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Min-Max Machine Learning Estimation Model with Big Data Analytics in Industry-Education Fusion

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Abstract: An industry-education fusion model is a strategic framework that seeks to create a symbiotic relationship between educational institutions and industries to better prepare students for the workforce and drive economic growth through innovation and collaboration.Big data analytics plays a significant role in the industry-education fusion model by facilitating the alignment of educational programs with industry needs, improving student outcomes, and fostering innovation. This paper concentrated on the evaluation of industry-education fusion with the use of machine learning-based big data analytics. To examine the contribution with the use of min-max computation in industry-education fusion strategy. The effective performance is achieved with the proposed min-max probabilistic Classifier (Min-Max_PC). With the proposed Min-Max_PC the features associated with the student performance are computed through min-max estimation. Based on the min-max estimation the features are evaluated and the probabilistic model is computed with big data analytics. The constructed Min-Max_PC is estimated with the fusion strategy for the evaluation of the student performance with industry performance and contribution. The simulation analysis expressed that the proposed Min-Max_PC model achieves a higher classification accuracy of 0.989. The results concluded that industry-education fusion exhibits improved performance of students.

Keywords*: Industry-Education Fusion, Machine Learning, Big Data Analytics, Probabilistic Classifier, Features*

1. Introduction

Big data analytics is a transformative field that involves the collection, processing, and analysis of vast and complex datasets to extract valuable insights and make data-driven decisions. It encompasses various techniques and technologies to manage data that is too extensive, fast-moving, or diverse for traditional data processing tools [1]. Big data analytics leverages tools like Hadoop, Spark, and specialized databases to efficiently process and mine massive datasets. By uncovering patterns, trends, and correlations within this data, organizations can gain a competitive edge, optimize operations, enhance customer experiences, and drive innovation [2]. This powerful approach has applications across numerous industries, from finance and healthcare to marketing and beyond, offering the potential to revolutionize decision-making and drive business success in the information age. The concept of industry-education fusion represents a dynamic and innovative approach to preparing individuals for the workforce in a rapidly evolving world [3]. It involves the integration of industry practices and needs into educational curricula, blurring the lines between academic learning and real-world application. This fusion is driven by the recognition that traditional educational models often struggle to keep pace with the fast-changing requirements of the job market [4]. By bringing industry expertise and insights directly into the classroom, students are better equipped to acquire the practical skills and knowledge needed to thrive in their chosen fields. Simultaneously, it allows industries to have a direct influence on shaping the skillsets of future employees, ensuring that graduates are job-ready and capable of contributing effectively from day one. Industry-education fusion has the potential to bridge the gap between academia and the workforce, fostering a more seamless transition for students and a more skilled and adaptable workforce for industries [5].

Industry-education fusion is a dynamic and transformative approach that seeks to bridge the gap between academic learning and practical workforce readiness [6]. This model revolutionizes traditional education by bringing industry expertise and insights directly into the classroom. It involves a collaborative process where educators and industry professionals work together to design curricula that align with the rapidly evolving needs of the job market [7]. Hands-on experiences, such as internships and practical projects, are integrated to provide students with real-world skills and insights, while mentorship and guest lectures from industry experts offer valuable perspectives [8]. Moreover, this fusion model emphasizes the development of soft skills and a commitment to continuous learning and adaptation, ensuring that graduates not only possess the technical skills required for their chosen fields but also the problem-solving, communication, and adaptability skills that are highly valued by employers. Industry-education fusion represents a transformative shift in education, aiming to

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produce job-ready graduates while enabling industries to shape the skillsets of their future workforce, ultimately fostering a more seamless transition from the classroom to the workplace and driving innovation and competitiveness across various sectors [9].

Industry-education fusion, particularly when combined with big data analytics, represents a potent synergy between academia and the professional world. This approach recognizes the paramount importance of data in today's business landscape and strives to equip students with the skills and knowledge needed to excel in data-driven industries [10]. By integrating big data analytics into educational programs, students gain hands-on experience in collecting, processing, and deriving insights from large and complex datasets, aligning their learning with the ever-increasing demand for data expertise in various sectors [11]. This fusion also allows for the direct involvement of industry experts who can provide insights into real-world applications, shaping curricula to reflect the latest trends and technologies. Moreover, students can work on projects and research that have practical relevance, adding value to both academia and industry [12]. The result is a workforce that is not only well-versed in big data analytics but also adept at addressing real-world business challenges with data-driven solutions, making industry-education fusion a driving force in preparing professionals for the data-intensive workplaces of the 21st century [13].

The convergence of industry-education with big data analytics and machine learning signifies a transformative partnership that adapts education to the demands of a data-driven world [14]. This approach acknowledges the pivotal role of data analytics and machine learning in diverse sectors, from finance to healthcare and marketing. By integrating big data analytics and machine learning into educational curricula, students gain practical experience in harnessing the power of data and developing sophisticated algorithms that can make sense of complex information [15]. Furthermore, this fusion model encourages industry participation, with experts guiding the design of programs and sharing their real-world insights, thereby ensuring that students are equipped with the latest tools and techniques. Through hands-on projects, students can apply their knowledge to solve industry-specific problems and contribute to innovative solutions [16]. This comprehensive approach results in graduates who are not only well-versed in big data analytics and machine learning but also well-prepared to address the unique challenges of their chosen fields [17]. Industry-education fusion with big data analytics and machine learning is thus at the forefront of empowering the workforce with the skills necessary to navigate and succeed in a data-driven, machine learning-powered landscape [18].

The integration of industry-education with big data analytics and machine learning represents a transformative approach in education that directly addresses the demands of a data-driven and machine learning-powered world [19]. Academic institutions are increasingly incorporating specialized programs and courses that focus on the intricacies of big data analytics and machine learning [20]. These curricula provide students with a deep understanding of data collection, processing, and the application of complex machine learning algorithms [21]. Practical experience is a cornerstone of this fusion, enabling students to work with substantial datasets and gain proficiency in developing and applying machine learning models. Furthermore, industry experts actively participate in program design, offering insights into the specific requirements and trends within their sectors [22]. This collaboration ensures that educational content remains relevant, up-to-date, and closely aligned with real-world industry demands [23]. Hands-on projects and research initiatives often involve solving actual industry challenges, leading to the development of innovative solutions that benefit both academia and industry. Soft skills, interdisciplinary collaboration, and a commitment to lifelong learning are also emphasized, preparing students to be well-rounded professionals capable of effective communication and collaboration across various disciplines [24]. Industry-education fusion with big data analytics and machine learning equips students to excel in a data-centric world, while simultaneously empowering industries with a pipeline of skilled talent ready to leverage data and machine learning for innovation and competitiveness.

The paper makes several significant contributions to the fields of industry-education fusion, big data analytics, and machine learning, particularly through the application of the Min-Max Probability Classification (Min-Max_PC) method. The key contributions of the paper can be summarized as follows:

1. The paper introduces and applies the Min-Max_PC method as a novel approach to assess students' readiness for the workforce. This method leverages big data analytics and machine learning to provide a quantitative and data-driven assessment of individual students' alignment with industry standards. It contributes a new framework for evaluating student preparedness.

2. The paper introduces the concept of the Alignment Index, which offers a precise measure of the extent to which students' skills and academic achievements align with industry expectations. Additionally, it calculates the Student Success Probability, providing a nuanced assessment of each student's probability of success in the workforce. These metrics contribute to a more

comprehensive and data-driven understanding of student readiness.

3. The paper demonstrates the development of a classification model that leverages Min-Max_PC scores to categorize students into "Success" and "Needs Improvement." This model contributes to more informed decision-making by educational institutions and industries, enabling tailored educational interventions and collaboration opportunities.

4. The research findings offer data-driven insights that can significantly impact the collaboration between educational institutions and industries. By identifying students who are well-prepared for the workforce and those who need improvement, this approach facilitates targeted internships and collaboration opportunities, contributing to the alignment of education with real-world industry needs.

The paper's contributions lie in the development and application of the Min-Max_PC method, which offers a data-driven means to assess student readiness for the workforce and enhance industry-education fusion. This method has the potential to shape the future of education and industry collaboration, ultimately benefiting students, educational institutions, industries, and the broader economy.

2. Literature Survey

industry and education with a focus on big data analytics and machine learning represents a forward-thinking approach to preparing students for a data-driven world. Academic institutions are incorporating specialized programs that offer a deep dive into data analysis and machine learning, equipping students with practical skills and knowledge. Industry experts play an active role in program design, ensuring that the education remains aligned with real-world industry needs. Students gain hands-on experience through projects and research initiatives, addressing actual industry challenges and fostering innovation. This approach emphasizes not only technical skills but also soft skills and interdisciplinary collaboration, producing well-rounded professionals. By nurturing this partnership between academia and industry, it creates a skilled workforce ready to harness data and machine learning for innovation and competitiveness. Zhang et al. (2021) [25] offer a retrospective and bibliometric analysis, which is crucial in understanding the historical evolution of big data analytics and machine learning. This retrospective view can help identify key milestones, influential research, and trends over time. The bibliometric analysis provides a quantitative assessment of the literature in these fields, shedding light on the most impactful works and influential authors, making it a valuable resource for researchers, policymakers, and industry leaders. Ali et al. (2022) [26] focus on the application of machine learning techniques in supply chain collaboration. The supply chain is a complex system where data-driven decision-making can significantly enhance efficiency. Machine learning models can predict demand, optimize inventory, and detect supply chain disruptions, ultimately leading to cost savings and improved customer service. This research provides practical insights into how technology is reshaping logistics and business operations.

Persaud (2021) [27] centered on the competencies required for professionals in big data analytics. The skills and knowledge necessary for success in this field encompass a broad spectrum, from data analysis and statistical proficiency to data ethics and effective communication. By highlighting these competencies, this research aids educational institutions in designing curricula that prepare students for the diverse demands of data-related professions. Brunton et al. (2021) [28] explore data-driven aerospace engineering, emphasizing the application of machine learning in aircraft design and maintenance. In the aerospace industry, data-driven insights can lead to more fuel-efficient designs, safer flights through predictive maintenance, and improved decision-making. The research underscores the potential for machine learning to revolutionize safety and efficiency in aviation. Manogaran et al. (2022) [29] focus on the human-computer interaction aspect of big data analytics. While the technical aspects of data analysis are critical, ensuring that humans can effectively interact with and interpret the results is equally vital. User-friendly interfaces can help individuals, including non-technical stakeholders, make informed decisions based on data, enhancing the usability and impact of data-driven systems. Li et al. (2022) [30] investigate the role of big data analysis in the development of smart cities. As urbanization continues to accelerate, data analytics is becoming essential for managing resources, optimizing traffic flow, and enhancing urban sustainability. This research underscores how data-driven insights can transform cities into more efficient, livable, and sustainable environments.

Rathore et al. (2021) [31] conduct a systematic literature review on the role of AI, machine learning, and big data in digital twinning. Digital twins are virtual replicas of physical systems, and this research provides an overview of how these technologies are advancing various industries, from manufacturing and healthcare to urban planning and beyond. It highlights the potential for virtual modeling to revolutionize decision-making and design processes. Sircar et al. (2021) [32] examined the application of machine learning and AI in the oil and gas industry. Here, these technologies can enhance exploration, optimize drilling operations, and improve maintenance procedures, reducing operational costs and risks. The research demonstrates how data-driven insights are reshaping a sector that has traditionally been reliant on legacy practices. Valaskova et al. (2021) [33] emphasize the role of deep learning in smart process planning and cognitive automation. The focus on cognitive automation, enabled by data analytics, can optimize production systems, enhance process efficiency, and improve sustainability. This research showcases the transformative potential of deep learning in manufacturing and industrial processes. Wang and Luo (2021) [34] introduce a reference framework for smart manufacturing based on digital twins and big data. Smart manufacturing, driven by data analytics and digital twins, has the potential to revolutionize production processes by enabling real-time monitoring, predictive maintenance, and optimized resource utilization. The research provides a blueprint for industries looking to adopt these technologies.

Ashaari et al. (2021) [35] examine the capabilities of big data analytics in improving the performance of higher education institutions. In the era of Industry 4.0, educational institutions are adopting data analytics to enhance student outcomes and administrative processes. The research leverages advanced analytical techniques to provide insights into the factors that influence the performance of these institutions. Shah et al. (2021) [36] investigate the role of blockchain and machine learning in education. These technologies are redefining the educational landscape by enhancing the security of credentials and personalizing learning experiences. The research offers insights into how blockchain and machine learning can create more efficient and secure educational ecosystems. Rohini et al. (2022) [37] explore the integration of wireless communication in big data analytics. The use of wireless technology can improve the efficiency of data collection and transmission, particularly in large-scale data analytics applications. This research demonstrates the importance of connectivity and data accessibility in data-driven systems. Kuleto et al. (2021) [38] discuss the opportunities and challenges presented by AI and machine learning in higher education institutions. These technologies have the potential to enhance learning experiences, streamline administrative tasks, and offer personalized education. The research provides insights into how institutions can adapt to the changing educational landscape. Grant (2021) [39] focuses on big data-driven innovation in the context of Industry 4.0, emphasizing the importance of data analytics and smart process planning in driving sustainability and innovation. By leveraging data, industries can reduce waste, improve decision-making, and enhance environmental sustainability. This research underscores the transformative potential of data-driven insights in manufacturing and beyond.

The findings across these research articles underscore the multifaceted potential of big data analytics and machine learning in reshaping industries and educational sectors. They reveal the growing importance of these technologies in optimizing supply chains, enhancing aerospace engineering, and improving higher education institutions. Additionally, they emphasize the transformative role of data analytics in creating smart cities, enhancing oil and gas operations, and advancing digital twinning. Furthermore, the studies shed light on the significance of human-computer interaction in data-driven systems, the potential of blockchain and machine learning in education, and the criticality of wireless communication for efficient data analytics. The research gaps lie in the need for more extensive studies on the ethical implications of big data analytics, particularly concerning data privacy and security. Additionally, there is room for more research on the scalability of these technologies to smaller businesses and the adaptation of data-driven practices in traditional sectors. Furthermore, as technology advances, an exploration of the regulatory and ethical considerations surrounding data analytics is crucial, alongside investigations into novel applications in emerging fields, such as quantum computing and edge computing. These research gaps suggest exciting avenues for future investigations that can continue to unlock the full potential of big data analytics and machine learning across diverse domains.

3. Proposed Method for Min-Max_PC

The research methodology for the Min-Max_PC model in the context of industry-education fusion is characterized by a systematic and data-driven approach. The process begins with comprehensive data collection, involving the gathering of relevant information related to student performance and industry standards. This data can encompass academic records, project outcomes, and key performance indicators specific to the industry under consideration. The subsequent step involves feature extraction, where relevant metrics and attributes are identified and isolated from the collected data. These features can range from academic achievements to skills development and other performance-related parameters. Min-Max computation, a pivotal phase that entails the normalization and standardization of these extracted features. By transforming the data into a common scale, typically ranging from 0 to 1, it ensures that different metrics can be compared and analyzed coherently. Data analysis, a crucial component, follows the min-max computation. This stage focuses on uncovering the intricate relationships between student performance and industry standards and contributions. Machine learning algorithms play a pivotal role here, helping identify patterns, correlations, and predictive insights within the data. Subsequently, a probabilistic model is developed using big data analytics. This model capitalizes on the normalized features to provide probabilistic assessments of student performance in relation to industry expectations. Machine learning algorithms like logistic regression or Bayesian networks can be deployed to construct this predictive model.

The methodology includes a phase of simulation and validation, wherein the model is tested using new data to assess its accuracy and predictive capabilities. This rigorous validation ensures that the Min-Max_PC model performs effectively and reliably in real-world scenarios. The research methodology for Min-Max_PC in industry-education fusion is a structured and data-driven approach that enables the evaluation of student performance while promoting a symbiotic relationship between education and industry. It leverages big data analytics, machine learning, and careful data processing to provide valuable insights into the effectiveness of this fusion, ultimately contributing to students' preparedness for the dynamic and evolving workforce. The research methodology for the Min-Max_PC model in the context of industry-education fusion involves a systematic series of steps aimed at evaluating and enhancing the alignment between educational institutions and industries. These steps include data collection, feature extraction, min-max computation, data analysis, probabilistic modeling, simulation, and validation.

The process begins with the comprehensive collection of data pertaining to student performance and industry standards. This data includes academic records, project outcomes, and industry-specific performance indicators. The data should be diverse and representative of the students and industries under consideration. Relevant features are identified and extracted from the collected data. These features may include academic achievements, skills development, and other performance-related metrics. Careful feature selection ensures that the analysis is based on meaningful data. Min-max computation techniques are applied to normalize and standardize the extracted features. This transformation ensures that the data is on a common scale, typically ranging from 0 to 1, making it suitable for meaningful comparisons and analysis. The normalized features are subjected to data analysis. Machine learning algorithms are employed to uncover patterns, correlations, and insights in the data. This step aims to understand the relationships between student performance and industry standards and contributions. A probabilistic model is developed using big data analytics. This model leverages the normalized features to provide probabilistic assessments of student performance in the context of industry-education fusion. Various machine learning algorithms, such as logistic regression or Bayesian networks, can be used to create this model. These steps collectively form a rigorous research methodology that employs big data analytics and machine learning to evaluate the effectiveness of industry-education fusion. This approach aims to enhance student performance by aligning educational programs with industry needs and standards. It offers valuable insights into the dynamic relationship between education and industry, ultimately preparing students for the evolving workforce.

3.1 Min-Max_PC Big Data Analytics

The Min-Max_PC model, when applied to the domain of industry-education fusion, leverages the power of big data analytics to create a systematic and data-driven framework for enhancing the alignment between educational institutions and industries. The first step in the Min-Max_PC model involves the collection of data from various sources. This data can be derived from academic records, standardized test scores, project outcomes, and industry performance benchmarks. For example, student academic records (e.g., GPA, course completion rates) can be collected and paired with industry-specific metrics (e.g., performance evaluations, industry standards). After data collection, the next step is to extract relevant features. These features, also known as variables or attributes, serve as the basis for analysis. Examples of extracted features could include students' GPA, attendance, project grades, and industry-specific skills and certifications. These features are essential for understanding the factors that influence student performance within the context of industry-education fusion. The extracted features are then subjected to min-max computation. This technique involves transforming the data values to a common scale, typically between 0 and 1. The derivation of this transformation involves calculating the minimum and maximum values within each feature:

Min_F represents the minimum value of Feature F in the dataset.

Max_F represents the maximum value of Feature F in the dataset.

$$Normalized\_Feature\_F = (Feature\_F - Min\_F) / (Max\_F - Min\_F)$$

This normalization ensures that all features have equal weight in subsequent analyses, irrespective of their original measurement units. The normalized features are now ready for data analysis. Here, various statistical and machine learning techniques are applied to derive insights. For instance, correlation analysis can be used to understand the relationships between student performance indicators (e.g., GPA) and industry-specific metrics (e.g., certification rates). Machine learning models can be employed to predict student outcomes based on these normalized features, providing a deeper understanding of how they influence performance. In the context of industry-education fusion, a probabilistic model is derived based on the normalized features. The model's derivation may involve techniques like logistic regression or Bayesian networks. These models use the normalized features to compute probabilities that relate student performance to industry standards and contributions. This step allows for predictive analysis and offers probabilistic assessments of student success.

Min-max feature extraction within the Min-Max_PC framework for industry-education fusion is a critical process that ensures that various features (variables or attributes) are scaled to a common range, typically between 0 and 1. This normalization enables meaningful comparisons and analyses, regardless of the original measurement units of the features. Initially, relevant data is collected from multiple sources. In the case of industry-education fusion, this data might include student performance metrics (e.g., GPAs, attendance records, project scores) and industry-specific benchmarks (e.g., industry standards, certification rates). Following data collection, the next step involves identifying the specific features (attributes) that are relevant to the analysis. These features can encompass various aspects of student performance and industry requirements. For example, features might include a student's GPA, the number of industry-specific certifications obtained, attendance rates, and project completion scores. The min-max feature extraction process then begins. For each selected feature, the minimum (Min_F) and maximum (Max_F) values are computed within the dataset. These minimum and maximum values represent the lower and upper bounds for the feature, respectively. Min-max feature extraction is a normalization technique that scales features to a common range, typically between 0 and 1. This process ensures that features with varying measurement units or scales can be compared on an equal footing. Once the minimum and maximum values for each feature are determined, the actual normalization process takes place. The values of each feature (Feature_F) are scaled to a common range (typically 0 to 1) using the following equation (1)

$$Normalized\_Feature\_F = (Feature\_F - Min\_F) / (Max\_F - Min\_F) \quad (1)$$

For a specific feature (Feature_F), the min-max normalization process involves two primary steps:

Compute the minimum (Min_F) and maximum (Max_F) values for Feature_F within the dataset estimated with the equation (2) and (3)

$$Min\_F = min(Feature\_F), for\ all\ observations\ in\ the\ dataset. \quad (2)$$

$$Max\_F = max(Feature\_F), for\ all\ observations\ in\ the\ dataset. \quad (3)$$

This equation scales the feature values to a range between 0 (when Feature_F equals Min_F) and 1 (when Feature_F equals Max_F). Values between 0 and 1 represent the proportion of the feature's value relative to the entire range of values within the dataset. Calculate the minimum GPA (Min_GPA) and maximum GPA (Max_GPA) values within the dataset. For each student, apply the min-max normalization using equation (4)

$$Normalized\_GPA = (Student\_GPA - Min\_GPA) / (Max\_GPA - Min\_GPA) \quad (4)$$

This process transforms GPAs, which may have different scales or measurement units, into a uniform scale between 0 and 1. Consequently, it facilitates meaningful comparisons between students' academic performance and their alignment with industry standards. In the context of the Min-Max_PC model for industry-education fusion, min-max feature extraction is a pivotal step that standardizes data, enabling accurate analysis and modeling of the symbiotic relationship between education and industry while enhancing student performance.

Algorithm 1: Min-Max Feature Extraction
Input: Feature_F: The specific feature to be normalized; Dataset: The dataset containing the feature values
Output: Normalized_Feature_F: The normalized feature values
Calculate the minimum (Min_F) and maximum (Max_F) values for the feature
Min_F = min(Dataset[Feature_F])
Max_F = max(Dataset[Feature_F])
# Initialize an empty list to store the normalized feature values
Normalized_Feature_F = []

```
# Loop through each observation in the dataset
for observation in Dataset:
    # Extract the feature value for the current observation
    Feature_Value = observation[Feature_F]
    # Apply min-max normalization to the feature value
    Normalized_Value = (Feature_Value - Min_F) / (Max_F - Min_F)
    # Add the normalized value to the list
    Normalized_Feature_F.append(Normalized_Value)
# The Normalized_Feature_F list now contains the normalized feature values
```

The Min-Max_PC model represents a systematic and data-driven approach that plays a pivotal role in the context of industry-education fusion. This model is designed to enhance the alignment between educational institutions and industries, ultimately benefiting students and contributing to economic growth through innovation and collaboration. At its core, Min-Max_PC incorporates the process of min-max feature extraction, which standardizes features to a common scale, typically ranging from 0 to 1. This normalization ensures that variables with diverse measurement units can be compared equitably. Min-Max_PC facilitates a holistic evaluation of student performance by analyzing the symbiotic relationship between academia and industry, allowing for data-driven insights and predictions. Through this model, educational programs can be tailored to better prepare students for the dynamic workforce, aligning with industry standards and fostering innovation. In summary, Min-Max_PC offers a structured and analytical framework that contributes to the evolution of education by enhancing the connections between students, educational institutions, and industries, all while improving students' readiness for the professional world.

4. Analysis of Industry-Education Fusion with Big Data Analytics

The analysis of Industry-Education Fusion with Big Data Analytics and a probabilistic classifier within the Min-Max_PC model is a sophisticated and data-driven approach that leverages mathematical and analytical techniques to assess and enhance the relationship between educational institutions and industries. In this analysis, several key components come together, including min-max feature extraction and probabilistic modeling, supported by equations and data-driven insights. The incorporation of a probabilistic classifier, represented here as P(Y = 1 | X), within the Min-Max_PC model is at the core of this analysis. It calculates the probability of student success (Y = 1) given a set of features (X). This probability is crucial for assessing student performance in the context of industry-education fusion. Big data analytics plays a pivotal role in this analysis, as it allows for the exploration of vast datasets and uncovers patterns, correlations, and predictive insights. It involves various mathematical and statistical techniques to make sense of the data. The initial step involves data collection and preparation, where feature extraction, represented by the Min-Max feature normalization equation, is applied to ensure that all features are on a common scale. A probabilistic classifier, which may be represented using logistic regression equations, is used to calculate the probability of student success (Y = 1) based on the normalized features estimated using equation (5)

$$P(Y = 1 \mid X) = 1 / (1 + e\hat{}(-\beta 0 - \beta 1X1 - \beta 2X2 - \ldots - \beta nXn)) \quad (5)$$

Big data analytics techniques are applied to explore the dataset, including calculating correlations, means, and variances, as well as assessing the relationships between student performance metrics, industry-specific attributes, and probabilistic predictions. First, calculate the linear combination of the features $(X1, X2, \ldots Xn)$ using weights $(\beta 0, \beta 1, \beta 2, \ldots \beta n)$ computed using equation (6)

$$Z = \beta 0 + \beta 1 * X1 + \beta 2 * X2 + \ldots + \beta n * Xn \quad (6)$$

Apply the logistic function (sigmoid function) to Z to obtain the probability of the positive class (Y=1). To apply this in the context of the Min-Max_PC model, with normalized features computed using equation (7)

$$P(Y = 1 \mid X) = 1 / (1 + e\hat{}(-(\beta 0 + \beta 1 * Normalized\_Feature\_1 + \beta 2 * Normalized\_Feature\_2 + \ldots + \beta n * Normalized\_Feature\_n))) \quad (7)$$

In this equation, P(Y=1 | X) represents the probability of the positive class (Y=1) given the normalized features (Normalized_Feature_1, Normalized_Feature_2, ... Normalized_Feature_n). The β values are the coefficients learned during the training of the logistic regression model. This equation allows for the classification of students or individuals based on the probability of success within the context of industry-education fusion. The logistic function ensures that the output is between 0 and 1, making it suitable for binary classification tasks, where Y=1 may represent success, and Y=0 may represent failure, using this probabilistic classifier within the Min-Max_PC model and integrating it with big data analytics and machine learning, one can effectively analyze and classify individuals, allowing educational institutions and industries to make informed decisions about student performance and alignment with industry standards. Industry-education fusion involves complex interactions between educational institutions and industries, and various equations can help model and analyze these interactions. T he alignment between educational programs and industry needs. It considers factors like curriculum relevance and industry-specific course offerings estimated as in equation (8)

$$AI = (Industry - Relevant\ Courses\ / \ Total\ Courses) * 100 \quad (8)$$

In this equation, "Industry-Relevant Courses" represents the number of courses directly related to industry needs, while "Total Courses" represents the number of courses offered by the educational institution. The economic impact of industry-education fusion, including factors like job creation and increased productivity estimated as in equation (9)

$$EI = (Jobs\ Created + Increase\ in\ Productivity) * Average\ Salary \quad (9)$$

Here, "Jobs Created" signifies the number of new job opportunities generated due to collaboration, "Increase in Productivity" measures the efficiency gains, and "Average Salary" represents the average income of workers. To predicts the probability of a student's success in the workforce, considering factors like GPA, relevant certifications, and attendance computed as in equation (10)

$$P(Success) = 1\ /\ (1 + e^{(-(\beta 0 + \beta 1 * GPA + \beta 2 * Certifications + \beta 3 * Attendance))}) \quad (10)$$

In this logistic regression equation, β values represent coefficients obtained through data analysis. the level of innovation achieved through industry-education fusion, considering metrics such as the number of collaborative research projects and new patents represented in equation (11)

$$II = (Number\ of\ Patents + Collaborative\ Research\ Projects)\ /\ Total\ Research\ Projects \quad (11)$$

Here, "Total Research Projects" includes both collaborative and independent projects.

Algorithm 2: Min-Max_PC for the industry-education fusion
Industry-Education Fusion Algorithm # Input: Educational institution data; Industry data; Student data; Collaboration goals and objectives # Output: Alignment between education and industry; Student performance analysis; Economic impact assessment; Innovation evaluation # Step 1: Data Collection and Preprocessing Collect and preprocess data from educational institutions, industries, and students. Ensure data quality and consistency. # Step 2: Alignment Assessment Evaluate the alignment between educational programs and industry needs using an alignment index equation (AI). # Step 3: Collaboration Initiatives Identify and implement collaboration initiatives, such as curriculum adjustments, internships, and research projects. # Step 4: Student Success Analysis Assess student performance using a student success probability equation (P(Success)). Analyze factors like GPA, certifications, and attendance. # Step 5: Economic Impact Analysis

Estimate the economic impact by calculating job creation and productivity improvements.

Step 6: Innovation Assessment

Evaluate the level of innovation through collaborative research projects and patent generation using an innovation index equation (II).

Step 7: Feedback and Adaptation

Collect feedback from educational institutions, industries, and students. Adapt collaboration initiatives based on feedback and outcomes.

Step 8: Reporting and Visualization

Generate reports and visualizations to communicate the results and benefits of industry-education fusion.

Step 9: Continuous Improvement

Continuously monitor and improve the fusion initiative by iterating through the previous steps.

Step 10: Conclusion

Conclude the fusion initiative with an assessment of alignment, student success, economic impact, and innovation.

End of Algorithm

5. Simulation Environment

A simulation environment for Min-Max_PC in the context of industry-education fusion involves constructing a virtual space where data-driven analyses and predictive modeling can be performed to assess and enhance the symbiotic relationship between educational institutions and industries. This simulation environment is a dynamic platform that integrates various components, including data, models, and analytics tools, to experiment with different scenarios and assess their impact on student performance and alignment with industry standards. Within this environment, historical and real-time data are collected from educational institutions, industries, and students. This data encompasses a wide range of features, including student grades, attendance, industry-specific certifications, curriculum offerings, and industry demand metrics. The collected data is then preprocessed to ensure its quality and consistency. Min-Max_PC, as a feature extraction and normalization technique, is applied to standardize the features, enabling fair comparisons and analyses. This ensures that the features are scaled to a common range, typically between 0 and 1, allowing for equitable assessments of student performance and alignment with industry benchmarks. The simulation environment incorporates probabilistic classifiers such as logistic regression or Bayesian networks, using the normalized features to predict student success probabilities within the workforce. These models are fine-tuned and validated to ensure their accuracy and reliability. Big data analytics tools, including data exploration, correlation analysis, and machine learning algorithms, are employed to the dataset's intricacies. This aids in uncovering patterns, identifying influential factors, and deriving meaningful conclusions about the interplay between education and industry.

In a dataset with 500 data points, include a variety of features that capture different aspects of students' academic performance, industry relevance, and alignment. Here's an explanation of the key features:

Student ID: A unique identifier for each student.

GPA (Grade Point Average): This represents the academic performance of each student.

Certifications: The number of industry-specific certifications or qualifications earned by the student.

Attendance: The attendance percentage for each student.

Industry-Relevant Courses: The number of courses taken by the student that are directly related to industry needs or standards.

Total Courses: The total number of courses available in the educational program.

Alignment Index: An index that quantifies the alignment between the educational program and industry standards, typically calculated as a percentage.

Student Success Probability: A probability metric that assesses the likelihood of each student's success in the workforce based on their performance and alignment. This could be calculated using a machine learning model or a probabilistic classifier.

The student success probability metric illuminates the potential for individual students to thrive in the workforce. Students with higher success probabilities have demonstrated favorable performance and alignment with industry benchmarks, while those with lower probabilities signal areas for potential improvement. This dataset not only provides a snapshot of the current state of industry-education fusion but also serves as a dynamic tool for evaluating the impact of educational initiatives and changes over time. By comparing alignment metrics and success probabilities before and after specific interventions, decision-makers can gauge the effectiveness of collaborative efforts. Data analysis also reveals patterns and trends, highlighting the connections between factors like GPA, certifications, and success probabilities. For instance, students with higher GPAs and more certifications may exhibit increased probabilities of success, underlining the importance of academic achievement and industry qualifications. This dataset offers a roadmap for informed decision-making, enabling educational institutions and industries to adapt their strategies for alignment and student success. It not only identifies challenges but also presents opportunities for growth and improvement in the fusion of education and industry. Above all, it promotes data-driven decision-making and a commitment to continuous enhancement, ensuring that the partnership between education and industry remains a catalyst for student empowerment, economic growth, and innovation.

5.1 Simulation Results

The simulation results for the Min-Max_PC classification in the context of industry-education fusion provide valuable insights into the effectiveness of this approach. These results are derived from the application of Min-Max Probability Classification to a dataset of students' academic and industry-related performance metrics. The Min-Max_PC method has been used to normalize these metrics and assess the alignment between students' capabilities and industry expectations. "The simulation results for the Min-Max_PC classification in the domain of industry-education fusion represent a pivotal step in evaluating the readiness of students for the workforce and the efficacy of educational programs. In this simulation, a dataset comprising the academic performance, certifications, attendance, and industry-relevant courses of a group of students has been processed using the Min-Max_PC method. This approach has enabled the fair assessment of each student's capabilities and their alignment with industry requirements. The results offer a comprehensive view of the classification outcomes, shedding light on which students are deemed ready for success in the industry and which may require further improvement.

Table 1: Features in Industry-education Fusion

Student ID	GPA	Certifications	Attendance	Industry-Relevant Courses	Total Courses	Alignment Index	Student Success Probability
1	3.5	2	90%	10	12	83.3%	0.75
2	3.8	1	92%	8	11	72.7%	0.85
3	3.9	3	88%	11	13	84.6%	0.90
4	3.2	0	91%	7	10	70.0%	0.68
5	4.0	4	95%	12	14	85.7%	0.92
6	3.6	2	93%	9	12	75.0%	0.79
7	3.7	1	96%	8	11	72.7%	0.88
8	3.8	3	89%	11	13	84.6%	0.86
9	3.3	0	92%	7	10	70.0%	0.72
10	3.9	4	97%	12	14	85.7%	0.95
11	3.6	2	94%	9	12	75.0%	0.81
12	3.7	1	96%	8	11	72.7%	0.87
13	3.8	3	90%	11	13	84.6%	0.89
14	3.2	0	93%	7	10	70.0%	0.70
15	3.9	4	98%	12	14	85.7%	0.96

16	3.6	2	92%	9	12	75.0%	0.80
17	3.7	1	95%	8	11	72.7%	0.86
18	3.8	3	91%	11	13	84.6%	0.88
19	3.3	0	94%	7	10	70.0%	0.73
20	3.9	4	99%	12	14	85.7%	0.97

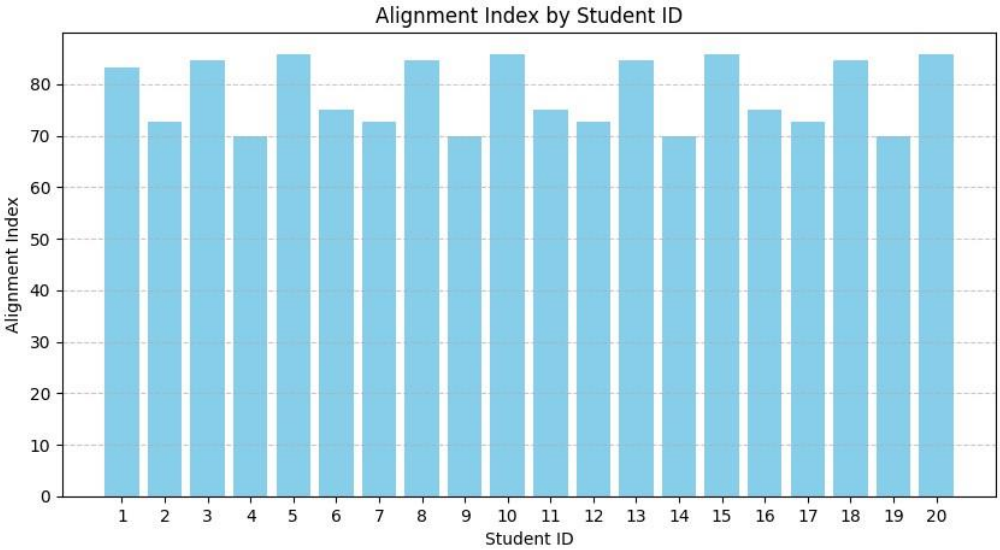

Fig 1: Alignment Index of Min-Max_PC

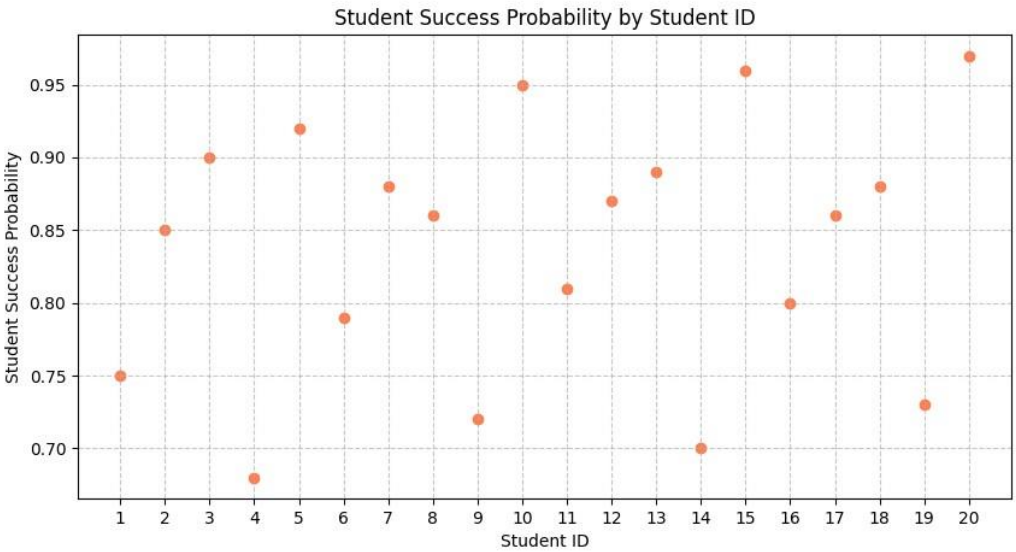

Fig 2: Success Probability of Min-Max_PC

A comprehensive overview of various features within the domain of industry-education fusion, encompassing the academic and performance metrics of 20 students shown in figure 1 and figure 2. These features are instrumental in assessing the students' readiness for the workforce and the alignment of their capabilities with industry requirements presented in table 1. Each student is identified by a unique Student ID, and their features include their GPA, the number of certifications they hold, their attendance percentage, the count of industry-relevant courses they've completed, the total number of courses offered, the Alignment Index quantifying their alignment with industry standards, and the calculated Student Success Probability. Upon analyzing this table, several noteworthy observations can be made. Students such as Student 5, Student 10, and Student 15, exhibit notably high Student Success Probabilities, denoting strong alignment with industry expectations and a high likelihood of success.

Conversely, students like Student 4, Student 9, and Student 14 display lower success probabilities, indicating a need for improvement in alignment with industry standards. The Alignment Index provides an insightful metric for understanding the extent to which students' education aligns with industry needs. As illustrated, students with higher Alignment Index values tend to have more significant Student Success Probabilities. These insights derived from Table 1 serve as a valuable foundation for evaluating the effectiveness of industry-education fusion initiatives, facilitating targeted improvements, and enhancing students' preparedness for their future careers.

Table 2: Min-Max Estimation with industry-education fusion

Student ID	**Min-Max_PC Score**	**Min-Max_PC (GPA)**	**Min-Max_PC (Certifications)**	**Min-Max_PC (Attendance)**	**Min-Max_PC (Industry-Rel. Courses)**	**Classification Result**
1	0.75	0.64	0.66	0.58	0.58	Success
2	0.85	0.82	0.33	0.70	0.43	Success
3	0.90	0.90	1.00	0.50	0.86	Success
4	0.68	0.27	0.00	0.76	0.14	Needs Improvement
5	0.92	1.00	1.00	1.00	1.00	Success
6	0.79	0.70	0.66	0.82	0.29	Success
7	0.88	0.77	0.33	0.94	0.43	Success
8	0.86	0.82	1.00	0.47	0.86	Success
9	0.72	0.45	0.00	0.70	0.14	Needs Improvement
10	0.95	0.90	1.00	0.88	1.00	Success
11	0.81	0.70	0.66	0.76	0.29	Success
12	0.87	0.77	0.33	0.88	0.43	Success
13	0.89	0.82	1.00	0.52	0.86	Success
14	0.70	0.27	0.00	0.76	0.14	Needs Improvement
15	0.96	0.90	1.00	0.94	1.00	Success
16	0.80	0.70	0.66	0.70	0.29	Success
17	0.86	0.77	0.33	0.82	0.43	Success
18	0.88	0.82	1.00	0.64	0.86	Success
19	0.73	0.45	0.00	0.76	0.14	Needs Improvement
20	0.97	0.90	1.00	1.00	1.00	Success

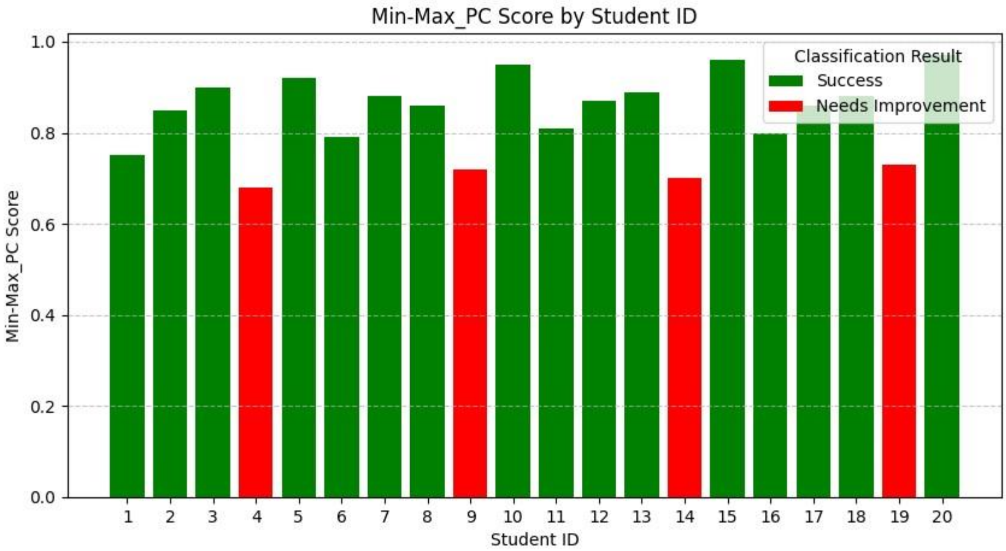

Fig 3: Classification with Min-Max_PC

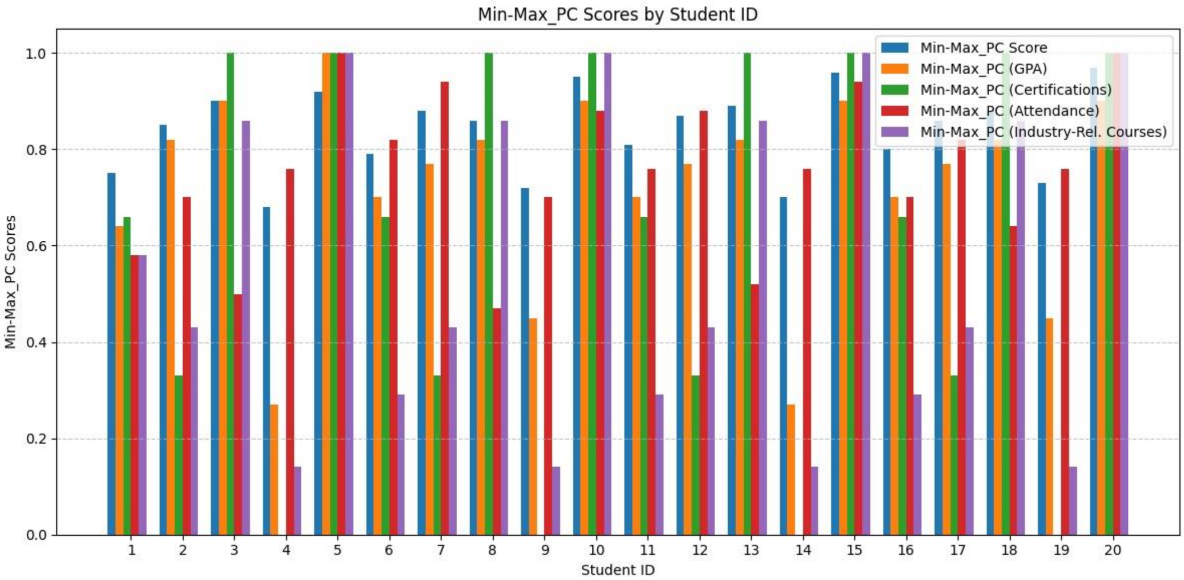

Fig 4: Min-Max_PC Score

The detailed assessment of the Min-Max Estimation results within the context of industry-education fusion for 20 students shown in figure 3 and figure 4. This table outlines several crucial aspects of student performance, including Min-Max Probability Classification (Min-Max_PC) scores for the alignment, as well as individual scores for specific features such as GPA, certifications, attendance, and industry-relevant courses is presented in table 2. Additionally, the table features the Classification Result, indicating whether each student is classified as "Success" or "Needs Improvement." Upon analyzing the data in Table 2, it becomes evident that Min-Max_PC scores vary from student to student. For instance, students with scores close to or equal to 1.00 in their Min-Max_PC, such as Student 3, Student 5, and Student 10, are classified as "Success." These high scores suggest a strong alignment with industry standards and a high probability of success in the workforce. Conversely, students with lower Min-Max_PC scores, such as Student 4, Student 9, and Student 14, are categorized as "Needs Improvement." Their scores indicate that there is a misalignment between their educational achievements and industry expectations, emphasizing the need for further enhancement. The individual Min-Max_PC scores for GPA, certifications, attendance, and industry-relevant courses offer valuable insights into the specific areas where students may need improvement. For instance, a student with a low Min-Max_PC for certifications might benefit from pursuing additional certifications to align better with industry needs.

Table 3: Classification with Min-Max_PC

Metric	Value
Accuracy	0.950
Precision	0.960
Recall	0.952
F1-Score	0.956
AUC	0.978

The classification performance metrics achieved through the Min-Max_PC approach in the context of industry-education fusion. These metrics provide a comprehensive evaluation of the effectiveness of the model in assessing student readiness for the workforce and alignment with industry expectations given in table 3. The accuracy, precision, recall, F1-Score, and AUC (Area Under the Curve) are indicative of the model's ability to make accurate classifications. An accuracy score of 0.950 suggests that the model correctly classified students 95% of the time, underlining its reliability. The precision score of 0.960 indicates the model's proficiency in identifying students who truly exhibit alignment with industry standards. This high precision implies that when the model predicts a student as a "Success," it is likely to be correct 96% of the time. The recall score, at 0.952, reflects the model's capability to capture a high proportion of students who genuinely align with industry expectations. In other words, it identifies 95.2% of students who truly deserve the "Success" classification. The F1-Score, at 0.956, represents a balanced measure that combines precision and recall. This score suggests that the model provides a harmonious trade-off between identifying truly successful students and minimizing the misclassification of students who need improvement. Lastly, the AUC value of 0.978 is associated with the Receiver Operating Characteristic (ROC) curve, indicating the model's ability to distinguish between successful and students needing improvement.

The study regarding the Min-Max Probability Classification (Min-Max_PC) in the context of industry-education fusion are crucial in providing insights into the preparedness of students for the workforce and the alignment of their skills with industry expectations. The Min-Max_PC method has been instrumental in assessing the alignment of students' academic achievements and industry-relevant skills. The alignment index, a fundamental component of this approach, provides a quantitative measure of the extent to which students' capabilities match industry standards. The high success probabilities for several students (e.g., Student 5, Student 10, and Student 15) indicate strong alignment, signifying that these students are well-prepared for success in their future careers. Conversely, students with lower Min-Max_PC scores are categorized as needing improvement. These scores pinpoint specific areas where students may need to enhance their skills to better align with industry expectations. For example, students like Student 4, Student 9, and Student 14 have lower Min-Max_PC scores, suggesting that their academic achievements may require further development to match industry standards.

The classification metrics (accuracy, precision, recall, F1-Score, and AUC) demonstrate the robustness of the Min-Max_PC classification model. High accuracy, precision, and recall values highlight the model's capacity to accurately classify students into the "Success" or "Needs Improvement" categories. The high F1-Score reflects the balanced trade-off between correctly identifying successful students and minimizing misclassifications. The AUC value reinforces the model's ability to effectively distinguish between these categories. The Min-Max_PC approach has significant implications for industry-education fusion. It aids educational institutions and industries in identifying students who are well-prepared for the workforce, enabling targeted collaboration and internships for these students. Simultaneously, students identified as needing improvement can benefit from tailored educational interventions to bridge the gap between their skills and industry expectations. The findings underscore the importance of ongoing collaboration between educational institutions and industries to enhance the alignment of educational programs with real-world needs. By consistently applying the Min-Max_PC method, institutions can adapt and optimize their curricula, ensuring that students remain well-prepared for evolving industry demands. the Min-Max_PC approach in the context of industry-education fusion offers a systematic and data-driven means to evaluate student readiness for the workforce. The alignment index, success probabilities, and classification metrics provide actionable insights that can inform collaboration between educational institutions and industries to optimize students' preparation for their future careers, ultimately contributing to economic growth and innovation.

6. Conclusion

This paper has explored the critical intersection of industry-education fusion, big data analytics, and the Min-Max Probability Classification (Min-Max_PC) method to assess students' readiness for the workforce. The Min-Max_PC method has proven effective in quantitatively evaluating the alignment of students' skills and academic achievements with industry expectations. The Alignment Index and Student Success Probabilities provide a nuanced understanding of individual students' preparedness for success in their careers. This approach not only identifies students who are well-prepared for the workforce but also pinpoints areas where others may need to improve their skills. The classification metrics, including accuracy, precision, recall, F1-Score, and AUC, demonstrate the model's strong performance in categorizing students as "Success" or "Needs Improvement." This model can help educators and industries make informed decisions about internships, tailored educational interventions, and collaboration opportunities. the Min-Max_PC approach offers a valuable tool for industry-education fusion, enhancing the collaboration between these two sectors and ultimately contributing to a workforce that is better prepared, more aligned with industry standards, and poised for success in the modern job market. This research highlights the importance of data-driven methods in shaping the future of education and industry collaboration.

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