LTA (Learn to Analyze) - A Teacher-Centric Analytical Dashboard for Illustrating Students Academic Progress, Backed by Machine Learning for Informed Performance Enhancement Recommendations.

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***Abstract*—Previous research has firmly established that a communication gap between teachers and students can have detrimental effects on the learning process and student behaviors. In our study, we aim to explore how the implementation of a teacher-centric analytical dashboard can serve as a vital tool in visualizing and addressing this gap.**

Our research underscores the critical role of monitoring each student's academic progress by their teachers for the purpose of enhancing overall performance. This paper will delve into the significance of this practice and how an analytical dashboard tailored to the needs of educators can facilitate this process. Through this exploration, we will highlight the key features and advantages of a teacher-centric analytical dashboard in fostering effective communication and ultimately improving the learning experience for students.

Keywords- teacher facing dashboard, learning analytics, students, teachers, visualize, analyze, education field, machine learning, deep learning.

I. Introduction

It is important to reduce the increasing gap between students and teachers that is arising between them now a days, so we came up with a solution of creating a teacher facing dashboard which will use machine learning algorithms to analyze students data and provide key recommendations to teachers for performance improvement of students. Over the period of time technology have evolved so much which makes understanding any procedure so simple. The technology were going to utilize is learning analytics which gives predictions based on past and current data. This technology lets you reduce the gap between student and teacher which is been increased over the period of time. Based on all the parameters related to students which will help in accurate outcome will be collected and analyzed accordingly. We are also used deep learning and machine learning technology which lets us analyze the data and get insights from data accurately. The system that we are going to create basically takes huge amount of students data with all the necessary attributes which will help to analyze the data, data not only contains the regular attributes but it also contain external factor attributes. When this data is collected the data is in very impure for which is not in normalized form, we make this raw data into proper information which will give proper insights from the data and which will give us accurate outcome. If the data which is been collected is not normalized then there will be redundancy in data, improper data, which

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will definitely give improper outcome. This teacher facing dashboard basically gives you students progressive graphs, charts, etc which is generated after the data is analyzed and machine learning algorithms are applied on that. Different python libraries are used to analyze the data like seaborn, matplotlib, etc. which helped us to represent our outcome in proper plots. Different machine learning algorithms like random forest, decision tree, SVC and many more are applied to get desired output. Teacher would get all the stats of students which will let them understand where student needs improvement or any suggestion, etc. This project helps the teacher to basically understand all the parameters related to students defining his studies, extracurricular activities, whether he is a fast learner or slow learner, what all parameters are affecting the performance of students, is he involved in extracurricular activities, is he doing any certifications which will help to teacher for analysis of student performance and based upon that he will give key recommendations. This teacher facing dashboard tries to reduce the gap between the students which has been increased over the years.

II. Proposed System

The proposed system is a web-based teacher-facing dashboard made by three key modules. The first module, GFM (Guardian Faculty Management), is granted access to all teacher data,providing comprehensive insights into the institution's structure and performance. Users,including teachers, can view the GFM dashboard to gain a broad institutional perspective without direct access to GFM's detailed data. In the proposed system, the technology stack includes Machine Learning and Deep Learning for data visualization, coupled with React, CSS, and Bootstrap for creating an intuitive and user-friendly dashboard. Data is stored in MySQL, with future plans to leverage cloud services like AWS for enhanced flexibility and performance.

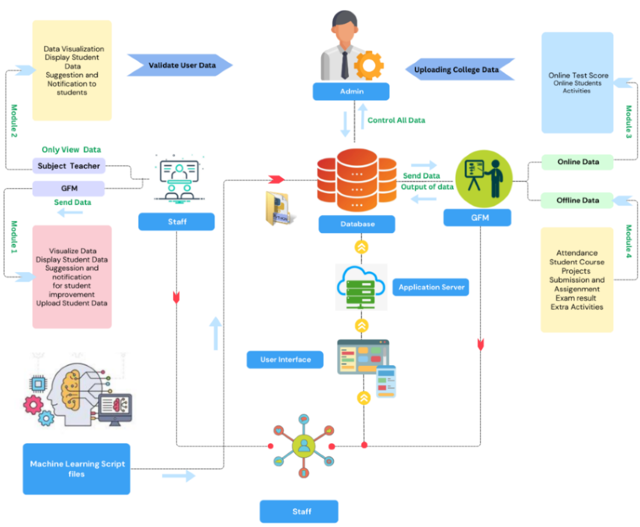


Figure: Flow Daigram

From a technical standpoint, the system employs advanced security measures, utilizing SHA algorithms such as SHA-256 for maintaining the confidentiality and integrity of student data. These algorithms play a crucial role in ensuring robust data security throughout the system. In terms of data processing, the Admin Module utilizes dynamic data access and management capabilities. Machine Learning and Deep Learning models are configured to optimize interactions with the data, allowing administrators to extract valuable insights beyond basic statistics. This involves the intricate analysis of student profiles, attendance records, mark sheets, academic performance indicators, and extracurricular activity logs. The graphical user interface (GUI) is not merely a display tool; it goes beyond by visualizing complex patterns and trends in student performance. This visualization is powered by sophisticated mathematical models integrated into the Machine Learning and Deep Learning components of the system. Furthermore, the proposed use of cloud services like AWS reflects a commitment to scalability and performance, ensuring that the system can efficiently handle large volumes of data storage while maintaining flexibility.

The web-based teacher-facing dashboard made by three key modules. The first module, GFM (Guardian Faculty Management), is granted access to all teacher data, providing comprehensive insights into the institution's structure and performance. Users, including teachers, can view the GFM dashboard to gain a broad institutional perspective without direct access to GFM's detailed data. The Staff/Teacher Module is tailored exclusively for teaching staff, offering granular access to student data, including profiles, attendance records, mark sheets, academic performance metrics, and extracurricular activities. What distinguishes this module is its deep learning integration, which goes beyond data analysis. It identifies slow and fast learners through multiple factors and delivers personalized recommendations for individual student performance enhancement. The third module, the Admin Module, serves as the core data hub, with administrators having dynamic data access and management capabilities. Admins can validate, upload, and manage college and student data, ensuring data accuracy and reliability. They configure machine learning and deep learning models, optimizing their interaction with the data. Furthermore, administrators can set up notification systems, keeping teachers and students informed about crucial events, proactive performance improvement recommendations, and alerts for students who may need additional support.

The system relies on a robust database, acting as a central repository for academic information, housing student profiles, attendance records, mark sheets, academic performance indicators, and extracurricular activity logs. Machine learning and deep learning models intricately analyze this data, providing deep insights that go beyond basic statistics. These insights are elegantly presented in an intuitive graphical user interface (GUI). The GUI doesn't merely display data but also visualizes complex patterns and trends, offering a comprehensive view of student performance. It further provides actionable recommendations for academic improvement. This system empowers teachers and administrators to monitor, analyze, and proactively enhance student academic performance. The GFM dashboard provides institution-wide insights while respecting data privacy, and the integration of data management, machine learning, and deep learning enables users to make informed, data-driven decisions. This dashboard promises to be a transformative tool, significantly impacting student success and educational outcomes.

In summary, the system intertwines technological components, advanced mathematical models, and security protocols to create a powerful tool for educators and administrators, promising transformative impacts on student success and educational outcomes.

III. MATHEMATICAL FORMULATION OF ALGORITHAMS

1. Random Forest

The mathematical formulation of a Random Forest is generic and doesn't change based on the specific dataset you're working with. However, the parameters and hyperparameters you use in training the Random Forest can be tuned to better suit your data.

The mathematical representation of a Random Forest algorithm involves a combination of decision trees, where each tree is trained on a random subset of the data and a random subset of the features.

Let's break down the process:

1. **Decision Trees:** A decision tree is a tree-like flowchart where each internal node represents a feature, each branch represents a decision based on that feature, and each leaf node represents the outcome or prediction. Mathematically, a decision tree can be represented by a set of rules or conditional statements:

$$h(x) = \sum_{i=1}^{N} w_i \cdot I(x \in R_i)$$

Where: - $h(x)$ is the prediction for input x. - N is the number of leaf nodes. - w_i is the predicted value associated with the ith leaf node. - R_i is the region in the feature space assigned to the ith leaf node. - $I(\cdot)$ is an indicator function that returns 1 if the condition inside is true and 0 otherwise.

2. **Random Forest:** A Random Forest is an ensemble of decision trees where multiple trees are built using different subsets of the data and features.

Each tree is trained on a bootstrapped subset of the dataset (selected randomly with replacement) and at each node, only a random subset of features is considered for splitting.

The final prediction of the Random Forest is obtained by averaging (for regression) or voting (for classification) the predictions of individual trees.

Mathematically, the prediction of a Random Forest for regression can be represented as an average of individual decision trees' predictions:

$$H(x) = \frac{1}{M} \sum_{j=1}^{M} h_j(x)$$

Where: - $H(x)$ is the prediction of the Random Forest for input x. - M is the total number of trees in the forest. - $h_j(x)$ is the prediction of the jth decision tree for input x.

For classification, the ensemble prediction could involve a majority voting scheme among the decision trees' predictions.

The core mathematical representation remains the individual decision trees' structure and the ensemble method used to aggregate their predictions, while the randomness and variations are introduced through the selection of subsets of data and features during the training process. Tuning parameters and hyperparameters in a Random Forest typically involves adjusting the depth of trees, the number of trees, the size of subsets used for training, and other settings that influence the tree-building process.

2. XGBoost

The mathematical formula of XGBoost remains the same regardless of the specific dataset. However, the parameters and hyperparameters can be tuned to better suit your data.

XGBoost (Extreme Gradient Boosting) is a boosting algorithm that builds an ensemble of weak learners (typically decision trees) in a sequential manner. The ensemble is formed by adding models that correct the errors of previous models, focusing on the samples that were poorly predicted.

The basic idea behind XGBoost involves the combination of weak learners (individual decision trees) into a strong learner, minimizing a specific loss function while also considering regularization terms.

The mathematical representation of the XGBoost algorithm involves the objective function and the iterative process of adding new models to minimize this objective function:

1. **Objective Function:** The objective function in XGBoost combines two main components:

a. **Loss Function (L):** This measures the difference between predicted values and actual target values and is specific to the problem being solved (e.g., regression or classification). For instance, in regression, the mean squared error (MSE) might be used as the loss function.

b. **Regularization Term ():** Regularization terms (e.g., L1 or L2 regularization) are added to the objective function to control the complexity of the model and prevent overfitting.

The objective function (Obj) for XGBoost can be represented as:

$$Obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Where: - n is the number of samples. - L is the chosen loss function measuring the model's performance. - $\hat{y}_i$ is the predicted value for the ith sample. - Ω represents the regularization term applied to each individual tree f_k. - K is the number of trees in the ensemble.

2. **Boosting Process:** XGBoost employs a boosting strategy where models are added sequentially to minimize the objective function. At each iteration, a new model (tree) is added to the ensemble to correct the errors made by the existing ensemble.

Mathematically, this can be represented as:

$$F_t(x) = F_{t-1}(x) + h_t(x)$$

Where: - $F_t(x)$ is the prediction of the ensemble at iteration t. - $F_{t-1}(x)$ is the prediction of the ensemble at iteration $t-1$. - $h_t(x)$ is the new weak learner (tree) added at iteration t to improve the predictions.

The core of XGBoost lies in optimizing the objective function by iteratively adding weak learners while considering the residuals (errors) of the previous iterations. Tuning parameters and hyperparameters in XGBoost involves adjusting tree-specific parameters, learning rate, depth of trees, regularization terms, and other settings that affect the boosting process and model complexity.

IV. System Interface Overview

Within the realm of academic data analysis, ”Learn to Analyse” stands as an intricately designed platform aimed at navigating the complex terrain of student journeys and extracting profound insights from diverse academic datasets. Our platform serves as an encompassing guide, providing a suite of advanced tools and profound analytical capabilities.

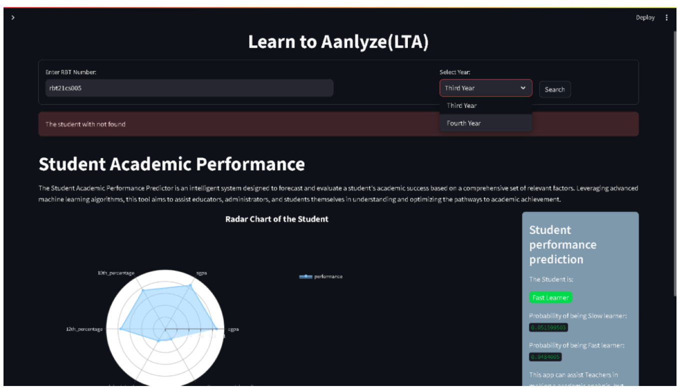


Figure: GUI IMAGE 1

At the forefront of our interface resides an intelligent search bar, meticulously engineered to empower users with the ability to efficiently locate specific students or tailor search criteria based on academic year parameters. Once a student of interest is identified, the platform presents a comprehensive profile, a repository teeming with an extensive array of academic data. This profile is meticulously crafted to offer a deeply nuanced understanding of the student's academic trajectory.

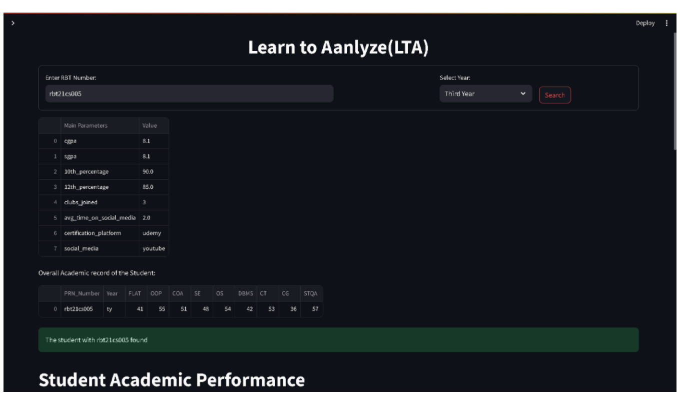


Figure: GUI IMAGE 2

Central to our analytical arsenal is the innovative integration of a radar chart. Beyond being a visually compelling representation, this sophisticated tool acts as a gateway to engage in a profound dialogue with the data. It aids in discerning a student's learning pace and fosters an intricate comprehension of the multifaceted interplay of various academic factors. Through this, it provides an avenue to explore the unique narrative woven by each student in their academic journey.

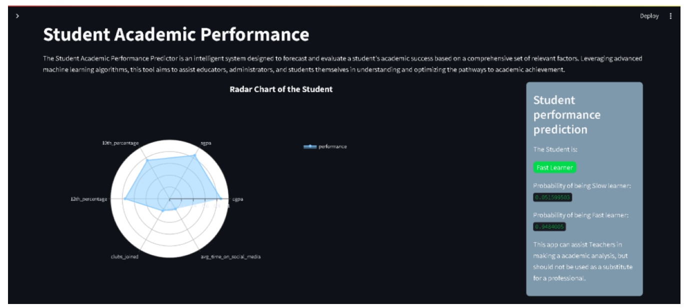


Figure: GUI IMAGE 3

Furthermore, our platform showcases a user-friendly bar graph, transcending the limitations of traditional grade displays. This graph serves as an insightful visual chronicle, meticulously illustrating a student's academic progression across multiple semesters. It meticulously showcases their milestones, triumphs, and evolution within the academic landscape.

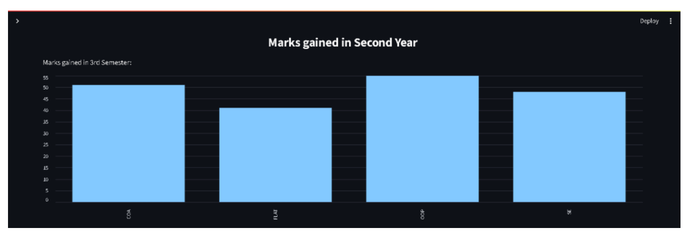


Figure: GUI IMAGE 4

”Learn to Analyse” transcends the conventional boundaries of an analytical tool; it emerges as a steadfast companion in the pursuit of profound revelations within academic data. It extends an open invitation to users, encouraging them to embark on a journey of exploration, decryption, and redefinition of academic analysis paradigms. Are you poised to embark on this transformative journey? Begin your exploration today and witness the rich narratives of students, meticulously unfolding in a manner that's discerning, insightful, and deeply human-centric.

V. Experimental Environment

In the course of our research for the teacher-facing dashboard, we utilized the Google Colab platform for our testing environment. The dataset we employed was carefully constructed using information sourced from our college's records. This dataset covered a range of pertinent details, including full names, PRN numbers, roll numbers, ages, genders, current areas of residence (with specific examples like Baner), permanent addresses, departments, academic years, divisions, CGPA and SGPA of the current semester, as well as percentages from 10th, 12th, and diploma examinations. Additionally, it included information regarding certifications that proved beneficial, specifying the course names and the platform typically used for certification. Furthermore, we gathered data related to the domain of EDI topics, specific EDI topics, club or chapter affiliations (including paid memberships or leadership roles), average time spent on social media, preferred social media platforms, hobbies, leisure activities, and annual fees paid (provided as accurate figures). Additionally, we accounted for whether participants were day scholars. This comprehensive dataset provided a solid foundation for our machine learning model testing.

```
The different Attribute in our Dataset Are:
Index(['Timestamp', 'Email address', 'Full Name', 'PRN Number',
       'Roll Number (Example:CS3265)', 'Age', 'Gender',
       'Current Address(Just mention Area name  Example: Baner)',
       'Permanent Address (Just mention Area name  Example: Baner)',
       'Department', 'Year', 'Division', 'CGPA(Of Current Semester)',
       'SGPA (Of Current Semester)', '10th  Percentage', '12th  Percentage',
       'Diploma Percentage',
       'Certification you did that benefited you(Full name of the Course)',
       'Platform on which you normally do certification',
       'Domain of EDI Topic', 'EDI Topic',
       'Are you part of any Club or Chapter(Paid Member or Head)',
       'Mention the Name of the Club or Chapter',
       'On Average how much time do you spend on social media',
       'On which social media do you spend the most time',
       'What are your hobbies(Only one)',
       'What do you like to do in your free time',
       'How much fees do you pay annually(Accurate Number)', 'Day Scholar'],
      dtype='object')
```

VI. Result and Discussion

The integration of Learn to Analyze (LTA) visualizations portraying group task progress and individual participation proved to be exceptionally beneficial in an educational setting. As underscored by Teacher LTA, these visualizations provided immediate, real-time insights. LTA remarked that a specific group, colloquially termed as the 'Slow Learner group,' lagged notably in their progress. This realization prompted teachers to take proactive steps towards assistance, establishing a direct link between visualized data and informed decision-making.

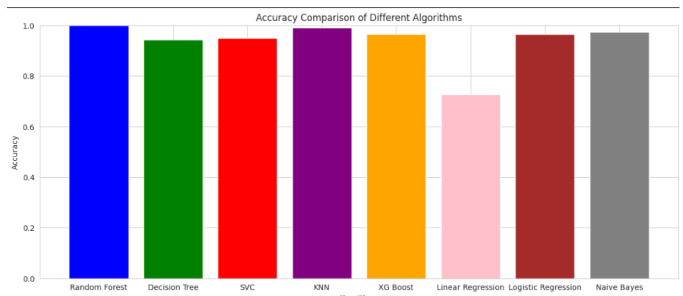
LTA's testimonial underscores how this tool enabled teachers to delve deeper into the dynamics and progress of specific individuals and groups. It addressed a common challenge faced by educators - the real-time assessment of each individual's solution. By presenting task-related information in this manner, teachers gained heightened awareness, enabling them to make well-informed decisions about classroom interventions.

Here are the accuracy metrics of various machine learning algorithms on our dataset:

- Random Forest: 100.0
- Decision Tree: 94.39
- Support Vector Classifier (SVC): 94.86
- K-Nearest Neighbors (KNN): 99.07
- XG Boost: 96.49
- Linear Regression: 72.71
- Logistic Regression: 96.49
- Naive Bayes: 97.37

Teachers commended how the tool facilitated swift individual and group comparisons and aided in making more informed decisions later in the class. Nevertheless, they also acknowledged the limitations of the data provided. They recognized the need for additional sources of information to form a comprehensive understanding of each individual and group's dynamics. LTA emphasized the immediate benefit of observing how individuals and groups were progressing, allowing them to quickly discern which individuals or groups were making headway and which were lagging behind. However, LTA noted that the visualizations did not offer insights into the specifics of who was driving the work, their strategies, or whether collaboration within the individuals and groups was equitable. This feedback collectively underscores the necessity for supplementary evidence sources that would enable teachers to conduct more thorough assessments of individuals and groups within the classroom. LTA aptly pointed out the importance of understanding verbal interactions, as this dimension of interaction can be indicative of individual contributions and engagement. This aligns with prior research that emphasized the value of providing differentiated speech summaries alongside logged individual contributions.

In summary, the incorporation of visualizations in the classroom setting garnered positive feedback, as it facilitated real-time decision-making and enhanced individual and group assessments. However, it was also acknowledged that while these visualizations were valuable, they should be complemented with additional sources of information to provide a comprehensive understanding of individuals and group dynamics and individual contributions.



VII. Litreture Review

In a comprehensive review conducted in (2023) by Rogers Kaliisa, Ioana Jivet, and Paul Prinsloo, the authors evaluated a total of 50 different learning analytics (LA) dashboards. Their findings shed light on a prevalent trend among these dashboards, which primarily focused on raising awareness rather than facilitating interventions. This review brought to the forefront several critical issues within the landscape of LA dashboards, including limited teacher engagement, a lack of grounding in learning theory, and a dearth of ethical considerations. To address these shortcomings, the review proposed the development of a comprehensive checklist to guide the creation and implementation of future LA dashboards.

Within this extensive review, one of the dashboards that received attention was MTClassroom, as discussed in the work by Martinez-Maldonado. MTClassroom is custom-tailored to support multi-tabletop classrooms, offering real-time insights into collaboration patterns, touch interactions, and task progress among students. Notably, this dashboard empowers teachers by facilitating rapid group comparisons and the identification of potential issues, underscoring the pivotal role of data in informing pedagogical decisions.

Another dashboard explored in the review was Cada (2022), which was examined in-depth by Rogers Kaliisa and Jan Arild Dolonen. Cada is seamlessly integrated within the Canvas Learning Management System (LMS) and harnesses the power of natural language processing to analyze online discussion data. By doing so, it equips teachers with valuable insights into student participation and discourse within virtual learning environments. This review emphasized the significance of actionable insights and customization features in LA dashboards to enhance their utility for educators.

The examination extended to the Process-Oriented Dashboard, the latest iteration of which was discussed in the work by Raphael A. Dourado (2021). Designed specifically for online courses, this dashboard offers feedback based on clickstream data, aligning its metrics with established learning theories. However, the review noted the need for improvements in user-friendliness to enhance its effectiveness.

Furthermore, Valle et al.'s recent review in 2021 added to the body of knowledge on student-facing LA dashboards. This review sought to map the theoretical foundations underpinning these dashboards and assess the alignment between their intended outcomes and the evaluation measures employed. The findings revealed a significant gap between intended outcomes and the metrics used for evaluation, underlining the necessity for more coherent development in the realm of LA dashboards.

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These collective reviews provide valuable insights into the state of LA dashboards, highlighting their strengths and areas in need of improvement. They underscore the importance of bridging the gap between data-driven awareness and actionable insights for educators and emphasize the significance of ethical considerations in dashboard development. While numerous literature reviews have significantly contributed to the field of Learning Analytics (LA) dashboards, a critical gap persists. None of these reviews has concentrated exclusively on teacher-facing LA dashboards. This gap is particularly noteworthy because there is a pressing need for more specialized research in this area of LA. The aim is to cultivate analytical knowledge and establish guiding principles that can assist researchers and designers in effectively engaging non-data experts, including teachers.

Our project's primary objective centers around the development of a Learning Analytics-powered teacher-facing dashboard. This dashboard is designed to empower teachers by providing them with the tools to visualize and comprehensively analyze students' academic performance. Moreover, it incorporates Deep Learning (DL) techniques to offer valuable recommendations for performance enhancement. As we continue to work diligently on this project, we are committed to making significant strides in bridging this gap in the existing literature. Our aim is to contribute valuable insights and guidance for the successful development and utilization of teacher-facing LA dashboards in educational contexts, ultimately benefiting both educators and students.

VIII. Prospects for Future Development

Our project aims to provide an exceptional teacher-facing dashboard, offering a robust platform to visualize and analyze students' academic performance. The emphasis is on integrating Deep Learning (DL) to generate key recommendations for enhancing performance. The primary focus is to deliver an outstanding user interface for an optimal user experience.The project's scope entails a comprehensive capability for teachers to delve into student performance analysis. Through an array of graphical representations and diverse chart presentations, the system facilitates a nuanced examination of academic accomplishments. This feature provides educators with a visually rich and detailed overview of students' strengths, weaknesses, and overall progress, enabling a more informed and targeted approach to academic support and guidance.

What sets this project apart is its response to a common limitation in existing educational software. While many platforms primarily focus on data management or serving as learning environments, our project uniquely emphasizes empowering teachers to concentrate specifically on enhancing student academic performance. Through thorough analysis, the system allows teachers to offer personalized suggestions and recommendations to students, actively contributing to their academic improvement. This distinctive approach positions our project as a tool that transcends conventional data management systems, actively working towards advancing student success and educational outcomes.

IX. Constraints and Limitations

The project has a few limitations to keep in mind. Firstly, even with a lot of student data, the system can't fully understand the emotional side of students. Emotional intelligence, which is crucial for understanding student needs, is hard to capture with just data. This makes it challenging to get a complete picture of individual students. Secondly, the project struggles to show emotional or mental state data in graphs. Emotions and mental well-being are complicated, and it's not easy to represent them visually. This means the project may not give a full picture of students' overall well-being. Third limitation of our project is its dependency on internet connectivity. In cases of poor internet connectivity, the user interface may become compromised, potentially leading to an improper user experience. This acknowledges that seamless functionality is contingent on a stable and reliable internet connection, and disruptions in connectivity may impact the system's performance and accessibility.

Lastly, it's important to know that no system is perfect. The accuracy of our project depends on having a lot of good-quality data. While we aim for precision, we can't guarantee 100

X. Conclusion

As higher education becomes increasingly digitized and datafed, institutions have access to greater variety and velocity of data, commonly shared through LMS dashboards. This study reported our practical experience related to designing a teacher-facing dashboard that aimed at supporting teachers in orchestrating scripted classroom collaboration.The findings of the study revealed how teachers made information on the dashboard actionable and how teachers actions induced positive change in students' activity participation. In our study, teachers mentioned that they missed chances of reacting to critical events during collaboration as they are concerned about the epistemic and social facets of the learning activity in real-time.This paper contributes to this direction by proposing a four-dimensional checklist for the planning, design, implementation and evaluation of LMS dashboards, which we hope can act as a guiding and discussion tool for researchers and technology developers during LMS dashboard development.The teachers' perspectives discussed in this paper portray the promises and challenges of introducing new technologies aimed at reducing the gap between students and teachers which has increased over the years.

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