates clustering and classification to enhance scalability across different contexts and institutions. This model outperforms ten other models from WEKA that did not use this methodology, addressing the lack of scalability in current employability models (Thakar, Mehta, et al., 2017). Kumar et al. experiment with computational statistics and educational data mining to examine the impact of variables such as gender, MBA specialization, and degree stream on corresponding variables like offered salaries, test percentages, and placement status. Their findings indicate no statistically significant differences between the salaries offered across gender and specialization (Kumar et al., 2021).

Peñalvo et al. employ a rigorous methodology using GridSearchCV to optimize parameters for Random Forest and conduct various clustering experiments to enhance machine learning model metrics in educational data mining. The most significant predictor for RF in predicting student employability was the university of graduation, followed by the student's opinion on the job's relevance to their context (García-Peñalvo et al., 2018). Aviso et al., in previous research, analyzed factors influencing the employability of chemical engineering graduate students using a hyperbox machine learning technique. The study reveals that research intensity and quality do not correlate with better employability, emphasizing the importance of transparency and interpretability in the models used (Aviso et al., 2020).

In conclusion, the body of research explored in this section highlights the significant strides made in predicting student employability through educational data mining and machine learning. These studies represent the potential of advanced analytics and predictive models to transform educational practices and align them more closely with labor market demands. As this field continues to evolve, it will be essential to focus on refining these models to enhance their accuracy and fairness, ensuring they are adaptable to diverse educational contexts. Further research will be critical in bridging the gap between educational outcomes and employment realities, which can contribute towards a more robust and responsive model.

3. Gap analysis, research contribution, and objective

The existing literature on predicting student employability often does not fully utilize the comprehensive scope of variables necessary for a holistic analysis, focusing predominantly on traditional academic metrics such as GPA and extracurricular activities. This oversight neglects critical personal and behavioral attributes such as mental alertness, self-confidence, and communication skills, which are vital for professional success. Moreover, while standard machine learning models like Support Vector Machines and Decision Trees are frequently explored, the versatility and advanced capabilities of deep learning models, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), remain underutilized. These models are particularly adept at processing sequential and time-series data, offering robust solutions for capturing complex, non-linear relationships within educational trajectories that are often overlooked in current research.

Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) are advanced recurrent neural network architectures that provide significant advantages for modeling temporal sequences, crucial for tracking educational and developmental progress over time. LSTMs, introduced by Hochreiter and Schmidhuber (1997), are designed to avoid the long-term dependency problem typical in standard recurrent networks, enabling them to remember information for prolonged periods without the risk of vanishing gradients (Hochreiter & Schmidhuber, 1997). This capability is achieved through the use of specialized structures known as gates—input, forget, and output gates—that regulate the flow of information, making them particularly effective for applications where historical data influences future outcomes. GRUs, a variant of LSTMs introduced by Cho et al. (2014), simplify the structure by combining the input and forget gates into a single update gate and using a reset gate to merge new input with past information. This streamlined architecture allows GRUs to achieve similar performance to LSTMs but with fewer parameters and faster training times, making them suitable for datasets where computational efficiency is a priority (Cho et al., 2014).

The research contribution of this study lies in its comprehensive application of a diverse array of variables alongside advanced machine learning and deep learning techniques to predict student employability. By integrating both traditional metrics and essential soft skills within the predictive models, and employing sophisticated algorithms like LSTM and GRU, this research addresses significant gaps in the existing literature. These advanced models' ability to analyze sequences and temporal patterns provides new insights into how students' attributes evolve and influence their employability prospects over time. Ultimately, the objective of this work is to present a predictive framework that can more accurately forecast employability outcomes, thereby informing targeted educational strategies and interventions that enhance students' preparedness for the job market.

The paper is structured into six main sections. Section 1: Introduction establishes the significance of student employability as a critical measure in higher education, defining key concepts and contextualizing the study. Section 2: Literature Review explores existing research, identifying gaps in the use of machine and deep learning models for employability prediction. Section 3: Gap Analysis, Contribution, and Objective highlights the study's novelty, emphasizing the integration of soft skills and advanced algorithms like LSTM and GRU. Section 4: Materials and Methods details the data sources, preprocessing techniques, the analytical framework, machine learning models, and evaluation metrics used. Section 5: Results present model performance through confusion matrices, ROC curves, and SHAP analysis, identifying key predictors of employability such as self-confidence and the ability to present ideas. Section 6: Discussion interprets findings, compares model performances, and underscores the importance of soft skills, while the Conclusion summarizes contributions and suggests future research directions.

4. Materials and Methods

The "Materials and Methods" section of this article is structured to provide a comprehensive overview of the research framework, detailing the data sources, analytical methods, and computational approaches utilized to investigate the impact of various student attributes on employability through educational data mining.

4.1. Data source, limitations, and scope of the work

The dataset utilized for this research was accessed from Kaggle, an online platform hosting various datasets for data science and machine learning projects. Specifically, the "Students Employability Dataset" was retrieved, which is designed to assess factors influencing student employability. The dataset was accessed on March 1, 2024, and is available publicly at the following URL: https://www.kaggle.com/datasets/anashamoutni/students-employability-dataset/data. This dataset was compiled to facilitate the exploration of how various personal and performance-related attributes may correlate with employability outcomes among students.

Upon thorough examination, the "Students Employability Dataset" provides a robust foundation for analyzing the different aspects of student employability, including both personal attributes and academic performance metrics. The dataset encompasses a range of variables from general appearance and communication skills to more quantifiable metrics such as student performance ratings. These diverse data points allow for a comprehensive investigation of the factors that potentially affect a student's transition into the workforce.

There are also certain limitations of this data. The dataset primarily focuses on a specific demographic or regional student population, which may not represent the global student body. This limitation could affect the generalizability of the findings, as employability factors can vary significantly across different cultural, economic, and educational contexts. While the dataset includes a range of variables, the depth and completeness of data for each variable can vary. Missing data or disproportionately represented attributes might lead to biased predictions and analyses. For instance, if certain attributes like "Mental Alertness" or "Physical Condition" are underreported, the models might undervalue their impact on employability. The dataset does not specify the timeframe during which the data was collected. Without this temporal context, it is challenging to account for changes in economic conditions, educational policies, or labor market demands that might influence employability outcomes.

Within the scope of the current work, it is also reported that this AI model is not intended to serve as an initial filter for employability; rather, its purpose is to identify the key and most influential variables contributing to hiring success, which can inform the development of intervention policies at the institutional level. It is important to clarify that the study does not propose using this model as a filtering mechanism, as that would be an entirely different and significantly more complex topic, involving considerable ethical considerations.

4.2. Overall panorama of the adapted framework including educational data mining

The adapted framework for predicting student employability incorporates a structured approach that uses educational data mining techniques, as outlined in Figure 1. This process begins with the collection of the "Student Employability Dataset," which provides the foundational data necessary for analysis. The initial stage involves exploratory data analysis (EDA), a critical step where preliminary insights into the data are gathered, and potential patterns or anomalies are identified.

Following EDA, the data undergoes preprocessing to ensure it is suitable for modeling. This involves cleaning the data, handling missing values, encoding categorical variables, and normalizing or scaling numerical data to enhance the performance of machine learning algorithms. The preprocessed data is then split into training and testing sets, a crucial step that facilitates the unbiased evaluation of the models developed during the training phase.

The core of the framework focuses on the fine-tuning of various predictive models using techniques like grid search, which optimizes the hyperparameters. This fine-tuning is validated through a 3-fold cross-validation process to ensure the models are robust and generalize well to unseen data. Following the fine-tuning, models are rigorously evaluated to assess their performance based on standard metrics such as accuracy, precision, recall, F1-score, etc.

The fine-tuned models are then compared to each other to identify the most effective approach in predicting employability. This comparison is crucial for understanding the strengths and limitations of each model in the context of the specific dataset. The best-performing model undergoes further analysis through SHAP (SHapley Additive exPlanations) to understand the influence of each feature on the prediction outcomes. This explanation is vital for stakeholders to grasp which factors are most predictive of employability, thereby informing educational strategies and interventions.

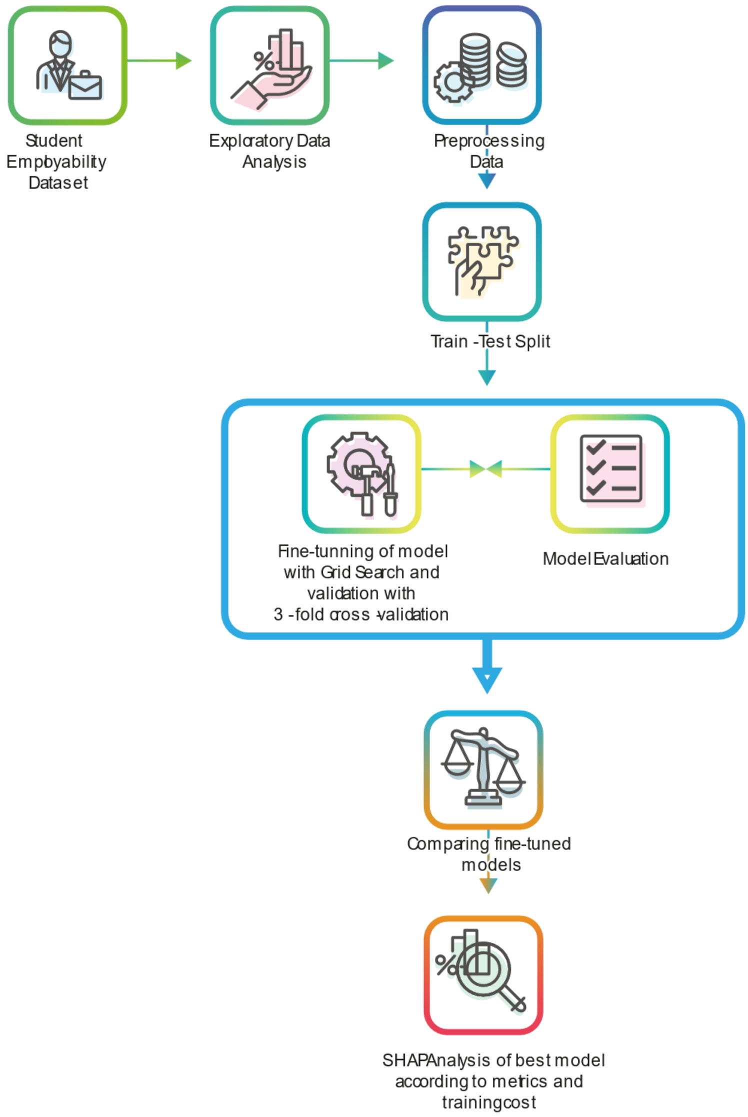

Figure 1. Flowchart for the ML and DL models.

4.3. Description of variables and their characteristics

The dataset utilized in this study comprises 10 distinct columns, incorporating a mix of categorical and numerical data types to evaluate various aspects of student employability. Below is a detailed breakdown of each variable and its characteristics:

1. **Name of Student:** This column is categorical and serves as a unique identifier for each student. Each entry is labeled in the format "Student X", where X is a sequential number representing the student.
2. **General Appearance:** A numerical variable rated between 2 and 5, assessing the overall physical presentation of the student.
3. **Manner of Speaking:** This numerical variable also ranges from 2 to 5, evaluating the clarity, confidence, and effectiveness of the student's verbal communication.
4. **Physical Condition:** Rated between 2 and 5, this variable assesses the student's physical fitness and overall health, which can impact their employability.
5. **Mental Alertness:** A numerical score from 2 to 5 that measures the student's cognitive sharpness and ability to think and respond quickly.
6. **Self-Confidence:** This variable scores the student’s level of self-assurance from 2 to 5, reflecting their confidence in their skills and abilities.

7. **Ability to Present Ideas:** Evaluated on a scale of 2 to 5, this measures the student's effectiveness in organizing and communicating ideas clearly and persuasively.
8. **Communication Skills:** Another crucial employability factor, rated from 2 to 5, focusing on the student's overall ability to communicate effectively in various contexts.
9. **Student Performance Rating:** A numerical rating from 3 to 5 that reflects the overall academic and extracurricular performance of the student.
10. **Class:** A categorical variable with two labels: "Employable" and "LessEmployable". This outcome variable categorizes students based on their assessed readiness for the workplace.

Table 1 offers a concise snapshot of the first five rows of the case study dataset, illustrating the diverse range of ratings for variables such as general appearance, manner of speaking, and mental alertness among different students. For instance, Student 1 demonstrates high scores across all attributes, aligning with their classification as "Employable." In contrast, Students 3 and 4, with lower ratings in key areas like mental alertness and self-confidence, are categorized as "LessEmployable." This table effectively encapsulates the dataset's structure and provides a clear example of how various factors contribute to the employability assessments within the study. As shown in Table 1, the sample data does not contain any sensitive or identifiable information that could raise privacy concerns.

Table 1. Preview of the first 5 rows of the case study dataset.

	Anonymous code	General appearance	Manner of speaking	Physical condition	Mental alertness	Self-confidence	Ability to present ideas	Communication skills	Student performance rating	Class
0	Student 1	4	5	4	5	5	5	5	5	Employable
1	Student 2	4	4	4	4	4	4	3	5	Employable
2	Student 3	4	3	3	3	3	3	2	5	LessEmployable
3	Student 4	3	3	3	2	3	3	3	5	LessEmployable
4	Student 5	4	4	3	3	4	4	3	5	Employable

A brief exploratory data analysis (EDA) was made so we can identify possible missing data, improve the format, or fix other anomalies. To make this, one-hot encoding was used to gather the statistics of all relevant columns which is presented in Table 2. This Table provides a statistical overview of the features and target variable within the dataset, encapsulating a variety of descriptive statistics such as count, mean, standard deviation, minimum, and maximum values, as well as quartiles for each measured attribute. This data set comprises data from 2982 students, ensuring a robust sample for analysis.

The average scores for the variables generally range from 3.5 to 4.6, indicating a relatively high performance across the board. Specifically, "Student Performance Rating" has a notably high mean of 4.6106, suggesting that students generally perform well academically and in related areas assessed by the dataset. "Communication Skills" shows the lowest average score of 3.5254, possibly highlighting a common area where students might struggle compared to other metrics.

The standard deviation across different attributes varies slightly but remains under 0.81, with "Self-Confidence" exhibiting the highest variability (std = 0.8076). This variation suggests differing levels of confidence among students, which could significantly influence their perceived employability. The minimum scores for all features except "Student Performance Rating" are at 2, indicating a baseline but not extremely low performance, while "Student Performance Rating" bottoms out at 3, showcasing a generally good academic standing.

The target variable "Class" is binary, with values 0 and 1, where 1 likely represents "Employable" and 0 "LessEmployable." The mean value of 0.4201 for the class indicates that a smaller proportion of the dataset is labeled as "Employable," demonstrating the potential stringency or high standards of employability criteria used in this analysis.

Table 2. Descriptive statistics of the features and target variable.

	General appearance	Manner of speaking	Physical condition	Mental alertness	Self-confidence	Ability to present ideas	Communication skills	Student performance rating	Class
count	2982	2982	2982	2982	2982	2982	2982	2982	2982
mean	4.2468	3.8846	3.9721	3.9627	3.9107	3.8138	3.5254	4.6106	0.4201
std	0.6785	0.7570	0.7441	0.7819	0.8076	0.7393	0.7438	0.6928	0.4936
min	2	2	2	2	2	2	2	3	0
25%	4	3	3	3	3	3	3	4	0
50%	4	4	4	4	4	4	3	5	0
75%	5	4	5	5	5	4	4	5	1
max	5	5	5	5	5	5	5	5	1

Figure 2 presents two visual representations of the class distribution within the dataset, showing the target column in both a bar graph and a pie chart. The bar graph on the left illustrates the count of students classified as "Employable" (red bar) and "LessEmployable" (blue bar), alongside the total count (green bar), with classes encoded as 0 for "Employable" and 1 for "LessEmployable." The pie chart on the right further clarifies the proportion of these classifications, with 58.0% of students categorized as "Employable" and 42.0% as "LessEmployable." These visuals underscore a relatively balanced distribution between the two classes, which is crucial for reducing bias in predictive modeling. This balanced approach ensures that machine learning algorithms can effectively generalize without overly favoring the majority class, thereby enhancing the reliability and fairness of employability predictions.

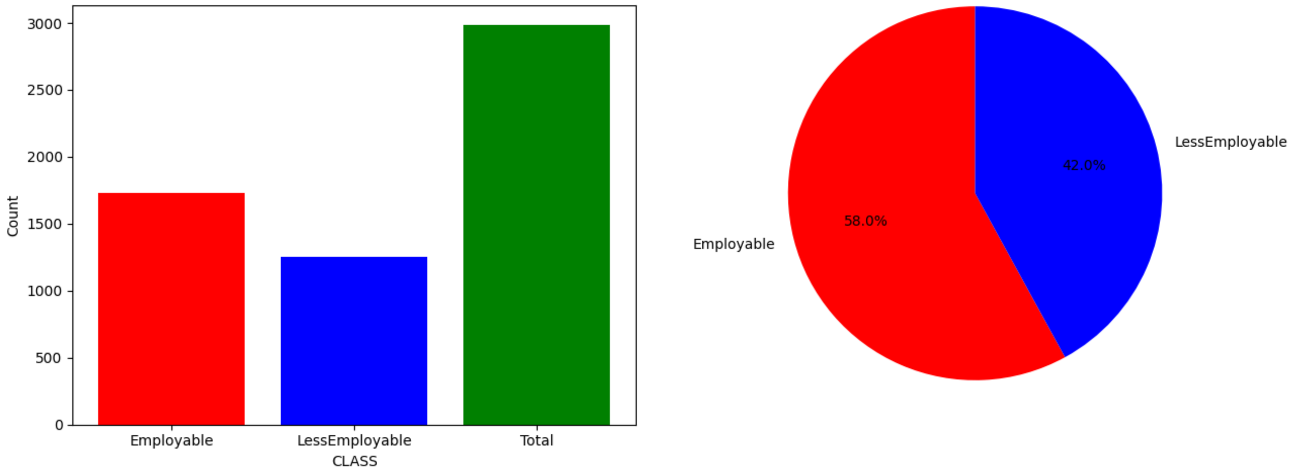

Figure 2. The distribution of the target column in numerical form, (left) column vector, (right) pie chart.

4.4. Data interpretation and visualization

The correlation heat map, in Figure 3, reveals that while key attributes such as "Manner of Speaking," "Physical Condition," and "Self-Confidence" strongly interrelate—indicative of interconnected skills enhancing student capabilities—they exhibit only weak correlations with the "Class" variable, which categorizes students as "Employable" or "LessEmployable." This suggests a complex relationship between individual attributes and employability outcomes, where no single trait dominates in determining a student's job readiness. For instance, the high correlation (0.73) between "Manner of Speaking" and "Ability to Present Ideas" emphasizes the importance of communication skills in overall student performance, yet the minimal direct impact on employability status highlights the criteria used in employability assessments.

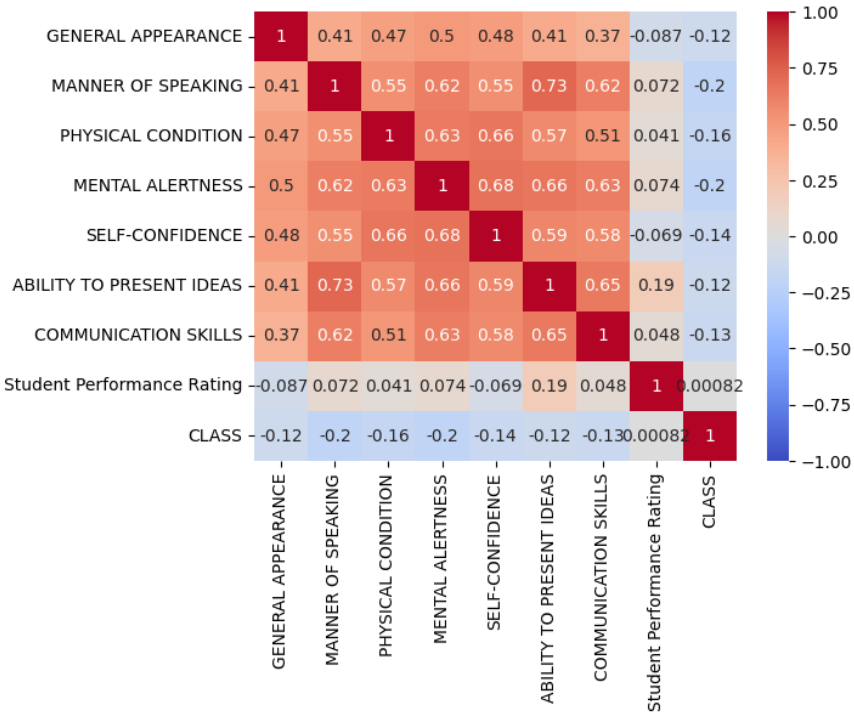

Figure 3. Correlation Heat Map, excluding the student number.

The parallel coordinate plot, in Figure 4, highlights the distribution of various attributes across the two employment categories, Employable (0) and LessEmployable (1), showcasing how each factor spans the spectrum of scores from 2 to 5. This visualization illustrates a discernible pattern where students categorized as Employable tend to cluster at higher values across most attributes, particularly in "Mental Alertness," "Self-Confidence," and "Communication Skills," suggesting these traits are pivotal in determining employability. Conversely, the lower scores in these attributes correspond more frequently with the LessEmployable category.

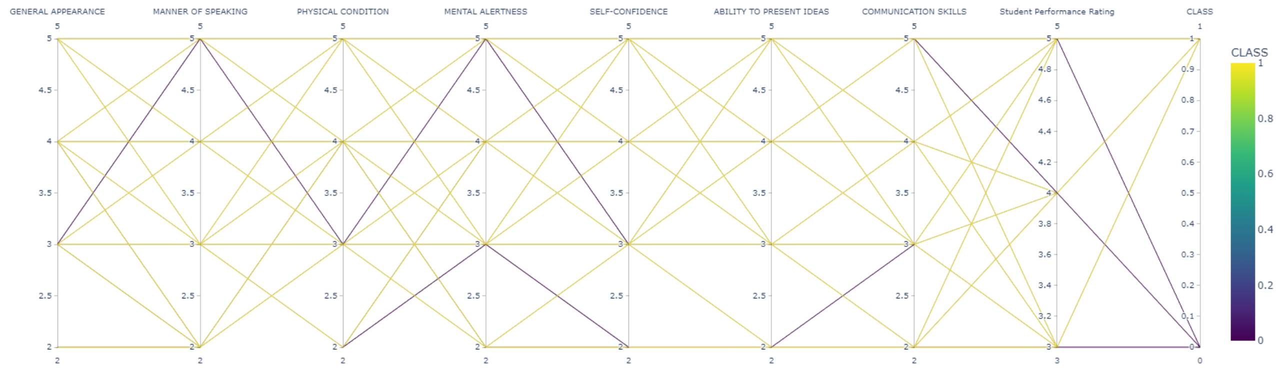

Figure 4. Parallel Coordinate Plot based on the target classes.

Figure 5, the scatter matrix, offers a granular view of how various attributes interact and distribute across the two classes of employability: Employable (0) and LessEmployable (1). Each matrix cell presents a scatter plot for a pair of attributes, with the diagonal showing the distribution of each attribute individually, differentiated by class through color coding. A critical analysis reveals several key observations. Attributes such as "Mental Alertness," "Self-Confidence," and "Ability to Present Ideas" show distinct distribution patterns where higher scores tend to correlate with the Employable class. This pattern underscores the importance of these traits in determining employability, suggesting that higher levels in these areas significantly boost employment prospects. While some attributes like "General Appearance" and "Physical Condition" show considerable overlap between the two classes, others such as "Communication Skills" and "Mental Alertness" demonstrate clearer separation. This indicates that certain traits may be more predictive of employability outcomes than others. The distribution plots on the diagonal indicate varying levels of skewness. For instance, "Communication Skills" and "Self-Confidence" are slightly skewed towards higher values, particularly for the Employable class, suggesting a tendency for these students to rate higher in these critical areas.

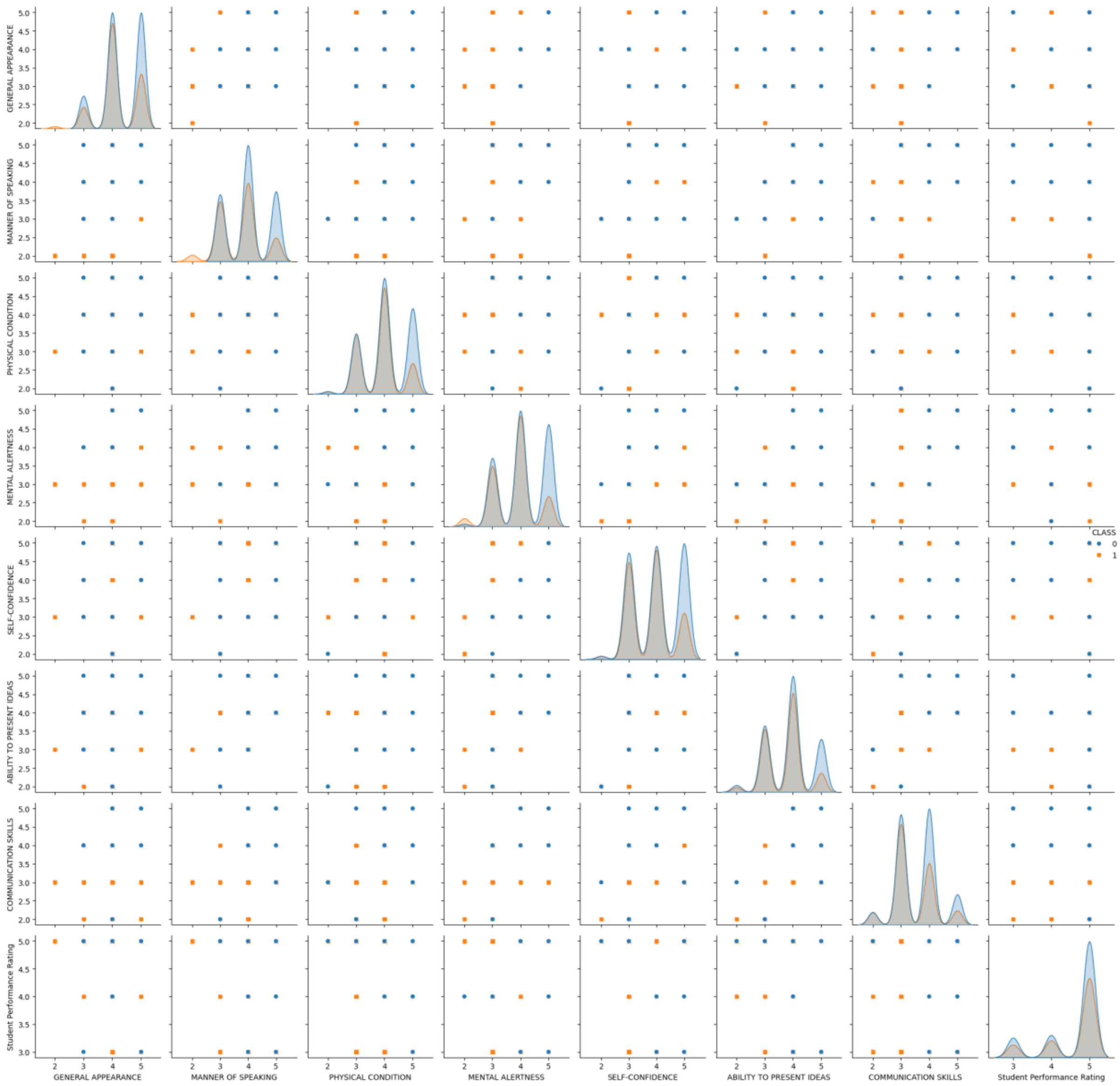

Figure 5. Scatter Matrix of the different classes.

4.5. Machine learning and deep learning algorithms: Computer setup and tuning parameters

For the classification component of this study, the dataset was divided into a train-test split, with 80% allocated for training and the remaining 20% for testing. The target variable was transformed into a numerical format to facilitate classification, ensuring that the class distribution was balanced enough to proceed without requiring sampling techniques to correct for bias.

Since, the objective of this research is to identify the most significant features in a mock job interview that affect employability. To achieve this, we used some classifiers proposed in past work as mentioned in section 2, including five machine learning models: Support Vector Machine (SVM), Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting, as well as three deep learning models: Artificial Neural Networks (ANN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM).

These computational experiments were conducted on an Intel Core™ i7-9750H CPU using Python 3.10.12 in Google Colab, ensuring robust computational support and environment consistency. The computer setup of each algorithm is given as follows:

1. **Support Vector Machine (SVM):** SVM is particularly effective in high-dimensional spaces. A Grid Search was conducted to optimize the hyperparameters, initially setting a linear kernel and C = 1. Variations included adjustments to the C value, kernel type, and gamma value to refine the model's performance.
2. **Logistic Regression:** This model was applied to predict binary outcomes—categorizing individuals as either "Employable" or "LessEmployable". The initial model used the "*lbfgs*" solver with a maximum iteration of 50. Grid Search explored variations with maximum iterations of 200, 500, and 1,000 to enhance the accuracy and reliability of the results.
3. **Decision Tree:** Utilized for its ability to manage categorical data, the base decision tree model (Matzavela & Alepis, 2021) employed the entropy criterion, the 'best' splitter, a maximum depth of 15, and no constraints on maximum features or class weight, enabling nuanced data segmentation.
4. **Random Forest:** An ensemble of Decision Trees, this model reduces classification variance, enhancing stability at the expense of some interpretability. It was configured based on the parameters of the underlying decision trees.
5. **Gradient Boosting:** This model aggregates "weak learners" into a robust ensemble classifier. Unlike Random Forest, Gradient Boosting sequentially corrects errors of the previous trees, focusing on challenging cases that prior trees handled poorly.
6. **Artificial Neural Networks (ANN):** The ANN architecture included three layers, each with 10 units using ReLU activation functions. It was compiled with the Adam optimizer, using "binary cross-entropy" for the loss function due to the binary nature of the classification task. The model underwent 100 epochs of training with a batch size of 64.
7. **Gated Recurrent Units (GRU):** Similar to ANNs but with added 'memory' functions to better capture dependencies in the data, the GRU model shares the architectural design with the ANN but incorporates memory units to enhance temporal data comprehension.
8. **Long Short-Term Memory (LSTM):** An extension of the GRU, the LSTM model includes a 'forget' function that allows it to maintain only the most relevant information over long sequences, making it particularly suited for tasks where long-term dependencies are critical for prediction.

Deep learning has emerged as a transformative tool in education, offering innovative solutions to enhance learning processes and institutional evaluations. Orosoo et al. (2025) demonstrate the potential of advanced deep learning architectures, such as MLP-LSTM, in transforming English language learning through speech recognition systems (Orosoo et al., 2025). Their study highlights the role of deep learning in delivering personalized education by adapting to individual learners' needs, improving engagement, and fostering more efficient language acquisition. Similarly, deep learning techniques, particularly recurrent neural networks (RNNs) and their advanced variants like LSTM and GRU, have proven effective in analyzing complex educational data. Faccin and Andrade (2025) utilize these models for textual analysis of teaching-learning evaluations in higher education, achieving an accuracy of 84.1% in sentiment classification (Faccin & de Andrade, 2025). Their findings reveal that deep learning can accurately interpret qualitative evaluations, categorizing them into sentiments such as praise, criticism, and suggestions. This capability provides valuable insights for institutions to improve teaching methods, faculty training, and policies. Collectively, these studies outline the significant role of deep learning in education, which is also gaining attention.

Overfitting is mitigated in this study as all machine learning and deep learning models underwent rigorous hyperparameter tuning using Grid Search, ensuring optimized model parameters. Additionally, k-fold cross-validation was performed to validate the generalizability of the models across different subsets of the data. The final evaluation on an independent test set yielded accuracy comparable to the training results, confirming the models' robustness and their ability to generalize effectively to unseen data.

4.6. Performance measurement of algorithms

The performance measurement of each algorithm is described through the confusion matrix, ROC curve, and various indicators which are listed as follows:

1. **Precision:** Precision is a measure of how the predicted value in a specific class is. It could be seen as the accuracy of the model on a specific class. Mathematically, it is written as:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

2. **Recall:** Recall is a metric that shows how well the model identifies the actual. It can be an extremely useful metric when the cost of the error of false negatives is high. It is written as:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

3. **Accuracy:** Accuracy is your standard metric where one measures how many predictions are correctly made from the total number of predictions. It is one of the most commonly used metrics to decide the best performing model. It is written as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

4. **F1 score:** F1 score is a harmonic mean between Precision and Recall, often being used for a better overall metric. It creates a more robust metric that levels out the difference between them, although, it should be taken into account that it is still sensitive to imbalanced classes. Mathematically, it is written using the equation:

$$F_1\ Score = \frac{2 * TP}{2 * TP + FP + FN} \tag{4}$$

5. **Matthew Correlation:** The Matthew correlation coefficient is a “measure of the quality of the binary and multiclass classification” (Chicco & Jurman, 2023). This means that it virtually is a correlation coefficient between how well the model predicts the class adequately. The nearer it is for 1, the closer the model is to produce a perfect classification. It is computed with the following formula:

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{5}$$

6. **Cohen Kappa Coefficient:** Cohen Kappa measures “the level of agreement between two annotators on a classification problem” (*Matthews_corrcoef, Scikit-Learn 1.5.1 Documentation*, 2024).The formula to calculate this is:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{6}$$

where p_o is the observed agreement ratio and p_e is the expected agreement when they assign randomly.

When evaluating the performance of classification models, it is important to understand several key metrics: True Positive (TP), where the model accurately identifies positive instances; False Positive (FP), where positive instances are incorrectly classified as negative; True Negative (TN), where the model correctly identifies negative instances; and False Negative (FN), where negative instances are mistakenly classified as positive. These concepts form the foundation of confusion matrix metrics, aiding in the assessment of a model's predictive accuracy and precision by distinguishing between correctly and incorrectly classified cases.

5. Results

The "Results" section of this article is organized to present a detailed analysis of the findings from the study, focusing on the efficacy of various predictive models and the significant features influencing student employability. It encompasses interpretations through confusion matrices and ROC curves, performance metrics, and explicates the contributions of individual predictors using SHAP values based on game theory, providing a thorough evaluation of the models' performance and interpretive insights.

5.1. Interpretation through confusion matrix and Receiver Operating Characteristic (ROC)

Figure 6 presents the confusion matrices for several machine learning and deep learning models used to predict student employability, including Support Vector Machine (SVM), Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, Artificial Neural Network (ANN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM). These matrices provide a detailed comparison of each model's ability to accurately classify students as "Employable" (0) and "LessEmployable" (1).

It is noted that SVM and Gradient Boosting show similar performance with high True Positives (TP) for the Employable class and relatively fewer False Positives (FP). However, Gradient Boosting slightly outperforms SVM in predicting the LessEmployable class with fewer False Negatives (FN). Logistic Regression struggles with a high number of FPs and a substantial number of FNs, indicating a poorer performance in correctly classifying both classes compared to other models. Decision Tree and Random Forest exhibit strong performance with a good balance between TP and TN for both classes. Random Forest, however, reduces FN more effectively than the Decision Tree, showcasing its robustness in handling class imbalances. ANN, GRU, and LSTM display superior performance with high accuracy in TP and True Negatives (TN). Notably, LSTM and GRU show almost identical confusion matrices, indicating their effectiveness in capturing temporal dependencies in data which is crucial for this classification task.

Several similarities and differences between the techniques are also observed. The tree-based models (Decision Tree, Random Forest, Gradient Boosting) generally show strong TP and TN but vary in their handling of FN and FP. Random Forest and Gradient Boosting are more efficient in reducing FN, likely due to their ensemble nature. Logistic Regression shows notable deficiencies in handling both positive and negative classes, suggesting limitations in linear models for this dataset's complexity. Advanced neural networks (ANN, GRU, LSTM) demonstrate high efficiency across all metrics. GRU and LSTM, in particular, excel in minimizing both FN and FP, highlighting their capability in sequence modeling and prediction.

Correct predictions are highest in LSTM and GRU, indicating their suitability for datasets where temporal patterns significantly influence outcomes. These models effectively learn and remember important traits over sequences, making them ideal for employment prediction based on historical data. Incorrect predictions, particularly FNs in Logistic Regression, suggest that this model may oversimplify the dataset, missing crucial nuances required for accurate employability classification. SVM and Gradient Boosting, while strong, still show room for improvement in minimizing FNs, essential for ensuring no potential "Employable" candidates are overlooked.

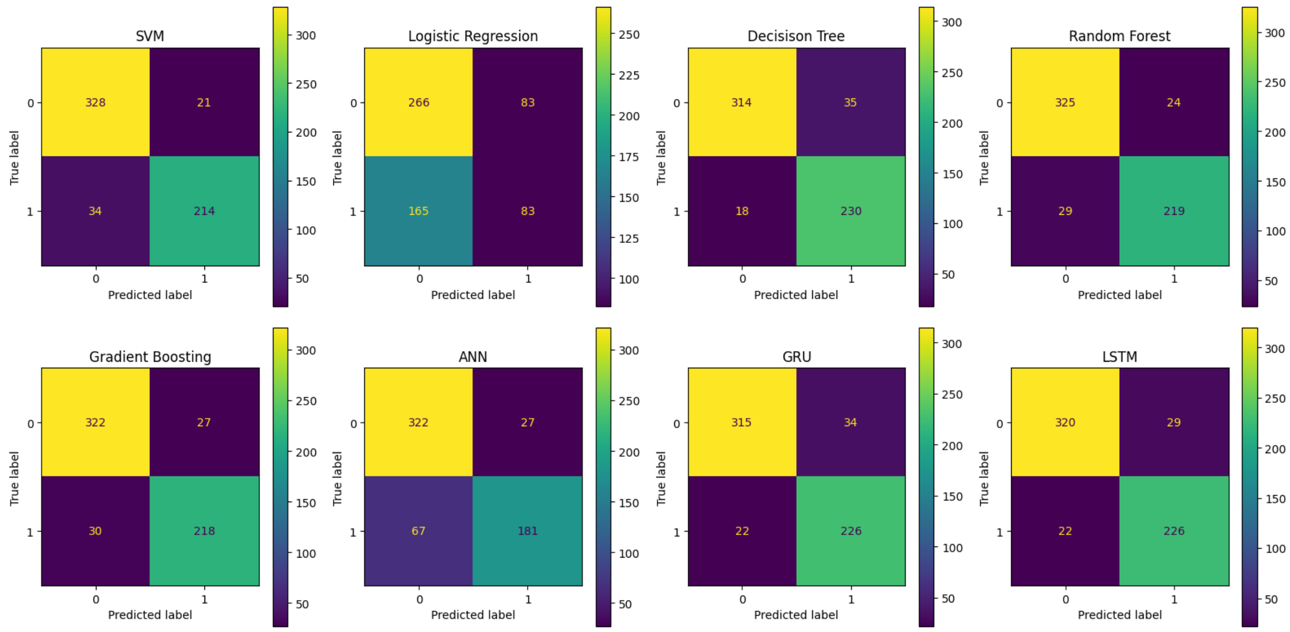

Figure 6. Confusion matrix of the ML and DL models

Figure 7 displays the Receiver Operating Characteristic (ROC) curves for all the predictive algorithms. These curves are instrumental in evaluating the true positive rate (sensitivity) against the false positive rate (1 - specificity), providing a visual representation of each model's ability to distinguish between the Employable and LessEmployable classes.

SVM and Gradient Boosting show ROC curves that rise quickly towards the top-left corner of the plot, indicating a high true positive rate with a relatively low false positive rate. These models demonstrate strong discriminative ability, suggesting effective classification of the employable status. Logistic Regression displays a ROC curve closer to the diagonal line, which represents random guessing. This indicates a less effective model for this specific task, as it struggles to adequately separate the two classes. Decision Tree and Random Forest exhibit ROC curves that are significantly above the diagonal, reflecting better performance than Logistic Regression, with Random Forest performing slightly better than the Decision Tree. This suggests that the ensemble approach of Random Forest successfully enhances the model's predictive accuracy. ANN, GRU, and LSTM show very similar ROC curves, which are among the best of the models analyzed. These curves approach the upper left corner, indicating excellent performance with high sensitivity and low false positive rates. The advanced capabilities of these deep learning models to capture complex patterns and dependencies in the data make them highly effective for this predictive task.

The ROC curves also allow for direct comparison of the models' effectiveness. Deep learning models (ANN, GRU, LSTM) and more sophisticated machine learning models like Gradient Boosting and Random Forest clearly outperform simpler models like Logistic Regression and basic Decision Trees in terms of both sensitivity and specificity. This superiority is likely due to their ability to model non-linear relationships and their robustness in handling varied data types and structures.

The analysis of ROC curves demonstrates that while some models can nearly perfectly classify students' employability status, others, particularly Logistic Regression, might require further tuning or a reevaluation of feature usage to improve their discriminative power. The close proximity of GRU and LSTM ROC curves suggests that their memory components and ability to process sequences provide a significant advantage in this context, likely capturing more aspects of the data related to student employability.

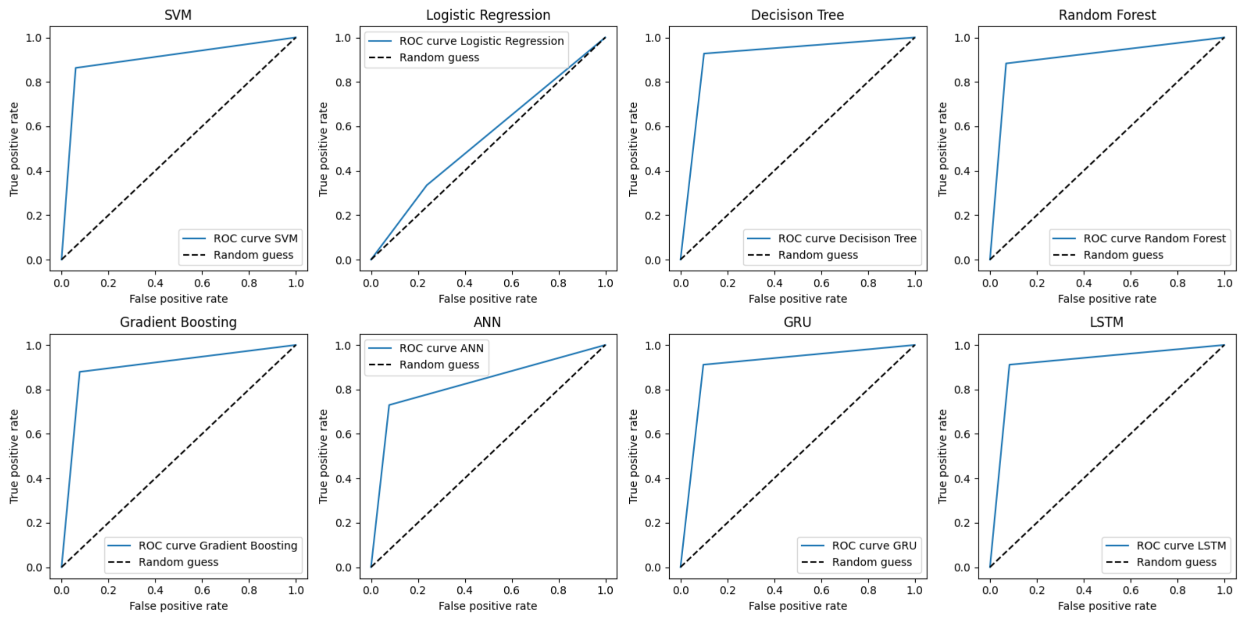

Figure 7. The ROC curve of ML and DL models

5.2. Interpretation through performance metrices

The performance of various predictive models for student employability has been systematically evaluated across several metrics, including precision, recall, F1-score, Matthew Correlation Coefficient, Cohen Kappa, and cross-validation accuracy. These metrics provide a nuanced understanding of each model's effectiveness in correctly classifying students as "Employable" or "LessEmployable."

The Support Vector Machine (SVM) (Table 3) displayed strong performance with a precision of over 90% for both classes, reflecting its robustness in accurately identifying employable students. Its overall accuracy reached approximately 90.79%, and the model demonstrated high stability with a cross-validation score of 91.15%. In contrast, Logistic Regression (Table 4) showed significantly weaker results, with a much lower precision and recall for the LessEmployable class, culminating in a low overall accuracy of 58.46%. This indicates that Logistic Regression may struggle with the complexity and nuances of the dataset used. Decision Tree (Table 5) and Random Forest (Table 6) models exhibited higher accuracy, with the Decision Tree achieving a slightly better balance between precision and recall across the two classes. The Random Forest model, using its ensemble nature, showed a slight improvement in minimizing false negatives, highlighted by its accuracy of 91.12% and cross-validation score of 90.69%. Gradient Boosting (Table 7) mirrored the performance of the Random Forest in many respects but with identical precision, recall, and F1-scores as Random Forest, indicating that both models manage class imbalances effectively. ANN (Table 8) provided a decent balance between precision and recall, especially for the Employable class, but it fell short in overall accuracy compared to more complex models, standing at 84.25%. Its cross-validation score, however, was relatively high at 88.17%, suggesting some resilience in model performance across different subsets of data. GRU (Table 9) and LSTM (Table 10) models showcased their superiority in handling sequential and time-series data, with both achieving high scores across all performance metrics. LSTM slightly outperformed GRU in terms of overall accuracy and F1-scores, which could be attributed to its sophisticated mechanisms that effectively capture long-term dependencies in data.

In summary, while models like SVM and Gradient Boosting performed well, deep learning models, particularly LSTM, demonstrated the highest efficacy by using their advanced capabilities to analyze complex patterns and sequences in the data. On the other side, the Gradient Boosting and Random Forest algorithm also has quite a similar performance as LSTM, however, it offers a much simpler computational model, and the choice between different models would also depend upon the end-customer requirement. The differences in performance metrics across models underscore the importance of choosing the right algorithm that aligns with the data characteristics and the specific prediction task. LSTM's superior performance highlights its potential as a powerful tool for predictive tasks in educational settings, particularly for applications requiring analysis of temporal data and sequence modeling.

Table 3. Classification report on Support Vector Machine SVC (C = 0.1, gamma = 1, kernel = rbf).

	Precision	**Recall**	**F1-Score**	**Support**
Class 0	0.906077	0.939828	0.922644	349
Class 1	0.910638	0.862903	0.886128	248
Macro average	0.908358	0.901366	0.904386	597
Weighted average	0.907972	0.907873	0.907475	597
Matthew Correlation: 0.809693				
Cohen Kappa: 0.808867				
Accuracy: 0.907873				
Cross Validation Accuracy Score for K-folds = 3: 0.911530				

Table 4. Classification report on Logistic Regression (max_iter = 200, random_state = 40)

	Precision	**Recall**	**F1-Score**	**Support**
Class 0	0.617169	0.5	0.682051	349
Class 1	0.762178	0.334677	0.400966	248
Macro average	0.558585	0.548428	0.541509	597
Weighted average	0.568496	0.58459	0.565286	597
Matthew Correlation: 0.106529				
Cohen Kappa: 0.101722				
Accuracy: 0.58459				

Cross Validation Accuracy with K-folds = 3: 0.597484

Table 5. Classification report on Decision Tree (class_weight= balanced, criterion = gini, max_depth = 15, max_features = 8, random_state = 40, splitter = random)

	Precision	**Recall**	**F1-Score**	**Support**
Class 0	0.945783	0.899713	0.922173	349
Class 1	0.867925	0.927419	0.896686	248
Macro average	0.906854	0.913566	0.90943	597
Weighted average	0.91344	0.911223	0.911586	597
Matthew Correlation: 0.820393				
Cohen Kappa: 0.819009				
Accuracy: 0.911223				
Cross Validation Accuracy with K-folds = 3: 0.904822				

Table 6. Classification report on Random Forest (n_estimators = 2, random_state = 40)

	Precision	Recall	F1-Score	Support
Class 0	0.914773	0.922636	0.918688	349
Class 1	0.889796	0.879032	0.884381	248
Macro average	0.902284	0.900834	0.901534	597
Weighted average	0.904397	0.904523	0.904436	597
Matthew Correlation: 0.803117				
Cohen Kappa: 0.803074				
Accuracy: 0.904523				
Cross Validation Accuracy with K-folds = 3: 0.906918				

Table 7. Classification report on Gradient Boosting (n_estimators = 20, max_depth = 6, learning_rate = 1, random_state = 40)

	Precision	Recall	F1-Score	Support
Class 0	0.914773	0.922636	0.918688	349
Class 1	0.889796	0.879032	0.884381	248
Macro average	0.902284	0.900834	0.901534	597
Weighted average	0.904397	0.904523	0.904436	597
Matthew Correlation: 0.803117				
Cohen Kappa: 0.803074				
Accuracy: 0.904523				
Cross Validation Accuracy with K-folds = 3: 0.907757				

Table 8. Classification report on Artificial Neural Network (ANN) (units per layer = 10, layers = 3, activation = ReLu, optimizer = adam, loss = binary_crossentropy, batch_size = 64, epochs = 50)

	Precision	Recall	F1-Score	Support
Class 0	0.827763	0.922636	0.872629	349
Class 1	0.870192	0.729839	0.872629	248
Macro average	0.848978	0.826237	0.833244	597
Weighted average	0.845389	0.842546	0.839907	597
Matthew Correlation: 0.674832				
Cohen Kappa: 0.668067				
Accuracy: 0.842546				
Cross Validation Accuracy with K-folds = 3: 0.881761				

Table 9. Classification report on Gated Recurrent Unit (GRU) (units per layer = 10, layers = 3, activation = ReLu, optimizer = adam, loss = binary_crossentropy, batch_size =32, epochs = 100)

	Precision	Recall	F1-Score	Support
Class 0	0.934718	0.902579	0.918367	349
Class 1	0.869231	0.91129	0.889764	248
Macro average	0.901974	0.906935	0.904066	597
Weighted average	0.907514	0.906198	0.906485	597
Matthew Correlation: 0.808894				
Cohen Kappa: 0.808210				
Accuracy: 0.906198				
Cross Validation Accuracy with K-folds = 3: 0.901887				

Table 10. Classification report on Long-Short Term Memory (LSTM) (units per layer = 10, layers = 3, activation = ReLu, optimizer = adam, loss = binary_crossentropy, batch_size = 32, epochs = 100)

	Precision	Recall	F1-Score	Support
Class 0	0.935673	0.916905	0.926194	349
Class 1	0.886275	0.91129	0.898608	248
Macro average	0.910974	0.914098	0.912401	597
Weighted average	0.915152	0.914573	0.914735	597
Matthew Correlation: 0.825065				
Cohen Kappa: 0.824827				
Accuracy: 0.914573				
Cross Validation with K-folds = 3: 0.904822				

5.3. Explicable insights through SHapley Additive exPlanations (SHAP) based upon game theory

This work uses SHapley Additive exPlanations (SHAP), derived from cooperative game theory, to quantify the impact of individual features on the predictive models' output for student employability. This analysis offers profound insights into how different attributes contribute to the classification decisions of our models, highlighting crucial factors that influence student employability across two categories: Employable (Class 0) and LessEmployable (Class 1).

Figure 8 showcases SHAP values in violin plots for both classes. These plots provide a visual representation of the distribution of impacts each feature has on the model's prediction. For Class 0 (Employable), features like Self-Confidence, Ability to Present Ideas, and General Appearance demonstrate higher positive SHAP values, indicating their strong positive influence on being classified as employable. Conversely, for Class 1 (LessEmployable), the impact of these features is notably less pronounced or even negative, suggesting that lower levels of these attributes may contribute to a less employable classification.

The comparison between the two classes in the violin plots reveals distinct patterns: high-impact features for employability tend to have reduced or opposite effects for less employability. For instance, Self-Confidence, which is highly beneficial for Class 0, shows a significant decrease in influence for Class 1, as depicted by the spread and median of SHAP values.

(a) (b)

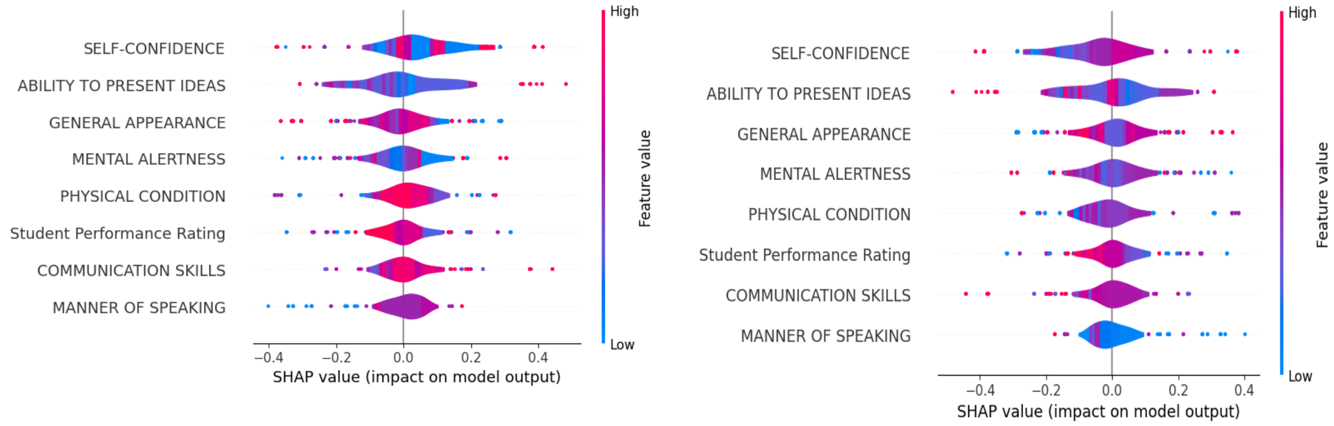

Figure 8. The SHAP values in the violin graph of the (a) class 0, and (b) class 1.

Figure 9 complements this analysis by presenting the mean SHAP values as bar graphs, quantifying the average impact of each feature on the model's output. The bar graphs align with the insights from the violin plots, where Self-Confidence, Ability to Present Ideas, and General Appearance are the top contributors. The graphical representation in Figure 9 allows for a clearer quantification of these impacts, reinforcing the critical roles these features play.

The SHAP analysis provides a robust framework for understanding the importance and effects of various attributes on employability predictions. By interpreting the contribution of each feature to the model's decisions, SHAP values enable stakeholders in educational and workforce planning to identify key areas of focus for improving student outcomes and employability skills.

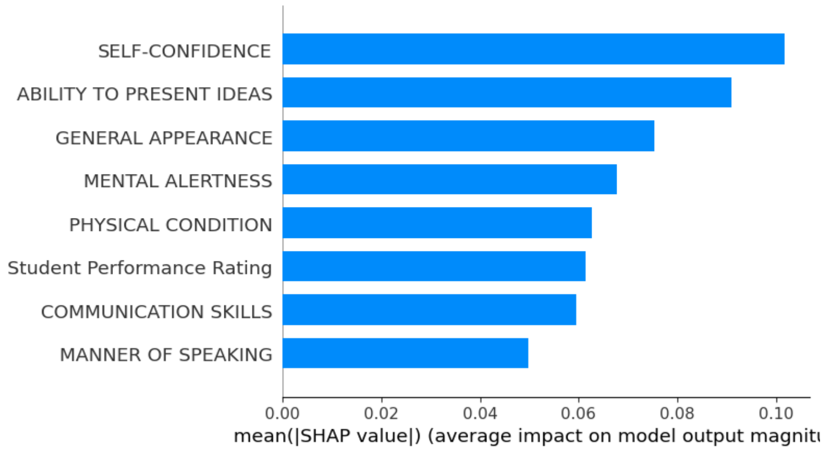

Figure 9. Mean SHAP values.

6. Discussion

Self-confidence was identified as the most impactful predictor of student employability. Self-confidence is a person's sense of his or her own competence or skill and perceived capability to deal effectively with various situations (Cheng & Furnham, 2002) Self-confidence along with its related constructs of self-efficacy and self-concept have been shown to be important predictors of academic achievement (Çiftçi & Yıldız, 2019; Möller et al., 2020). In our study, we further highlight its importance for student employability. Students with self-confidence can project a positive image of themselves along with a positive presence that has consequences on the assessment of employability. Our results support the model of (Pool & Sewell, 2007) where self-confidence is one of the mediators that link knowledge and skills with employability.

Another impactful predictor of student employability is the ability to present ideas. Many employment settings involve presentation skills, ideation, creativity, and problem-posing and problem-solving, all of which require the ability to present ideas. Indeed, past studies have highlighted the importance of the ability to present ideas as being important to employers in different sectors (Cheng & Furnham, 2002; Hinchliffe & Jolly, 2011; Saad, 2014) (Saad & Majid, 2014; Hinchliffe & Jolly). However, it is somewhat surprising that communication skills and manner of speaking in our analysis did not then rank highly as important predictors. One potential explanation is that in a multivariate model involving other predictors, communication and speaking skills may not be as valued in comparison to specifically presenting ideas, which is a much narrower skill of communication. In other words, it is not communication and speaking that are not important in and of themselves but rather what is being communicated, in this case, presenting ideas clearly and convincingly, for employability purposes. Educational institutions may consider focusing on student fluency with ideas in different forms and how to communicate them with clarity, organization, and persuasion in order to maximize student employability.

A striking finding is the poor performance of some models, in particular logistic regression. Logistic regression is a classical machine learning model that linearly combines variables in order to predict a binary outcome variable. This limitation contrasts with other machine learning and deep learning models that are well-known to be able to mine highly complex, nonlinear relationships in the data. Studies in other fields suggest that other nonlinear machine learning and deep learning models may not necessarily outperform logistic regression (Christodoulou et al., 2019). However, this was not the case in our dataset and modeling. Logistic regression had comparatively much lower performance, driven by poorer recall, compared to other nonlinear machine and deep learning models. This result agrees with previous research (Ali & Ang, 2022), suggesting that there may be complex signals that nonlinear machine and deep learning models can be used in educational research for improved prediction.

Conclusion

This article uses educational data mining integrated with machine learning and deep learning methodologies to explore the determinants of student employability, a critical issue in the context of competitive educational environments and evolving job markets. Through a detailed analytical approach, incorporating a range of predictive models and the insightful application of SHapley Additive exPlanations (SHAP), we have identified key traits that significantly influence employability outcomes. The following are the key conclusion points:

- Our findings report the importance of soft skills, such as Self-Confidence, Ability to Present Ideas, and General Appearance, which were consistently highlighted by the SHAP analysis as critical predictors of employability. This emphasizes the need for educational institutions to integrate soft skills development into their curricula actively, ensuring students are not only academically prepared but also equipped with essential interpersonal and professional skills.
- The performance of the predictive models, particularly the superior results from Long Short-Term Memory (LSTM) networks, illustrates the robust capability of deep learning techniques in handling complex, nuanced datasets typical of educational settings. The LSTM's ability to effectively process and learn from sequential and temporal data suggests that it can be a valuable tool for ongoing and future research in educational data mining.

The essence of this article lies in its exploration of potential avenues for future intervention policies that could be developed based on SHAP analysis. To fully refine and validate the model, further research is necessary using a more diverse and comprehensive dataset. In conclusion, this research contributes significantly to the body of knowledge on the application of AI in education, particularly in understanding and predicting student employability. It offers empirical evidence on the efficacy of various predictive models and sets a precedent for the use of explainable AI in educational research. These insights can guide the development of more personalized, effective educational programs that are aligned with the demands of the modern workforce, ultimately improving student outcomes and success in the job market.

The limitations of this study provide opportunities for future research to enhance the applicability and robustness of employability models. Future studies should explore the use of real-world hiring data instead of mock interviews to better capture the complexity of actual recruitment processes. Longitudinal research could address the evolving nature of job requirements and skill demands, ensuring that models remain relevant over time. Efforts to quantify difficult-to-measure soft skills, such as emotional intelligence and cultural fit, should be prioritized to improve the comprehensiveness of employability predictions. Additionally, future research could focus on developing adaptable AI models that account for institutional differences, addressing scalability challenges across various educational structures. Incorporating external factors, such as economic conditions, industry trends, and professional networks, into employability models would provide a more holistic understanding of employment outcomes. Real-world testing of AI models in educational institutions is also necessary to evaluate their practical performance and identify gaps that may not emerge in controlled environments. Establishing continuous feedback loops with employers can help refine these systems, allowing for real-time adjustments and improvements. Finally, adaptive frameworks that integrate predictive mechanisms for emerging skills and market demands are essential to ensure that employability models remain dynamic and future-proof.

In the future, the experimentation can be improved given the dataset's lack of detailed rubrics or explanations for each evaluated trait, it is challenging to gain deeper insights into the factors influencing employability in the mock job interviews. The lack of details regarding the criteria for grading each feature complicates the application of feature engineering to enhance model performance and more comprehensively encapsulate the dataset's features. Additionally, this study employs all features from the dataset for model training, regardless of their linear correlation values, which may not always yield optimal results. Another critical issue is related to the scalability challenges as each institution might require a unique model configuration which could be answered through a viable strategy to address scalability challenges to develop a decentralized AI model that generates generic predictions and can be locally trained on institution-specific datasets, ensuring data privacy and compliance with institutional policies. This also eliminates the concern about the size of the database because it would eventually depend upon the institutional size. Lastly, the fine-tuning of the deep learning techniques could benefit from exploring alternative methods to determine the best configurations more effectively for improving model accuracy.

Disclosure of interest

None declared.

Funding

None declared.

Declaration of Interest statement

None declared.

CRediT author statement

All authors have read and approved the final version of the manuscript.

Rasikh Tariq: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration, Funding acquisition

Diego Gutiérrez Vargas: Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft.

Farhan Ali: Methodology, Validation, Investigation, Writing - Original Draft, Writing - Review & Editing, Supervision.

Miguel Gonzalez-Mendoza: Methodology, Validation, Investigation, Writing - Original Draft, Writing - Review & Editing, Supervision.

Acknowledgment

The authors would like to thank Tecnológico de Monterrey for the financial support provided through the 'Challenge-Based Research Funding Program 2023', Project ID #IJXT070-23EG99001, titled 'Complex Thinking Education for All (CTE4A): A Digital Hub and School for Lifelong Learners.' The authors acknowledge the technical support of Writing Lab, Institute for the Future of Education, Tecnologico de Monterrey, Mexico, in the production of this work.

Data availability statement

The data is available on the link: https://www.kaggle.com/datasets/anashamoutni/students-employability-dataset/data. The full code of this work is available on the website: https://github.com/RasikhTariq/hello-world/blob/main/Students_Employability.ipynb. The data that support the findings of this study are available from the corresponding author, [R. T], upon reasonable request.

References

Akilandeswari, J., & Jothi, G. (2017). Performance Comparison of Machine Learning Algorithms that Predicts Students' Employability. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3134357

Ali, F., & Ang, R. P. (2022). Predicting How Well Adolescents Get Along with Peers and Teachers: A Machine Learning Approach. *Journal of Youth and Adolescence*, *51*(7), 1241–1256. https://doi.org/10.1007/S10964-022-01605-5/METRICS

Ali, F., Ow-Yeong, Y. K., & Tilley, J. L. (2024). Are schools becoming more unequal? Insights from exploratory data mining of international large-scale assessment, TIMSS 2003-2019. *Studies in Educational Evaluation*, *81*, 101330. https://doi.org/10.1016/J.STUEDUC.2024.101330

Alnasyan, B., Basheri, M., & Alassafi, M. (2024). The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, *6*, 100231. https://doi.org/10.1016/J.CAEAI.2024.100231

Armas-Cervantes, A., Abedin, E., & Taymouri, F. (2024). Dusting for fingerprints: Tracking online student engagement. *Computers and Education: Artificial Intelligence*, *6*, 100232. https://doi.org/10.1016/J.CAEAI.2024.100232

Ashraf, W. M., Uddin, G. M., Tariq, R., Ahmed, A., Farhan, M., Nazeer, M. A., Hassan, R. U., Naeem, A., Jamil, H., Krzywanski, J., Sosnowski, M., & Dua, V. (2023). Artificial Intelligence Modeling-Based Optimization of an Industrial-Scale Steam Turbine for Moving toward Net-Zero in the Energy Sector. *ACS Omega*, *8*(24), 21709–21725. https://doi.org/10.1021/ACSOMEGA.3C01227/ASSET/IMAGES/LARGE/AO3C01227_0012.JPEG

Aviso, K. B., Demeterio, F. P. A., Janairo, J. I. B., Lucas, R. I. G., Promentilla, M. A. B., Tan, R. R., & Yu, D. E. C. (2021). What university attributes predict for graduate employability? *Cleaner Engineering and Technology*, *2*, 100069. https://doi.org/10.1016/J.CLET.2021.100069

Aviso, K. B., Janairo, J. I. B., Lucas, R. I. G., Promentilla, M. A. B., Yu, D. E. C., & Tan, R. R. (2020). Predicting Higher Education Outcomes with Hyperbox Machine Learning: What Factors Influence Graduate Employability? *Chemical Engineering Transactions*, *81*, 679–684. https://doi.org/10.3303/CET2081114

Baffa, M. H., Miyim, M. A., & Dauda, A. S. (2023). Machine Learning for Predicting Students' Employability. *UMYU Scientifica*, *2*(1), 001–009. https://doi.org/10.56919/USCI.2123_001

Bai, A., & Hira, S. (2021). An intelligent hybrid deep belief network model for predicting students employability. *Soft Computing*, *25*(14), 9241–9254. https://doi.org/10.1007/S00500-021-05850-X/METRICS

Baker, R. S., & Inventado, P. S. (2014). Educational Data Mining and Learning Analytics. *Learning Analytics: From Research to Practice*, 61–75. https://doi.org/10.1007/978-1-4614-3305-7_4

Berntson, E., Sverke, M., & Marklund, S. (2006). Predicting Perceived Employability: Human Capital or Labour Market Opportunities? *Http://Dx.Doi.Org/10.1177/0143831X06063098*, *27*(2), 223–244. https://doi.org/10.1177/0143831X06063098

Boehme, R., Coors, S., Oster, P., Munser-Kiefer, M., & Hilbert, S. (2024). Machine learning for spelling acquisition: How accurate is the prediction of specific spelling errors in German primary school students? *Computers and Education: Artificial Intelligence*, *6*, 100233. https://doi.org/10.1016/J.CAEAI.2024.100233

Bressane, A., Zwirn, D., Essiptchouk, A., Saraiva, A. C. V., Carvalho, F. L. de C., Formiga, J. K. S., Medeiros, L. C. de C., & Negri, R. G. (2024). Understanding the role of study strategies and learning disabilities on student academic performance to enhance educational approaches: A proposal using artificial intelligence. *Computers and Education: Artificial Intelligence*, *6*, 100196. https://doi.org/10.1016/J.CAEAI.2023.100196

By, S., & Thakare, S. (2023). HARNESSING THE POWER OF MACHINE LEARNING FOR PREDICTING STUDENTS EMPLOYABILITY. *BioGecko*, 1–9. https://www.researchgate.net/profile/Sarita-By/publication/376046224_HARNESSING_THE_POWER_OF_MACHINE_LEARNING_FOR_PREDICTING_STUDENTS_EMPLOYABILITY/links/6568233ace88b870311fc7f3/HARNESSING-THE-POWER-OF-MACHINE-LEARNING-FOR-PREDICTING-STUDENTS-EMPLOYABILITY.pdf

Casuat, C. D. (2020). Predicting Students' Employability using Support Vector Machine: A SMOTE-Optimized Machine Learning System. *International Journal of Emerging Trends in Engineering Research*, *8*(5), 2101–2106. https://doi.org/10.30534/IJETER/2020/102852020

Celine*, S., Dominic, M. M., & Devi, M. S. (2020). Logistic Regression for Employability Prediction. *International Journal of Innovative Technology and Exploring Engineering*, *9*(3), 2471–2478. https://doi.org/10.35940/IJITEE.C8170.019320

Chaipidech, P., Srisawasdi, N., Kajornmanee, T., & Chaipah, K. (2022). A personalized learning system-supported professional training model for teachers' TPACK development. *Computers and Education: Artificial Intelligence*, *3*, 100064. https://doi.org/10.1016/J.CAEAI.2022.100064

Cheng, H., & Furnham, A. (2002). Personality, peer relations, and self-confidence as predictors of happiness and loneliness. *Journal of Adolescence*, *25*(3), 327–339. https://doi.org/10.1006/JADO.2002.0475

Chicco, D., & Jurman, G. (2023). The Matthews correlation coefficient (MCC) should replace the ROC AUC as the standard metric for assessing binary classification. *BioData Mining*, *16*(1), 1–23. https://doi.org/10.1186/S13040-023-00322-4/FIGURES/11

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. *EMNLP 2014 - 2014 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*, 1724–1734. https://doi.org/10.3115/v1/d14-1179

Christodoulou, E., Ma, J., Collins, G. S., Steyerberg, E. W., Verbakel, J. Y., & Van Calster, B. (2019). A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. *Journal of Clinical Epidemiology*, *110*, 12–22. https://doi.org/10.1016/J.JCLINEPI.2019.02.004

Çiftçi, Ş. K., & Yıldız, P. (2019). The Effect of Self-Confidence on Mathematics Achievement: The Meta-Analysis of Trends in International Mathematics and Science Study (TIMSS). *The Effect of Self-Confidence on Mathematics Achievement: … International Journal of Instruction*, *12*(2), 683. https://doi.org/10.29333/iji.2019.12243a

Courtial, E., & Garrouste, C. (2014). Model Predictive Control Strategy to Forecast Employability in Earth Sciences. *IFAC Proceedings Volumes*, *47*(3), 10731–10736. https://doi.org/10.3182/20140824-6-ZA-1003.02563

Elsharkawy, G., Helmy, Y. K., Yehia, E., & Helmy, Y. (2022). Employability Prediction of Information Technology Graduates using Machine Learning Algorithms. *Article in International Journal of Advanced Computer Science and Applications*, *13*(10), 2022. https://doi.org/10.14569/IJACSA.2022.0131043

Employability noun, Oxford Advanced Learner's Dictionary at OxfordLearnersDictionaries.com. (2024). https://www.oxfordlearnersdictionaries.com/definition/english/employability

Faccin, H., & de Andrade, T. A. N. (2025). Textual analysis of teaching–learning evaluations in higher education: Deep learning and lexical investigation approaches. *Expert Systems with Applications*, *265*, 125982. https://doi.org/10.1016/J.ESWA.2024.125982

García-Peñalvo, F., Cruz-Benito, J., Martín-González, M., Vázquez-Ingelmo, A., Sánchez-Prieto, J. C., & Therón, R. (2018). Proposing a Machine Learning Approach to Analyze and Predict Employment and its Factors. *International Journal of Interactive Multimedia and Artificial Intelligence*, *5*(Special Issue on Big Data and Open Education), 39–45. https://doi.org/10.9781/IJIMAI.2018.02.002

Girase, M., Lad, S., & Pachpande, P. (2018). Student's Employability Prediction Using Data Mining. *International Journal of Scientific & Engineering Research*, *9*(4). http://www.ijser.org

Gribble, C., & Blackmore, J. (2012). Re-positioning Australia's international education in global knowledge economies: implications of shifts in skilled migration policies for universities. *Journal of Higher Education Policy and Management*, *34*(4), 341–354. https://doi.org/10.1080/1360080X.2012.689181

Hinchliffe, G. W., & Jolly, A. (2011). Graduate identity and employability. *British Educational Research Journal*, *37*(4), 563–584.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/NECO.1997.9.8.1735

Hugo, L. S. (2018). *A Comparison of Machine Learning Models Predicting Student Employment*.

Jantawan, B., & Tsai, C.-F. (2013). The Application of Data Mining to Build Classification Model for Predicting Graduate Employment. *IJCSIS) International Journal of Computer Science and Information Security*, *11*(10). https://arxiv.org/abs/1312.7123v1

Jiang, L., Chen, Z., & Lei, C. (2023). Current college graduates' employability factors based on university graduates in Shaanxi Province, China. *Frontiers in Psychology*, *13*, 1042243. https://doi.org/10.3389/FPSYG.2022.1042243/BIBTEX

Khanmohammadi, S., Musharavati, F., & Tariq, R. (2022). A framework of data modeling and artificial intelligence for environmental-friendly energy system: Application of Kalina cycle improved with fuel cell and thermoelectric module. *Process Safety and Environmental Protection*, *164*, 499–516. https://doi.org/10.1016/J.PSEP.2022.06.029

Kumar, D., Verma, C., Singh, P. K., Raboaca, M. S., Felseghi, R. A., & Ghafoor, K. Z. (2021). Computational Statistics and Machine Learning Techniques for Effective Decision Making on Student's Employment for Real-Time. *Mathematics 2021, Vol. 9, Page 1166*, *9*(11), 1166. https://doi.org/10.3390/MATH9111166

Lemay, D. J., Baek, C., & Doleck, T. (2021). Comparison of learning analytics and educational data mining: A topic modeling approach. *Computers and Education: Artificial Intelligence*, *2*, 100016. https://doi.org/10.1016/J.CAEAI.2021.100016

Maaliw, R. R., Quing, K. A. C., Lagman, A. C., Ugalde, B. H., Ballera, M. A., & Ligayo, M. A. D. (2022). Employability Prediction of Engineering Graduates Using Ensemble Classification Modeling. *2022 IEEE 12th Annual Computing and Communication Workshop and Conference, CCWC 2022*, 288–294. https://doi.org/10.1109/CCWC54503.2022.9720783

Malika, S. M. M. (2024). DATA MINING FOR STUDENTS' EMPLOYABILITY PREDICTION. *Computer Science & Engineering: An International Journal (CSEIJ)*, *14*(1). https://doi.org/10.5121/cseij.2024.14101

Maniyan, S., Ghousi, R., & Haeri, A. (2024). Data mining-based decision support system for educational decision makers: Extracting rules to enhance academic efficiency. *Computers and Education: Artificial Intelligence*, *6*, 100242. https://doi.org/10.1016/J.CAEAI.2024.100242

matthews_corrcoef, scikit-learn 1.5.1 documentation. (2024). https://scikit-learn.org/stable/modules/generated/sklearn.metrics.matthews_corrcoef.html#sklearn.metrics.matthews_corrcoef

Matzavela, V., & Alepis, E. (2021). Decision tree learning through a Predictive Model for Student Academic Performance in Intelligent M-Learning environments. *Computers and Education: Artificial Intelligence*, *2*, 100035. https://doi.org/10.1016/J.CAEAI.2021.100035

Mishra, T., Kumar, D., & Gupta, S. (2016). Students' Employability Prediction Model through Data Mining. *International Journal of Applied Engineering Research*, 1–8.

Mishra, T., Kumar, D., & Gupta, S. (2017). Students' Performance and Employability Prediction through Data Mining: A Survey. *Indian Journal of Science and Technology*, *10*(24), 1–6. https://doi.org/10.17485/IJST/2017/V10I24/110791

Modibane, M. (2019). *A Machine Learning Approach to Predicting the Employability of a Graduate*.

Mohamed, S., & Ezzati, A. (2019). A data mining process using classification techniques for employability prediction. *Indonesian Journal of Electrical Engineering and Computer Science*, *14*(2), 1025–1029. https://doi.org/10.11591/ijeecs.v14.i2.pp1025-1029

Möller, J., Zitzmann, S., Helm, F., Machts, N., & Wolff, F. (2020). A Meta-Analysis of Relations Between Achievement and Self-Concept. *Review of Educational Research*, *90*(3), 376–419. https://doi.org/10.3102/0034654320919354/ASSET/IMAGES/LARGE/10.3102_0034654320919354-FIG1.JPEG

Moumen, A., El Bakkouri, I., Kadimi, H., Zahi, A., Sardi, I., Tebaa, M. S., Bousserrhine, Z., & Baraka, H. (2022). *Machine Learning for Students Employability Prediction*. 274–278. https://doi.org/10.5220/0010732400003101

Mpia, H. N., Mburu, L. W., & Mwendia, S. N. (2023). CoBERT: A Contextual BERT model for recommending employability profiles of information technology students in unstable developing countries. *Engineering Applications of Artificial Intelligence*, *125*, 106728. https://doi.org/10.1016/J.ENGAPPAI.2023.106728

Okoye, K., Nganji, J. T., Escamilla, J., & Hosseini, S. (2024). Machine learning model (RG-DMML) and ensemble algorithm for prediction of students' retention and graduation in education. *Computers and Education: Artificial Intelligence*, *6*, 100205. https://doi.org/10.1016/J.CAEAI.2024.100205

Orosoo, M., Raash, N., Treve, M., Hassan, H. F., Alshammry, N., Ramesh, J. V. N., & Rengarajan, M. (2025). Transforming English language learning: Advanced speech recognition with MLP-LSTM for personalized education. *Alexandria Engineering Journal*, *111*, 21–32. https://doi.org/10.1016/J.AEJ.2024.10.065

Othman, Z., Shan, S. W., Yusoff, I., & Kee, C. P. (2018). Classification Techniques for Predicting Graduate Employability. *International Journal on Advanced Science, Engineering and Information Technology*, *8*(4–2), 1712–1720. https://doi.org/10.18517/IJASEIT.8.4-2.6832

Piad, K. C., Dumlao, M., Ballera, M. A., & Ambat, S. C. (2016). Predicting IT employability using data mining techniques. *2016 3rd International Conference on Digital Information Processing, Data Mining, and Wireless Communications, DIPDMWC 2016*, 26–30. https://doi.org/10.1109/DIPDMWC.2016.7529358

Pool, L. D., & Sewell, P. (2007). The key to employability: Developing a practical model of graduate employability. *Education and Training*, *49*(4), 277–289. https://doi.org/10.1108/00400910710754435/FULL/XML

Premathilaka, W. S. C. S., & Imalka, K. H. J. (2021). PREDICTING UNDERGRADUATES' EMPLOYABILITY USING NAÏVE BAYES CLASSIFICATION METHOD. *Https://Vau.Ac.Lk/VUIRC-2021/*. http://drr.vau.ac.lk/handle/123456789/396

QS Graduate Employability Rankings 2022. (2024). https://www.topuniversities.com/employability-rankings

Quintero-Gámez, L., Tariq, R., Sánchez-Escobedo, P., & Sanabria-Z, J. (2024). Data analytics and Artificial Neural Network framework to profile academic success: case study. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2024.2433807

Rahman, N. A. A., Tan, K. L., & Lim, C. K. (2017). Supervised and Unsupervised Learning in Data Mining for Employment Prediction of Fresh Graduate Students. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, 155–161.

Ramirez-Montoya, M. S., Morales-Menendez, R., Tworek, M., Escobar, C. A., Tariq, R., & Tenorio-Sepulveda, G. C. (2024). Complex competencies for leader education: artificial intelligence analysis in student achievement profiling. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2024.2378508

Rodway, P., & Schepman, A. (2023). The impact of adopting AI educational technologies on projected course satisfaction in university students. *Computers and Education: Artificial Intelligence*, *5*, 100150. https://doi.org/10.1016/J.CAEAI.2023.100150

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(3), e1355. https://doi.org/10.1002/WIDM.1355

Römgens, I., Scoupe, R., & Beausaert, S. (2020). Unraveling the concept of employability, bringing together research on employability in higher education and the workplace. *Studies in Higher Education*, *45*(12), 2588–2603. https://doi.org/10.1080/03075079.2019.1623770

Saad, M. S. M. (2014). Employers' perceptions of important employability skills required from Malaysian engineering and information and communication technology (ICT) graduates. *Global Journal of Engineering Education*.

Saidani, O., Menzli, L. J., Ksibi, A., Alturki, N., & Alluhaidan, A. S. (2022). Predicting Student Employability Through the Internship Context Using Gradient Boosting Models. *IEEE Access*, *10*, 46472–46489. https://doi.org/10.1109/ACCESS.2022.3170421

Saini, B., Mahajan, G., Sharma, H., & Ziniya. (2021). An Analytical Approach to Predict Employability Status of Students. *IOP Conference Series: Materials Science and Engineering*, *1099*(1), 012007. https://doi.org/10.1088/1757-899X/1099/1/012007

Sarker, S., Paul, M. K., Thasin, S. T. H., & Hasan, Md. A. M. (2024). Analyzing students' academic performance using educational data mining. *Computers and Education: Artificial Intelligence*, *7*, 100263. https://doi.org/10.1016/J.CAEAI.2024.100263

Segbenya, M., Bervell, B., Frimpong-Manso, E., Otoo, I. C., Andzie, T. A., & Achina, S. (2023). Artificial intelligence in higher education: Modelling the antecedents of artificial intelligence usage and effects on 21st century employability skills among postgraduate students in Ghana. *Computers and Education: Artificial Intelligence*, *5*, 100188. https://doi.org/10.1016/J.CAEAI.2023.100188

Sein Minn. (2022). AI-assisted knowledge assessment techniques for adaptive learning environments. *Computers and Education: Artificial Intelligence*, *3*, 100050. https://doi.org/10.1016/J.CAEAI.2022.100050

Srinivasan, V., & Murthy, H. (2021). Improving reading and comprehension in K-12: Evidence from a large-scale AI technology intervention in India. *Computers and Education: Artificial Intelligence*, *2*, 100019. https://doi.org/10.1016/J.CAEAI.2021.100019

Sun, T., & He, Z. (2023). Developing intelligent hybrid DNN model for predicting students' employability – A Machine Learning approach. *Journal of Education, Humanities and Social Sciences*, *18*, 235–248. https://doi.org/10.54097/EHSS.V18I.11000

Tariq, R., Ali, M., Sheikh, N. A., Shahzad, M. W., & Xu, B. Bin. (2023). Deep learning artificial intelligence framework for sustainable desiccant air conditioning system: Optimization towards reduction in water footprints. *International Communications in Heat and Mass Transfer*, *140*(December 2022), 106538. https://doi.org/10.1016/j.icheatmasstransfer.2022.106538

Tariq, R., Mohammed, A., Alshibani, A., & Ramírez-Montoya, M. S. (2024). Complex artificial intelligence models for energy sustainability in educational buildings. *Scientific Reports 2024 14:1*, *14*(1), 1–17. https://doi.org/10.1038/s41598-024-65727-5

Tariq, R., Sheikh, N. A., Livas-García, A., Xamán, J., Bassam, A., & Maisotsenko, V. (2021). Projecting global water footprints diminution of a dew-point cooling system: Sustainability approach assisted with energetic and economic assessment. *Renewable and Sustainable Energy Reviews*, *140*(110741). https://doi.org/10.1016/j.rser.2021.110741

Tariq, R., Tariq, R., Casillas-Muñoz, F., Hassan, S., & Ramírez-Montoya, M. (2024). Synergy of Internet of Things and Education: Cyber-physical Systems... *Journal of Social Studies Education Research*, *15*(2), 305–352. https://www.learntechlib.org/p/224826/

Thakar, P., Mehta, A., & Manisha. (2017). A unified model of clustering and classification to improve students' employability prediction. *International Journal of Intelligent Systems and Applications*, *9*(9), 10–18. https://doi.org/10.5815/IJISA.2017.09.02

Thakar, P., Scholar, R., & Professor, A. (2017). Role of Secondary Attributes to Boost the Prediction Accuracy of Students Employability Via Data Mining. *International Journal of Advanced Computer Science and Applications*, *6*(11). https://doi.org/10.14569/ijacsa.2015.061112

Tight, M. (2023). Employability: a core role of higher education? *Research in Post-Compulsory Education*, *28*(4), 551–571. https://doi.org/10.1080/13596748.2023.2253649

Usita, M. M. (2022). Graduates Employability Analysis using Classification Model: A Data Mining Approach. *Journal of Positive School Psychology* , *6*(3), 2788-2796–2788–2796. https://mail.journalppw.com/index.php/jpsp/article/view/2055

van Hooft, E. A. J., Kammeyer-Mueller, J. D., Wanberg, C. R., Kanfer, R., & Basbug, G. (2021). Job search and employment success: A quantitative review and future research agenda. *Journal of Applied Psychology*, *106*(5), 674–713. https://doi.org/10.1037/APL0000675

Vo, M. T., Nguyen, T., & Le, T. (2023). OPT-BAG Model for Predicting Student Employability. *Computers, Materials & Continua*, *76*(2), 1555–1568. https://doi.org/10.32604/CMC.2023.039334

Wan Pauzi, W. N. D., Hasan, H., & Mahmud, Z. (2021). Supervised and Unsupervised Data Mining Techniques on Employability of Public Higher Learning Institute Graduates in Malaysia. *Journal of Physics: Conference Series*, *2084*(1), 012004. https://doi.org/10.1088/1742-6596/2084/1/012004

Wang, Y. (2024). Prediction of Student Employability through Internship based on Big Data Analysis. *Journal of Electrical Systems*, *20*(3s), 2749–2761. https://doi.org/10.52783/JES.3171

Working age population, OECD. (n.d.). Retrieved August 8, 2024, from https://www.oecd.org/en/data/indicators/working-age-population.html

Xu, X. (2024). Forecasting Student Employment Trends in Colleges and Universities Education Using Time Series Analysis Algorithms. *Journal of Electrical Systems*, *20*(6s), 2166–2177. https://doi.org/10.52783/JES.3131