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Data Analytics in Informatics Education: Measuring and Improving Student Outcomes

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Abstract – Upon finishing a course or program in higher education, students are expected to have learned and demonstrated the specified learning objectives. Another way of looking at it is as the end goal of learning, specifically the knowledge and abilities that are meant to be acquired. Incorporated into the course material. The delivery of targeted learning experiences and the subsequent assessment of student progress are essential for achieving learning outcomes. In the absence of clearly defined learning objectives and outcomes, the implementation of a program is likely to be disregarded. As a result, the program's evaluation strategy should incorporate all of the declared findings. Evaluations of student work reveal both the strengths and places for growth in terms of knowledge acquisition. This report examines the academic policies and practises of Srinivas Institute of Management Studies in Mangalore. Topics covered include the college's explicitly stated learning outcomes and the methods used to make them known to students and staff, the efforts made by the institution to track and share students' progress and performance throughout the program, the analysis of students' results to identify any discrepancies, the structure of the institution's teaching, learning, and assessment strategies to help students achieve these outcomes, and the initiatives and measures taken to make the courses more relevant to society and the economy.

Keywords—Student Performance in Higher Education Institution, Learning Outcomes, Higher Education.

I. INTRODUCTION

Universities nowadays are increasingly focusing on equipping students with both hard skills, such as professional talents and cognitive knowledge, and soft skills, such as problem-solving and collaborative abilities. Traditional education has long been the standard, with teachers playing the role of the transmitter of the knowledge and students playing the role of the receptor of the information. This makes it hard to achieve objectives that are associated with skills. Because of this, students may not be able to fully engage in class discussions and may end up learning only the bare minimum. Developing students' research ability is given more weight in university curricula, particularly at research universities, than teaching them marketable or professional skills. There may be a mismatch between what students learn at university and what companies need if this happens[1]. Providing students with opportunity to work on real-world challenges and get experience in professional settings is the suggested approach. Student achievement, problem behavior, and dropout rates could all benefit from a more positive school climate. The quality of interactions amongst all parties involved, including instructors, students, support staff, and parents is impacted by school climate, which is a reflection of the school's greater social and instructional aims. The school climate is comprised of various elements, including the caliber of teaching, the relationships within the school community, the school's structure and organization, and the general atmosphere. Thus, school is more than simply a place to study, it's also a place where students learn to express themselves, behaviorally, emotionally, grow socially, and form lasting friendships[2]. Mathematics gives one the mental tools to think critically and analytically. The iceberg is much larger than the sum of all measurements, counts, calculations. It should be read by all scientific sectors. Having students take an active role in the process of discovering and developing mathematical concepts is the main goal of mathematics education. One of the fascinating things about math education is how it teaches students to think analytically and critically in order to solve problems. These puzzles and problems stimulated people's imaginations and stimulated their curiosity[3]. Students' ability to think analytically, logically, and creatively is enhanced when problem-solving activities are included in the curriculum. The ability to solve mathematical problems is rapidly becoming a standard component of mathematics courses throughout. In addition, students need to learn how to correctly understand mathematical applications, and math lessons should make sense. Effective teaching strategies and tactics are fundamental for memorization of new information[4]. The effectiveness of a teacher's teaching is reflected in the level of understanding that students achieve in their class. Effective and successful teaching strategies center on helping students learn with comprehension. Students nowadays often have some say over when, where, and how much they study because of blended learning, which combines online resources with more conventional classroom education. Although there are other blended learning approaches, the flipped classroom model has proven to be the most effective. Instead of listening through teacher-led lectures, students in flipped classrooms—which were first popular in the United States are given homework or work on group projects outside of class. Particularly well-received by students was the convenience of pre-class video lectures, which they could view at their leisure. Students also greatly appreciated the use of small group discussion-based activities in the flipped classroom's in-person sessions. This was because the workshops increased students' enthusiasm, involvement, and drive to learn.

II. LITERATURE SURVEY

Using Machine Learning (ML) to improve learning environments is a win-win. It can track and analyze how students are learning in the classroom, forecast their academic performance so teachers can tailor their support accordingly, assess the effectiveness and efficiency of different teaching strategies, and give insightful comments to everyone involved. [5]implemented an Artificial Neural Network (ANN) prediction model for student performance by analyzing their own assessments. An ANN achieved a maximum classification accuracy of 95.35% in this investigation. They were used to calculate recall, accuracy, kappa statistics performance, precision as a statistical decision-making tool to find the best classification methods. To test a model based on ML for forecasting students' performance, [6] utilized Wolkite University as a case study. After pre-processing the data, the authors of this ref utilized Neural Networks (NNs), Naive Bayesian, and Support Vector Machine (SVM). In comparison to SVM and Multi-Layer Perceptron (MLP) network, the Naïve Bayesian approach achieved a performance of 95.8%, as reported by the Department of Information Technology. Using the Naive Bayes (NB) Algorithm, [7] were able to predict students' academic performance. The data reported here was obtained via a questionnaire with a scoring system for feedback. Using a prediction accuracy of 92.8%, the results show that the NB Algorithm can accurately anticipate students' performance in approximately 2 seconds. In their work, [8] looked at how to use learning analytics with Multiple linear regression to predict students' academic performance. The Statistical Package for the Social Sciences (SPSS) was utilized as the analytical instrument. A method called Linear Regression was used. Statistical hypothesis testing was then used to validate the model at a 5.2% significance level. Using information about kids' academic background, demographics, parental involvement, and behavioral behaviors, [9] developed a system to categorize students' grades into three groups. Although the authors explored a number of methods based on ensemble filtering, the results were best generated by the ANN model. In addition, utilizing normalized learning-behavior data, [10] published a ML method to classify students into the five conventional grading categories. A SVM model outperformed the other baseline models. Using a variety of machine models, [11] were able to classify students' performance into two or more groups according to their demographics and learning styles. Findings showed that Random Forest (RF) and Gradient Boosting (GB) were the two most effective approaches for binary and multiclass classification, respectively. In addition, with a few secondary factors, such as intermediate quiz performance and class attendance, learning behaviors were utilized by [12] to predict the learner's grade category. This reference tried K-Nearest Neighbor algorithm (KNN) in addition to SVM, but KNN ended up being the most accurate option. In order to forecast academic performance based on behavioral data, [13] presented a model. After analyzing a large number of ML models, and the authors found that RF performed the best. [14] proposed a NB algorithm using the Laplace smoothing approach to forecast students' performance and generate midterm-stage warnings. Using evaluation, attendance, and other learning-behavior factors, the model beat prior techniques on a one-course dataset. Using a Linear Regression model (LR) to estimate students' grades based on statistical variables extracted from log data, then used a Deep Neural Network (DNN) to categorize students into three categories. The students' assignment submission patterns and ARM scores were utilized by [15] to determine their course pass/fail status. In [16], a set of ML algorithms (ANN, Decision Tree (DT), and Batch Normalization (BN)) was used to build prediction models that took into account students' individual characteristics, their academic abilities, and input factors. To measure how well the forecast worked, the system looked at several metrics, including recovery rate and total accuracy rate. The following methods were proposed for similar jobs in [17], Deep Learning (DL), GB, linear models, DT, and NB. In terms of accuracy, DL and GB stood out. We can now anticipate dropout rates with the help of supervised learning methods, according to new research: Classifiers such as NB and SVM were proposed for a variety of uses, including but not limited to: predicting individual dropouts and detecting students struggling in the third week with a 97.4% accuracy rate [18]. Consequently, RF did a good job of predicting student dropout based on a number of binary classification performance metrics. In addition, ANN, SVM, LR, NB, and DT were investigated for comparable purposes in [19] using data acquired by e-learning technologies. In this case, ANN and SVM produced the best outcomes. When compared to other ML algorithm, NB fared better on an online tool that predicted how new students would do. When it came to predicting academic success, SVM outperformed the other three approaches analyzed in [20]. For the purpose of predicting the students' early performance (GPA), we also utilized Bayesian Belief Networks (BNNs). Also at this stage were LR and SVM useful. Nevertheless, the prediction systems can be made more accurate by performing extensive study and using a variety of algorithmic components.

III. Methodology

As several administrations have attempted to increase the sector's efficiency and hold it more responsible for the use of public monies, higher education (HE) has undergone a storm of transformation in the past three decades. One of the biggest problems that higher education is having right now is the increasing number of students, especially non-traditional students, and the demands to accommodate them. Accurately defining learning outcomes allows institutions to demystify and make education accessible to a wider audience, while also serving as a baseline for ensuring quality and efficiency in higher education.

A. Learning Analytics:

Learning Analytics (LA) has been defined and referred to in a variety of ways in both academic and popular circles due to its status as a relatively new field of study. The use of data analytics in educational settings is one definition of LA. Learners and their learning processes are the center of attention in LA, as opposed to academic analytics and educational data mining. Learner profiles, learning resources, and the learning environment are the three main components of learning analytics, which gather, integrate, and analyze both static and dynamic data. Scheduled or real-time predictions of learning elements and descriptive modelling are then possible.

1) Exploring the Varieties of Learning Analytics:

a) Content Analytics:

When it comes to providing contextualized interpretations of textual documents, one subset of learning analytics is content analysis. Analyzing texts for hidden meanings is the goal of content analysis, which can be done manually or with the help of computers. Literate text, iconic text, spoken text, audiovisual text, and hypertext are the five basic types of texts that can be found in an educational setting. online crawling and other machine learning algorithms are two examples of recent advances in online analytics that have sparked a fresh interest in studying websites' hypertext.

b) Social Learning Analytics:

A unique branch of learning analytics, social learning analytics places an emphasis on student-to-student communication and cooperation as a means of enhancing the learning process. Social Learning Analytics takes a social view of learning and argues that expanding one's horizons is about more than just academic success, in contrast to Discourse Analytics, which focuses on students' actual speech patterns in the classroom. Prior research on the effects of social networks on academic achievement provides a concise illustration of this point[21]. Case in point: investigated the connections between academic success and social network interactions using social network analysis (SNA). This study's results call for more investigation into the conditions under which social network metrics might serve as valid indicators of students' actual performance in the classroom. On the other hand, the research cautions against using social network elements as the exclusive basis for prediction. Additionally, the results of this study support the idea that data visualization can be a valuable asset to social learning analytics.

c) Discourse Analysis:

Analytical tracking of user interactions allows for the exploration of meaningful information regarding the language features utilized in the learning discourse. Discourse analytics looks at how students talk rather than what they write, whereas content analysis finds important information in texts. Using tools like online learning communities, discourse analytics can pick up on students' voices where they already congregate. Metadata and discourse data analytics have been made possible by the development of text mining and log tracking. In a similar vein, social learning analytics has grown in popularity among educators. In contrast to discourse analytics, which focuses on the language and substance of learned discourse, social learning analytics is more concerned with how students work together.

d) Applications:

Visualizations can be a practical way to bolster learning analytics reports and provide users with more useful information. Visualizations help in finding trends, patterns, connections, and critical concerns by graphically communicating massive volumes of complicated data. In the field of education, visualizations can be used to showcase analyzed data collected from both instructors and students. While utilizing visualization tools for learning analytics, it is important to keep data confidentiality, multi-user support, and accessibility in mind. The development of visual analytics tools for learning has been an area of interest for many scholars. For Gradient's Learning Analytics System (GLASS), a web-based platform for data visualization. An end-user needs-must focus informed the bottom-up paradigm that GLASS's visualization methods were built upon. A primary goal in developing this tool was to facilitate the introduction of new visualizations for the purpose of displaying data pertaining to learners, teachers, and the educational process. Consequently, GLASS provides the ability to generate visual representations of contextual events and actions involving learners. Lastly, adaptive learning systems and learning customisation have been made possible in higher education by learning analytics. Personalized or individualized learning applications are a subset of adaptive learning systems that can modify their behavior in response to small amounts of data produced by students. The learning analytics engine gathers and analyzes data in real-time, making it the fundamental component of an adaptive learning system. To improve adaptive English language learning, for instance, suggested a personalized learning system based on fuzzy logic. A student's current English proficiency and the need to expand their vocabulary can inform the system's article recommendations.

2) Academic Analytics

Using data analytics in conjunction with information, organizational culture, technology, and other comparable elements is what academic analytics (AA) is all about when it comes to managing an institution. Finding significant patterns in educational data to indicate academic issues (such as the dropout rate) and to assist strategic decision-making is what academic analytics is all about. This is an example of educational business intelligence. The methodology is primarily designed to assist educational administrators and policymakers. School administrators are contemplating the use of academic analytics to monitor and improve key performance indicators (KPIs) such as student retention, while students seek out data analytics to aid with course planning and execution. In a nutshell, academic analytics is a way for schools and other educational institutions to gather the information they need to manage their finances and operations well. The usage of data analytic methodologies and technologies to support institutional operations and decision making is more widely characterized as academic analytics, as opposed to learning analytics. Almost all professors care about keeping tabs on and forecasting their students' grades as it's one of the most important KPIs in the academic world. Additionally, AA can derive useful information from educational data in order to identify the best methods and facilitate the pedagogical adjustments made by the faculty to meet the demands of the students. Academic analytics may provide

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valuable information to the executive officers to aid in their decision-making process. Academic analytics provides a different set of KPIs than what is provided in conventional classrooms. After learning about the percentage of students who are at risk, the vice chancellor may decide to reassess the school's approach to teaching and learning. In order to maximize efficiency, the top brass may also consult scholarly analytics.

TABLE I. ACADEMIC AND LEARNING ANALYTICS(%)

Types of Analytics	Object of Analysis	Who Benifits
Learning Analytics	Departmental: predictive modelling, patterns of success/failure	Faculty, Learners
	Course-level: conceptual development, social networks, discourse analysis, intelligent curriculum	Faculty, Learners
Academic Analytics	National and international	Education authorities, National governments,
	Regional: comparisons between systems	Administrators, Founders

B. *Student Performances*

1) The Learning Outcomes

The learning outcomes that the college has set out are crystal clear. The College's Mission, Vision, and Objectives outline some of the educational goals that the institution has set for itself. Here are a few examples of the declared goals for the course:

- Subject knowledge
- Character building
- Business acumen
- Employability skills
- Values & Ethics
- Intellectual capabilities
- Morality

The institution's goals, vision, and mission all speak to the learning outcomes. Students learn this through both words (in the form of the college calendar and other visible college hoardings) and deeds (in the form of comprehensive life skills training that includes everything from financial literacy to personal development). As new faculty members become acclimated to the organization's culture, they will become aware of the learning outcomes. Learning outcomes are the detailed descriptions of the knowledge and skills that students should acquire and be able to demonstrate upon finishing a certain course or program in a university setting[22]. It is also possible to look at it as the end goal of learning, when all the necessary skills and knowledge have been acquired. Providing students with targeted experiences and then assessing their progress toward learning targets is essential. Students' performance on assessments shows where they have learned and where they still need work. With clearly articulated learning outcomes, the college has been educating students in three crucial areas: IT, business management, and social service. These are achieved through the use of institutional measures.

2) *Strategies for Institutions:*

The following are examples of institutional measures taken to track and report on students' performance and development throughout the course or program, as well as to analyze their outcomes and identify trends or variations in their performance across different courses or programs:

a) *Attendance:*

Throughout the semester, the College keeps track of each student's attendance for every class. This is checked for shortages on a regular basis (once a month) and notified to the parents of the affected pupils through text message. When it comes to the University's required attendance policy, the college is dead serious.

b) *Leave of Absence Form for the Class:*

The college has a novel approach to preventing pupils from skipping class. Afterwards, for every hour of absence, a declaration form needs to be filed to the relevant faculty member. The following details are included in the declaration form: total number of classes held, number of classes attended by the students in question, explanation for absence, student signature (which must be countersigned by faculty members), and the document must be kept in the student's possession. This is useful for keeping tabs on when classes are lost.

3) *Teaching, Learning, and Assessment Strategies:*

The institution's methodologies for teaching, learning, and evaluation are designed to achieve the learning outcomes that were described earlier:

a) *Subject Knowledge:*

First, instructors; second, course materials; third, student motivation; and fourth, assessment of instruction and student performance make up the teaching, learning, and assessment technique for subject matter acquisition. An educational setting that is fundamentally focused on the needs of the students is something that the school works hard to achieve.

b) *Character Building:*

Through its partnerships with other groups, the institute provides its members with opportunities for personal growth and spiritual development.

c) *Business Acumen:*

Because this is a school for business management and all of the classes are career-and job-specific, the goal is to help students develop their business skills and knowledge via classroom instruction, mentorship, and real-world experience.

d) *Employability Skills:*

Recruiting and training is a full-time position at the institute. The college goes above and above by providing students with a range of certificate programs to enhance their employability. Soft skill training is a feature of every course.
Tasks and practicals provide hands-on experience in a real-world work setting.

e) *Values & Ethics:*

All aspects of the institution, including admissions, appointment, and methodology, are secular. Both wealthy and impoverished students are treated with the same respect. Both the pupils and the professors value each other's contributions in the classroom. Both sexes have equal access to opportunities.

f) *Intellectual Capabilities:*

The instructional strategy prioritizes curricular, co-curricular, and extra-curricular activities that promote creativity, encourage free expression of ideas, and test students' ability to think creatively.

C. *Exploratory Data Analysis:*

An exploratory data analysis (EDA) was carried out to evaluate the acquired data's quality and structure before moving on with predictive modeling[23]. Finding outliers, missing values, or discrepancies that could affect our models' accuracy was the most important part of this stage. Important steps in the EDA process included:

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1) Descriptive Statistics:

Every variable had its mean, median, standard deviation, and range calculated using descriptive statistics. This gave a rough idea of how the data was distributed and brought any outliers or extreme values to light.

2) Visualization:

The data distribution and interactions between variables were graphically represented using a variety of visualization methods, including histograms, box plots, and scatter plots. Because of this, trends and patterns were easier to spot, which aided our modeling efforts.

3) Correlation Analysis:

The connections between the variables were investigated using a correlation analysis. The multicollinearity among the independent variables was better understood, and possible dropout and retention predictors were identified, as a result.

Prior to moving on to predictive modeling, the dataset's properties were better understood thanks to the exploratory data analysis. Our ability to choose suitable modeling techniques and accurately interpret analysis results was greatly enhanced by a comprehensive comprehension of the available data. In order to guarantee the authenticity and dependability of our research, this preliminary step was crucial.

IV. Results and Discussion

The last 20 years have seen a proliferation of treatments grounded in theory with the goal of bettering academic performance in universities. Carefully designed interventions grounded in theories of motivation and social psychology have achieved remarkable success in addressing educational issues by zeroing in on their root causes. The purpose of this review is to assess the existing literature on targeted interventions in higher education in light of forthcoming theoretical and conceptual concerns on intervention science.

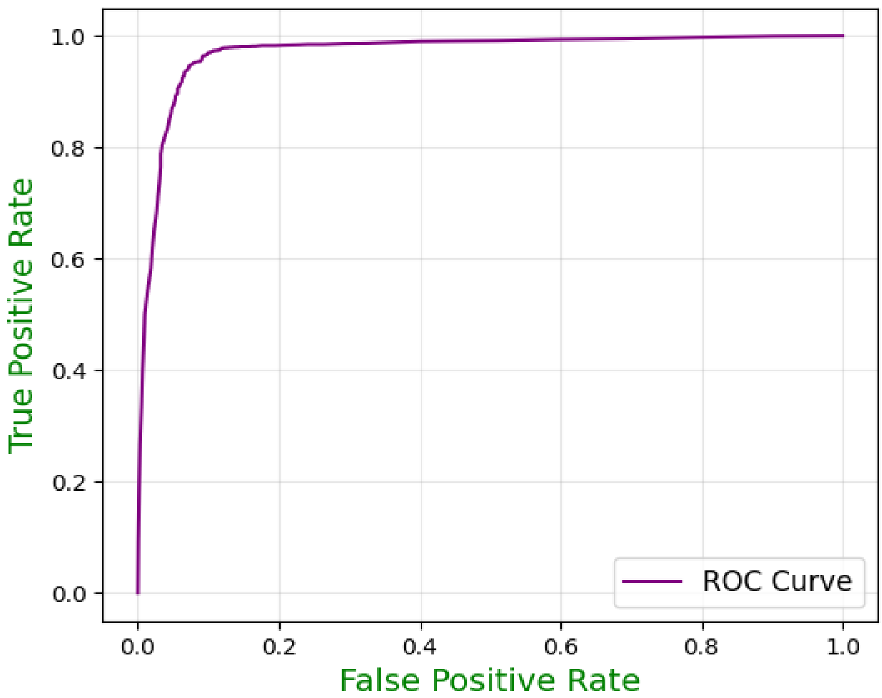

Fig. 1. ROC Comparison of Various Methods

The ROC curve, shown in Figure 1, measures how well a model can predict educational outcomes, like passing or failing, for students. The y-axis shows the True Positive Rate, which shows the percentage of successful students that were accurately identified, and the x-axis shows the percentage of unsuccessful students that were misclassified. It appears the model is very precise, as indicated by a curve close to the upper left corner. In order to intervene with pupils who are at risk, this can help teachers.

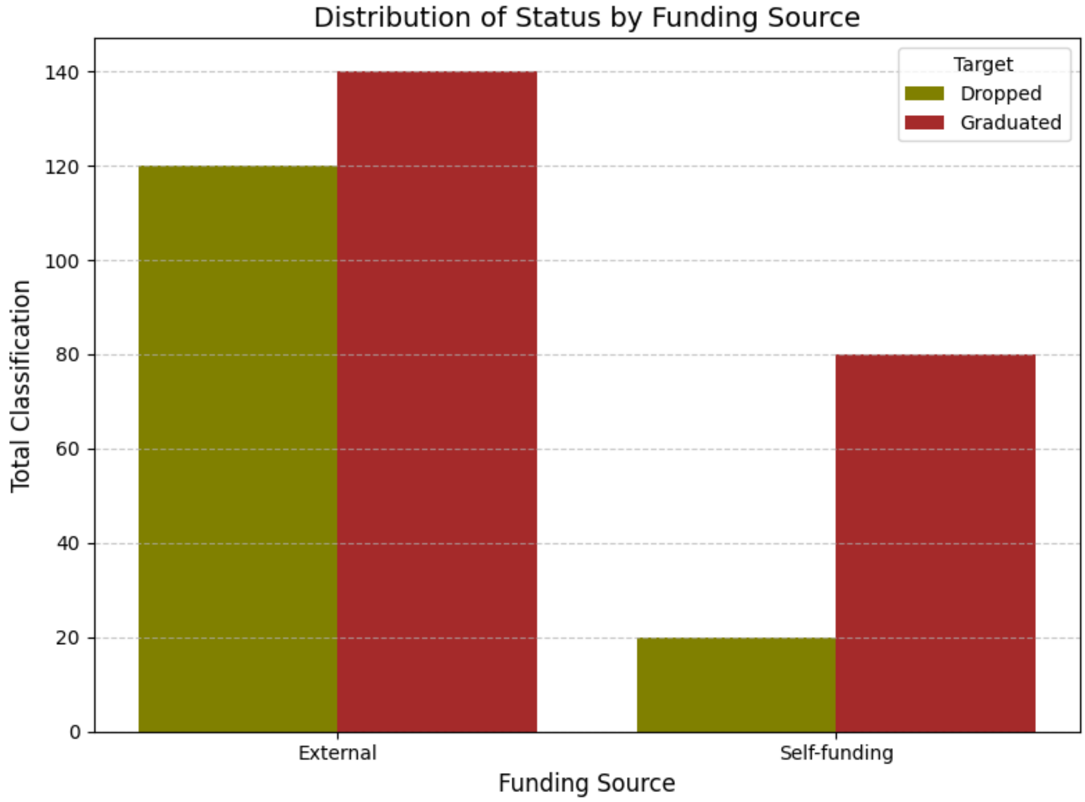

Fig. 2. Distribution of Status by Funding Sources and Debt Status

Figure 2 It is clear that students who receive scholarships are less likely to drop out of school compared to those who do not. A higher percentage of kids who are considered debtors also drop out of school.

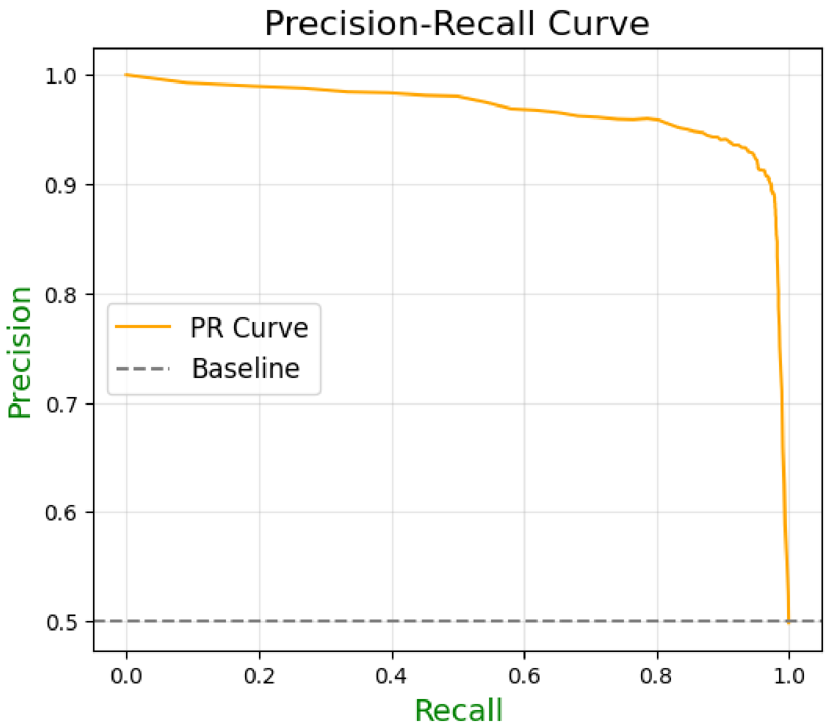

Fig. 3. Precision-Recall Comparison of Proposed Models

When assessing a model's efficacy, like in the case of educational tasks such as student outcome prediction (see Fig. 3), a Precision-Recall (PR) curve is employed. The orange curve shows the effectiveness of the model at different thresholds, representing the trade-off between recall and precision. The baseline precision level, which is probably just guesswork, is represented by the dashed line. Critical for accurately identifying successful or at-risk kids, a larger PR curve signifies stronger predictive performance.

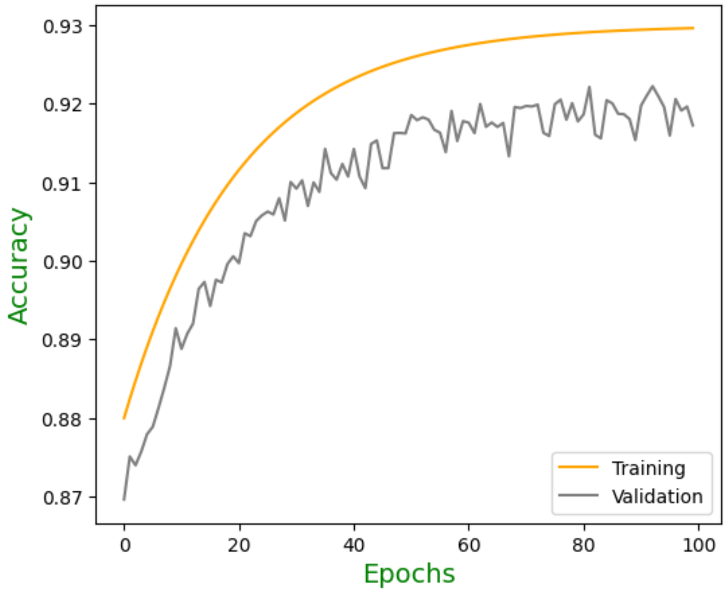

Fig. 4. Training and Validation Accuracy of Proposed Models

Accuracy in predicting student education outcomes using a learning curve tracking model is shown in Fig. 4. Training accuracy, shown by the orange line, rises gradually and levels off at about 0.93, indicating that the model is learning. Validation accuracy is shown by the gray line, which peaks at approximately 0.92 and indicates good generalization with occasional volatility. When the two curves are so closely aligned, it means that overfitting is not a problem, which is great for accurate prediction in educational contexts.

V. Conclusion and Future Directions

The language of results and competence is undeniably prevalent in commercial and industrial settings, as well as, to a lesser extent, in public and academic institutions. Stakeholders who want openness and quality as measured by results often yell out for accountability. Questions regarding instructional performance have been associated with a rising trend in higher education to connect learning to industrial goals and economic imperatives. Evidence of the value-added benefit of higher education instruction has been the target of a widespread push for assessment in the US, UK, and AU. One result, if not a primary goal, of both teaching and higher education is student learning. Student outcomes have the potential to inform evaluations of instruction when used with care and consideration. However, there is a complicated interaction between variables specific to a school, the classroom setting, and student personality that determines the results of learning. Measuring these outcomes requires a range of approaches, both immediate and retrospective, due to the fact that learning is an ever-changing, uniquely individual process that is based on social interactions and practices. Our proposed model reaches the highest accuracy of 93.23%. Because of this, it is essential to integrate macro-level evaluation with micro-level, teacher-directed evaluation of student outcomes, and faculty members should be involved in creating criteria and data gathering procedures for macro-level evaluation.

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