JSPM's

RAJARSHI SHAHU COLLEGE OF ENGINEERING

TATHAWADE, PUNE-33

(An Autonomous Institute affiliated to Savitribai Phule Pune University, Pune)

VISION OF INSTITUTE

"To satisfy the aspirations of youth force, who want to lead nation towards prosperity through techno-economic development"

MISSION OF INSTITUTE

"To provide, nurture and maintain an environment of high academic excellence, research and entrepreneurship for all aspiring students which will prepare them to face global challenges maintaining high ethical and moral standards."

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RAJARSHI SHAHU COLLEGE OF ENGINEERING
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DEPARTMENT OF COMPUTER ENGINEERING

VISION OF DEPARTMENT

To create quality computer professionals through an excellent academic environment.

MISSION OF DEPARTMENT

1. To empower students with the fundamentals of Computer Engineering for being successful professionals.
2. To motivate the students for higher studies, research, and entrepreneurship by imparting quality education.
3. To create social awareness among the students.

A PROJECT REPORT ON

"LTA (LEARN TO ANALYZE) - A TEACHER-CENTRIC ANALYTICAL DASHBOARD FOR ILLUSTRATING STUDENTS ACADEMIC PROGRESS, BACKED BY MACHINE LEARNING FOR INFORMED PERFORMANCE ENHANCEMENT RECOMMENDATIONS."

SUBMITTED BY

SHUBHAM ASBE	**RBTL21CS001**
AKANKSHA LUGADE	**RBTL21CS002**
YASH MORE	**RBTL21CS003**
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Under the guidance of
Dr.K.V.Deshpande

DEPARTMENT OF COMPUTER ENGINEERING

JSPM's RAJARSHI SHAHU COLLEGE OF ENGINEERING
(An Autonomous Institute affiliated to Savitribai Phule Pune University, Pune)

PUNE-MUMBAI BYPASS, HIGHWAY, TATHAWADE, PUNE 411033

SAVITRIBAI PHULE PUNE UNIVERSITY

2023 -2024

CERTIFICATE

This is to certify that the project report entitles

"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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is a bonafide student of this institute and the work has been carried out by him/her under the supervision of **Dr.K.V.Deshpande** and it is approved for the partial fulfillment of the Final Year B. Tech requirement of Savitribai Phule Pune University.

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Signature of Internal Examiner

Signature of External Examiner

Place : Pune
Date :22-12-2023

ACKNOWLEDGEMENT

It gives us great pleasure in presenting the project report on “**Learning analytics powered teacher facing dashboard to visualize, analyze students’ academic performance and give key dl(deep learning) recommendations for performance improvement”**

We have great pleasure in expressing my deep sense of gratitude to **Dr. R. K. Jain**, Director. JSPM's RSCOE, Tathawade for providing necessary infrastructure and creating good environment

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ABSTRACT

Previous studies have unequivocally demonstrated that poor communication between instructors and students can negatively impact both the learning process and the conduct of the students. Our goal in this study is to investigate how the application of a An essential tool in education can be a teacher-centric analytical dashboard. illustrating and filling in this gap. Our findings highlight the vital importance of keeping an eye on each teachers' assessments of their students' academic performance in order to improving performance as a whole. This essay will examine the importance of this procedure and the manner in which an analytical dashboard adapted to teachers' requirements can help to speed up this process. During this investigation, we will emphasize the salient characteristics and benefits of an analytical dashboard focused on teachers for promoting efficient communication, which eventually enhances learning expertise in students.

Institutions now have access to a wider range and faster speed of data as higher education gets more digitalized and data-fed. This data is typically shared via LMS dashboards. This study detailed our hands-on experience with designing a dashboard designed for teachers with the intention of assisting them in planning classroom group projects that follow a script. The results of the study demonstrated how educators created content on the dashboard's action-ability and the way in which teachers' actions improvement in the involvement of students in activities. In our investigation, Teachers reported that they passed up opportunities to respond to crucial incidents that occur during cooperation because they are worried about the social and epistemic components of the educational process in real time.

By offering a four-dimensional checklist for the planning, design, implementation, and evaluation of LMS dashboards, this paper advances this direction. Our hope is that this checklist will serve as a useful guide and discussion starter for researchers and technology developers as they work on developing LMS dashboards. The promises and difficulties of implementing new technologies to close the growing gap between students and teachers are illustrated by the teachers' perspectives in this paper.

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CHAPTER I

INTRODUCTION

01.Introduction

Learning analytics systems use and analyze student behaviors and interaction data to understand and optimize learning experiences. Analytics applications for learning are used in educational institutions for a variety of purposes, including instructional systems for teachers, learning platforms for college students, and student performance tracking tools for educational counselors. So-called early warning systems, or dashboards, analyze educational data to spot underperforming students and allow tutors or academic advisors to intervene in time. Interest in Learning Analytics (LA) has grown rapidly in recent years in educational institutions (HEIs) around the world. The purpose of LA is to use data to optimize learning and thus the environments in which it takes place. LA is focused on students and teachers with excellent opportunities to address educational challenges. The Association for the Study of Learning Analytics defines learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts to understand and optimize learning and thus the environment in which it occurs." Several applications are proposed to support this definition (eg, LA visualization, researcher tracking data analysis, large-scale feedback for different course modalities (eg, blended and online courses), using different content (eg, track data and text data). more advanced contexts, the need to live, demonstrate and improve is growing in educational institutions. performance. As a result, learner analytics is an alternative solution to problems related to improving student retention, progression and student success. As a result, learning analytics is changing. Learning analytics focuses to solving educational challenges, using human judgment and supporting learning. Data are not objective entities and cannot fully represent the identity, interests and values of an individual. However, in the era of massive data, these characteristics are often attributed to data. The data creates false representations of the individuals who supported their interactions with the technologies, effectively reducing them to fragmented representations. With the proliferation of online teaching and learning, learning platforms are increasingly being used in education. Digital learning forms and academic data are growing rapidly. Transforming this educational information into useful information and information that continues to influence both the impact of student learning and the teaching methods of teachers has become difficult due to educational management and resource allocation decisions. In addition, the new trend is smart learning environments need extensive learning analytics studies. Despite the potential of learner analytics (LA) to support the daily practice of teachers, its implementation has not been fully implemented due to the low involvement of teachers in the systems and interventions. Therefore, a panel aimed at the teacher is needed, so that he knows how the examinees actually understand what is being taught or not, and also his general evaluation.

1.1 Overview:

Our project aims to create a "Teacher Facing Dashboard" that helps a teacher summarize, visualize and analyze educational data (researchers) and understand student performance using Machine Learning (ML) and Deep Learning (DL). The code we will write is in Python. With many Python-specific libraries such as Numpy, Scipy, Theano, Scikit, Keras, Seaborn, PyTorch, TensorFlow, Pandas, BeautifulSoup, Matplotlib, Scrapy, PyCaret and Caffe. Our project basically contains three main modules: 1) student, 2) teacher, 3) administrator. To manage user-data. Learning analytics is the main method we intend to use. Because online students leave behind a trail of data, learner analytics can collect this data from various sources and student activities, analyze it, and provide meaningful insights and visualizations to educational leaders, teachers, and learners.

1.2 Motivation:

According to the study, learning analytics can be applied not only to virtual learning environments (VLEs), but also to online education, social learning and cognitive tutoring. Thus, our research shows that learning analytics can be applied to many types of learning analytics that can reduce the communication between students and teachers and also help improve the learning environment. In recent years, technology has become an important tool that supports students and teachers in creating more effective learning experiences. To realize the potential of analyzing these data, student analytics emerged as a field focused on the collection, analysis and reporting of data on students and learning contexts. The use of learning analytics can bring concrete benefits to students, teachers and educational institutions. Learning analytics has been widely studied and used in higher education primarily because data analytics tools are ripe for adoption in these institutions. In the context of a higher secondary school, there are many educational challenges that concern all stakeholders in the teaching and learning processes. Learning analytics can be used to address these challenges, such as dropout and collaboration difficulties. Students, developing scientific argumentation and writing and developing computational thinking, which is an emerging skill for this age group.

1.3 Problem Definition and Objectives:

As we can see, there is a lack of students and what are the different steps that a teacher can take to improve student performance and whether or not this concept should be revised. We noticed that most of the scientists who published the articles we read made the same mistake in their research, so we realized that the concept of artificial intelligence should be re-examined and we should try not to repeat the same mistake in our research The main goal of our project is to create a "Teacher Facing Dashboard" that helps a teacher summarize, visualize and analyze education (academic) data and understand student performance using Machine Learning (ML) and Deep Learning. (DL).

Objectives:

1) Collection of the data.
2) Pre-processing of the data.
3) Student Performance Analysis.
4) Performance Visualization.

1.4 Project Scope and Limitations:

Basically, our project aims to provide you with one of the best dashboards for teachers that tries to visualize, analyze the learning of students and provide important recommendations to improve performance using DL (Deep Learning). Our project aims to provide the best user interface to the user.

Limitation of our project, improper interface when internet connection is bad.

CHAPTER II

LITERATURE SURVEY

02.Literature Survey

They focused on three main areas, specifically 1. Analysis of learning scenario data using naive cells, neural networks, decision trees and clustering. 2. Presentation and visualization 3. Corrective actions based on data analysis. The result shows that "social infrastructure" and "technological infrastructure" are necessary for the learning analytics potential of an institution[2022]. [2] Their research had both theoretical and practical implications; they found that the first BOY to do so was a single screen that included descriptive, predictive, and data-driven prescriptive analyses. Finally, they want to discuss possible future directions and areas of excellence for the LA panel in the short to medium term. LA panels are widely used in the education sector to improve the quality of learning. Identifying the barriers to LAD projects is preferred, followed by an analysis of the advantages and disadvantages of current LADS projects. they presented a dashboard that is currently in use at the testing institute[2022]. [3] The issues teachers face today are information security, poor choices, and inefficient ways to collect, use, or store information. Emphasis is on innovative growth strategies for higher education in India[2022]. [4] The built system was an anti-dashboard for students and teachers, with the aim of creating transparency between teacher and student by implementing a conscious design in practice and carefully considering users. this included some aspects such as theoretical models [2022]. [5] This chapter updates and summarizes a growing body of research examining the difficulties of implementing systemic change through LA in complex educational settings. The work describing its implementation uses the most promising framework for institutional LA implementations - the SHEILA framework[2022]. [6] This study uses a human-centered approach to analyze possible differences in student expectations to examine the ideal of students (ie, indicate their desired results) and projected expectations (ie, reveal what they actually expect from LA). service). to be) THE. Data was collected from 32 students and the analysis used the LCA technique [2022]. [7] Library research is defined as research that uses library information about books as a subject. The author examines and evaluates the information found in the literature related to the topics covered in this work. Most sources of information can be found in books or other written materials such as journals, magazines, newspapers, newsletters, etc. [8] They used understanding, ideas and actions during two design cycles. We started by creating paper prototypes and testing them in focus groups. The dashboard was developed in a second iteration and improved on infidelity prototypes as described below. This study presents preliminary data and ideas for the design and evaluation of teacher-directed LAD feedback aimed at behavioral processes in online courses. Our results complement previously available data and task taxonomy and also provide initial support for the utility of our panel design [2022]. [9] They obtained cases from both experts and novices using two methods. There are many recommendations for sample size for a single case study, from 4 to 30. For a very homogeneous population, a sample of six is sufficient to identify relevant themes and useful interpretations. How ARD is designed to provide an environment for trainees to practice delivering bad news to patients. The teacher user interface includes a pedagogical dashboard that uses learning analytics to provide teachers with information about group interactions and student learning paths. It was tested in groups of students with specific scripts that reproduced certain group dynamic patterns [2022]. [10] This study examined the influence of social and psychological factors on energy saving practices. Amos 23.0 and SPSS 22.0, both written in computer multidisciplinary technology, were the two main software used. A new variable called "personal moral standard" was added to the Model of Planned Behavior (TPB). According to the TPB hypothesis, men living in a dormitory have more behavioral variability and behavioral intentions than women. The results help promote energy conservation activities by providing a better understanding of student behavior in the residential area[2022]. [11]In this article, the author tries to investigate how teachers increase their analytical awareness in the real classroom. Two interviews were conducted with each teacher, one in the middle of the semester and one at the end. The results show that teachers were not only ready to deal with the difficulties of not routinely using analytics in their practice, but also experienced an initial learning curve trying to make analytics useful in teaching [2021]. [12] The author took teacher feedback to show the harmonizing effect of teacher dashboards on elementary classroom feedback. After giving feedback, a total of 372 feedback actions took place, of which 210 are panel-driven and 162 human-driven. Mean = 1] Feedback actions given by teachers per lesson is 10.63.2] Feedback actions given by the individual (SD 5.61). From this average, they got only three teachers who gave suggestions to people and ten teachers who gave invitations to the panel[2021]. [13] In this article, the author used the concept of averages, standard deviations and correlations to show the importance of strengthening the emotional relationship between teacher and student. They took over the management of data collection at the beginning of the academic year (October 2018). and a second time at the end of the academic year (June 2019). Correlation analysis shows that at both T1 and T2, magnitude of teachers' emotional support was significantly and negatively related to school burnout. dimensions (p ¡ 0.01). The mean level of all school burnout indicators increased significantly from T1 to T2. The results of three stepwise hierarchical multiple regressions show that only teacher sensitivity at T1 significantly and negatively predicted emotional exhaustion at T2. = 25, t = 3.82, p ¡ 0.01).[2021]. [14] The author of this article emphasizes the value of promoting a positive emotional bond between teachers and students using the concepts of means, standard deviations, and correlations. At the beginning of the academic year, they used administration to collect data (10.10.2018). and a second time at the end of the academic year (June 2019). Correlation analysis shows that the perceived dimensions of teachers' emotional support are significantly and negatively correlated with school burnout indicators at both T1 and T2 (p 0.01). Between T1 and T2, the mean level of each component of school burnout increased significantly. Results of a three-step hierarchical multiple regression analysis show that only teacher sensitivity at T1 significantly and negatively predicted emotional exhaustion at T2 (= 25, t = 3.82, p 0.01).[2021] [15] Naive Bayes, KNN, Decision tree and artificial neural network. Clustering and classification algorithms were used in this study. They tried to improve the learning process and study student behavior for student profile, and improve student recall and evaluate student feedback in MOOCs and learning management system. The result shows that applied prescriptive analysis is 5 percent, predictive analysis 58 percent and descriptive analysis 37 percent[2021]. [18] They developed a tool called Modul PRT (Program Review Tool) that allows users to conduct a standardized review using the academic results of students who started the program together. PRT converts the raw data into outputs and images to display the review questions created in the design phase described earlier. They proposed a case study that highlights three characteristics of an imaginative and innovative project that used LA in program evaluation. They have developed a state-of-the-art PRT tool also known as the definitive LA-based program review [2021]. [19] We investigated the impact of key factors on LA adoption using ENA analysis and further explored these relationships by extracting interviews categorized under recurring themes. The quantitative ethnographic method depends mainly on culture to show how extremely 1 1 1 1 1 1 1 1 4 7 7 7 8 8 8 13 17 17 2 .

Below are the 8 base IEEE survey papers that we have referred :

Sr No.	Authors	Year	Methodogy	Remarks	Conclusion
1	Laecio Araujo Costa, Marlo Vieira das Santos e Souza, Lais do Nascimento Salvador, Ricardo Jose Rocha Amorim	2019	LAS and SapeS	A Literature Systematic Review (LSR) was performed aims seeking to know how the coordinated use of l. a. and Ontologies can contribute to the evaluation of the student's academic performance.	The goal of this proposal is to assemble pieces of evidence, mainly from the scholar behavior within the LMS, about the Educational objectives that are achieved by
2	Reet Kasepalu	2020	As the next step in the design science research the focus is going to be developing a flexible dashboard to suit the needs of different teacher profiles. Four different types of teachers were differentiated as a result of a cluster analysis: 1) Reflecting Observer, 2) Novice Assessor, 3) Potential User, 4) Confide nt Experienc ed Practitione r (using an explorative k-	During collaborative learning (CL) teachers have little to no information about what's happening within the groups, however, they're expected to plan, monitor, support, consolidate and reflect upon student interactions. Multimodal learning analytics (MMLA) could offer teachers valuable insights into the CL process, however, not many MMLA outputs are utilized in real practice today, and designing such MMLA dashboards remains a challenge.	Although there is an abundance of dashboards designed for teachers, there is a problem transferring the findings reached by researchers into actual classroom practice, which is solved by them.

			means clustering using mostly variables after the dashboard had been introduced to them in order to see the reaction to the tool).		
3	Damiano Distante, Massimo Villa, Nadia Sansone and Stefano Faralli University of Rome Unitelma Sapienza Rome, Italy.	2020	This study represents the MILA, a prototype interactive Learning Analytics tool for the Moodle learning management system which helps to analysis and improvement of teaching and learning process	Possible to do dynamically investigate several aspects of the students' learning processes and the usage of the platform/courses/resour ce s.	In this paper they was presented MILA as an interactive LA for the Moodle LMS which is able to analyze both of the Moodle standard logs and SCORM tracking data. This study confirmed that the interactive visualizations done by MILA is giving valuable information on courses, included learning resources, and students' behavior.
4	Xuewang Geng,Yufan Xu,Li Chen,Hiroaki Ogata,Atsushi Shimada,Masano ri Yamada	2020	Research was performed in a seven-week of math course, and the participants was 80 10th grade students in three classes.50 minutes of time allotted to one lecture.	Performed ANOVA and Tukey post-hoc analyses of learning behaviors among the three classes. Divide three 3 class in A B and C and the result related to teacher teaching style and instruction. conducted a correlation analysis of Z- score differences, between Behavior, Performance and Motivation results of the correlation coefficients which shows only statistically significant results less than the significance value of 0.1.	In this paper they analyzed the 7 weeks of learning logs in DLMR. They conclude that they observed the teaching performance at 3 different level that is learning performance, learning behavior and relationships among learning motivation. Also, they want to explore further work which will be based on ARCS model.

5	Tuti Purwoningsih, Harry B. Santoso, Zainal A. Hasibuan	2020	Learning Management Systems (LMS) are used in e-learning to facilitate teacher tracking of student performance. learning approaches.	A combination of demographic profile data and eLearning activities provides a predictive approach to prescriptive and predictive analytics of student learning outcomes that is based on the characteristics of students participating in e- Learning. made for developing efficient and effective eLearning instructional designs that maximize learning outcomes.	The goal of this study was to examine the students who participated in online eLearning activities at universities with ODL systems. Machine learning and exploratory data analysis are methods used to gain knowledge from different types of data in the context of learning. This study describes how the Minmax scalar technique is used to calculate profile data from activity data and the label encoder technique to compute profile data from categorical data to calculate maximum accuracy of up to 100%. It was found that support vector machine (SVM) classification is a robust
6	Aline de Campos, Sílvio César Cazella	2019	The aim of this study is to determine how Cognitive Computing can be applied to the process of Learning Analytics in higher education. We are in the process of developing this stage and developing it through theoretical and methodological reference, correlation of works, as well as systematic mappings of the technical resources in the LAs and CCs.	Based on the use of these resources, this research proposal confirms the improvement of motivation and engagement of students in learning processes by using Learning Analytics and Cognitive Computing in the development of resources to support personalized learning in Higher Education. As part of this active project, students will be offered personalized processes in addition to teachers receiving a prescriptive analysis of data that will support their decision- making and more assertive design of learning experiences.	Our research may contribute to the area of Educational Technologies because we provide a methodology supported by a platform for assessing and validating the potential of Cognitive Computing for the development of Learning Analytics resources aimed at supporting teachers in engaging students in personalized learning. Comparatively to similar studies, this study advances in the development of a personalized learning framework supported by an analytics platform.

7	Li-Minn Ang, Senior Member, IEEE, Feng Lu Ge, and Kah Phooi Seng, Member, IEEE	2017	In this study, we look at how educational predictive analytics can be used to forecast how well a student will perform on a learning activity and identify students who are at risk. Prediction of student performance On their Big data architecture, the authors cover Big data, learning analytics, and natural language processing (NLP) in higher education.	Big data has demonstrated significant value in higher education as a result of the proliferation of mobile devices and the rapid development of ICT. The fifth section discusses various approaches to data analytics for big education data, such as predictive analytics and learning analytics. predictive analytics for student performance. On their Big data architecture, the authors cover Big data, learning analytics, and natural language processing (NLP) in higher education, and present an integrated analytics model with predictive analytics for student performance.	The fifth section discusses various approaches to big education data data analytics and investigates a cross-institution learning analytics scenario to demonstrate the usefulness and technological challenges encountered. The field of Big Education Data research is constantly evolving. For the most recent research, readers can consult forums and periodicals.
8	Justian Knobbout and Esther van der Stappen	2019	We conducted a systematic review of the existing literature on learning analytics interventions to examine how it operationalizes affected learning.	Learning technologies enable interventions in the learning process with the goal of improving learning. Learning analytics provides such interventions based on learner data analysis. Interventions in the learning process are made	Throughout this study, we sought to answer the following question: How does the existing literature on learning analytics interventions operationalize affected learning? Only 62 of the 1932 search hits on learning analytics describe measurable, quantitative effects of complete learning analytics cycles in

OBSERVATION ON SURVEY:

The idea behind this system is completely useless and has only one program to maximize interaction between students and teachers. The articles we read used various machine learning techniques, such as supervised machine learning, unsupervised machine learning, semi-supervised machine learning, and reinforcement techniques. different algorithms like KNN, SVM, decision tree etc. We have seen that student performance has been influenced by many different factors that lead to poor student performance. One of the main reasons was lack of communication between teacher and student. That's why we try to analyze and solve these problems, and everyone tries to give the best result to our project.

CHAPTER III

SOFTWARE & HARDWARE REQUIREMENT SPECIFICATION

0.3. Software and Hardware Requirements Specification:

3.1 Assumptions and Dependencies:

- It is assumed that all the Users can access the system through internet.
- The administrative and teachers can manage all the data through internet of student.
- The students performance can be viewed on the website
- Common features including Login, Logout, forgot password, Change Password, User management features etc. which will be used across all software applications as part of Mission Mode Project will be developed commonly and uniformly.
- The web browser shall be latest and all the plug-ins will work on the client machines to access the Portal.

3.2 System Requirements:

3.2.1 Database Requirements:

- Secure data storage.
- Scalable content hosting
- Data backup
- NoSql

3.2.2 Software Requirements:

- Various Languages (HTML5, CSS3, Python)
- Streamlight Framework
- Learning Analytics, Machine Learning and Deep learning.

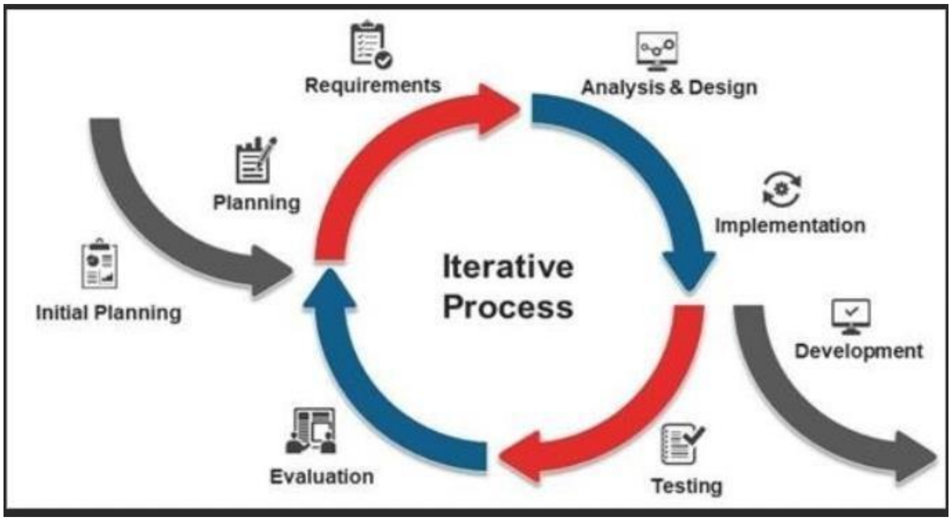
✓ **Functional requirements:**

1) Registration (Login/Logout)
2) Authentication
3) Authorization.
4) User friendly interface.
5) Attendance management.
6) Survey and feedback.
7) Smart search operation.
8) Result based on quiz graph representat

3.2.3 Hardware Requirements:

- Processor (CPU): Intel Core i5 or higher (or equivalent AMD processor). A faster processor is beneficial for handling data processing tasks associated with a dashboard.
- Speed: 2.0 GHz or higher. A faster clock speed ensures smoother performance, especially when dealing with data visualization and interactive elements on the dashboard.
- RAM: 8 GB or higher. A larger amount of RAM is essential for handling concurrent tasks, data processing, and ensuring a responsive user experience.
- Storage: A solid-state drive (SSD) with at least 256 GB of storage. SSDs provide faster data access, which can improve the loading speed of the dashboard and the efficiency of data retrieval.
- Graphics: Integrated graphics are usually sufficient for a dashboard website, as long as it doesn't involve heavy graphics processing. If the dashboard includes complex visualizations, a dedicated graphics card might be beneficial.
- Display: A 15-inch monitor with a resolution of 1920 x 1080 (Full HD) or higher. A larger screen and higher resolution provide a better viewing experience, especially for detailed data presentation.
- Operating System: Windows 10, macOS, or a Linux distribution. Ensure that the chosen operating system is compatible with the web browsers and tools used for the dashboard.
- Network Connectivity: A reliable internet connection is crucial for accessing and updating data on the dashboard. A wired connection is preferable, but a stable Wi-Fi connection should suffice.
- Web Browser: Latest versions of popular web browsers like Google Chrome, Mozilla Firefox, or Microsoft Edge. The dashboard website should be optimized for compatibility with these browsers.
- Input Devices: Standard keyboard and mouse. Depending on the dashboard's interactivity, a mouse with additional features like a scroll wheel may enhance the user experience.
- Security Features: Ensure that the system has up-to-date antivirus software and security protocols to protect sensitive data accessed through the dashboard.

3.3 Agile Model: SDLC Model to be applied:



1. **Requirement Gathering:**

   The software development team continues to work on the project from this point forward. The team attempts to extract as much information as it can about the requirements by holding talks with different stakeholders from the issue area. The requirements are thought through and divided into three categories: functional, system, and user requirements. The following methods are used to gather the requirements:

   - ✓ researching the software and system that is already in use or has become outdated
   - ✓ Interviewing developers and users,
   - ✓ consulting the database or compiling questionnaire responses.

2. **Feasibility Study:**

   Following requirement collection, the team develops a preliminary software process plan. At this point, the team assesses whether the software can be developed to meet every user need and whether it may eventually become obsolete. The viability of the project from a financial, practical, and technological standpoint for the organization is determined. Numerous algorithms are available to assist developers in determining whether a software project is feasible.

3. **System Analysis:**

   At this stage, the developers choose a plan's roadmap and work to identify the best software model for the undertaking. Understanding software product limitations, learning about system-related issues or necessary modifications to already-existing systems, determining and addressing the project's impact on the organization and its personnel, and other things are all included in system analysis. The project team evaluates the project's scope before allocating resources and creating a schedule.

4. **Software Design:**

   The next stage is to design the software product using all of the requirements and analysis knowledge that has been gathered. The inputs for this step are the data acquired during the requirement gathering phase and user inputs. Both the logical design and the physical design are the products of this step. Logical diagrams, data-flow diagrams, meta-data and data dictionaries, and occasionally pseudo-code are created by engineers.

5. **Coding:**

   The programming phase is another name for this stage. The first step in putting software design into practice is writing code in the appropriate programming language and creating effectively designed, error-free executable programs.

6. **Testing:**

   It is estimated that testing should account for half of the entire software development process. From a critical level to the software's own removal, errors can destroy it.

   Software testing is done by developers while they are coding, and comprehensive testing is carried out by testing specialists at different code levels, including program, module, and product testing as well as in-house and user-end testing. Reliable software relies on the early detection of errors and the prompt correction of them.

7. **Integration:**

   It might be necessary to integrate software with databases, libraries, and other programs. This software development life cycle step involves integrating software with external entities.

8. **Implementation:**

   Installing the software on user computers is what this entails. Software occasionally requires user configurations after installation. Software is tested for adaptability and portability, and problems with integration are resolved during deployment.

9. **Operation and Maintenance:**

   This stage verifies that the software is operating with greater efficiency and fewer errors. When necessary, the users receive training or assistance with the documentation explaining how to use and maintain the software. The program is updated on a regular basis to reflect changes in the user's end environment and in technology. Unidentified real-world issues and hidden bugs could present difficulties during this phase.

10. Deployment:

The software's performance might deteriorate over time. It might become totally outdated or require significant upgrades. As a result, there is an urgent need to remove a significant chunk of the system. During this phase, the necessary software components and data are archived, the system is shut down, disposal activities are planned, and the system is terminated at the proper end-of-system time.

CHAPTER IV

SYSTEM DESIGN

0.4. System Design

4.1. System Architecture:

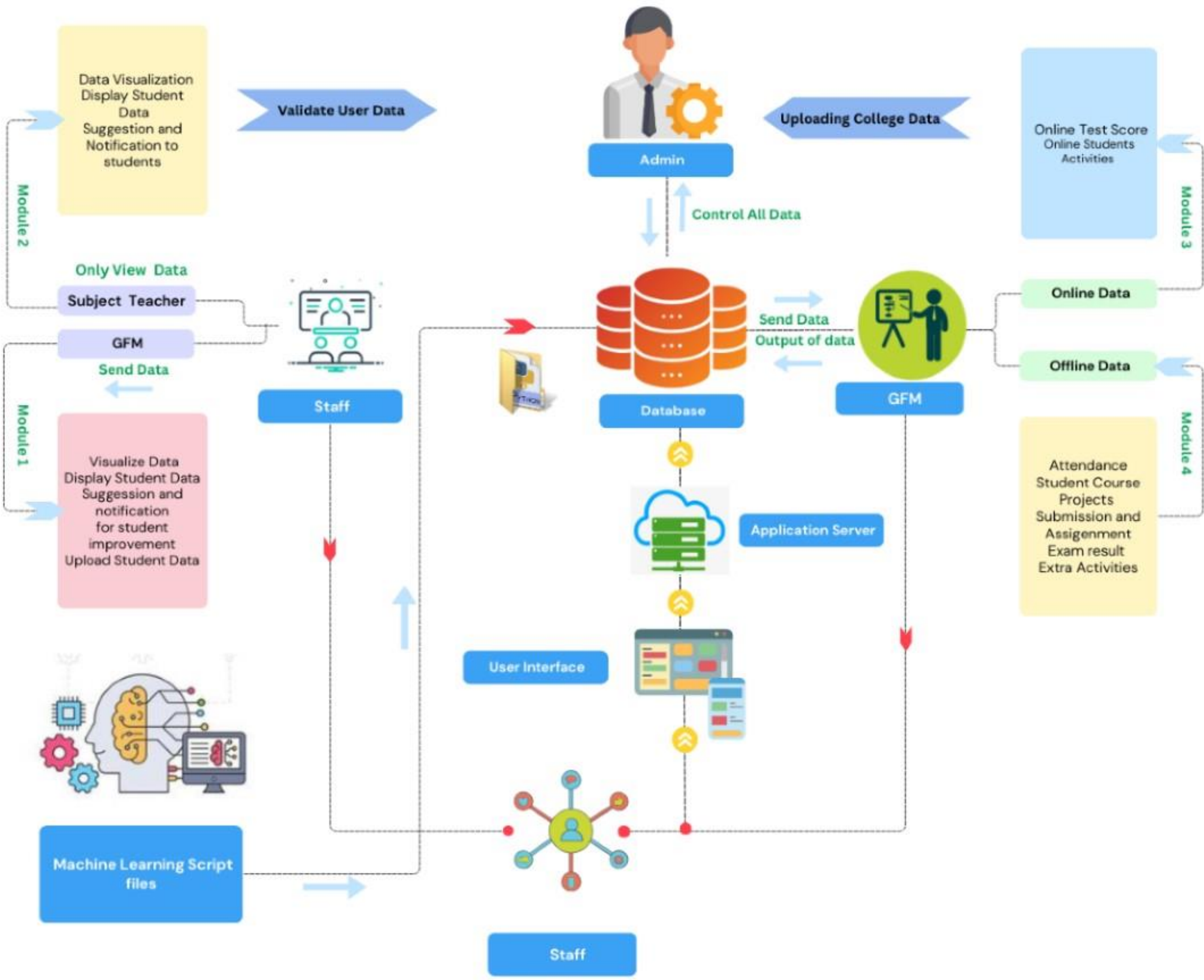


Fig 4.1: System Architecture of Web Portal

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**.**

4.2. <u>Mathematical Model</u>:

- ✓ **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) = X N i=1 wi · I(x ∈ Ri)

   Where: - h(x) is the prediction for input x. - N is the number of leaf nodes. - wi is the predicted value associated with the ith leaf node. - Ri is the region in the feature space assigned to the ith leaf node. - I(·) 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) = 1 M X M j=1 hj (x)

   Where: - H(x) is the prediction of the Random Forest for input x. - M is the total number of trees in the forest. - hj (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. ree-building process.

- ✓ **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 over-fitting.

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

Obj = Xn i=1 L(yi , yˆi) +X K k=1 Ω(fk)

Where: - n is the number of samples. - L is the chosen loss function measuring the model's performance. - yˆi is the predicted value for the ith sample. - Ω represents the regularization term applied to each individual tree fk. - 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:

Ft(x) = Ft−1(x) + ht(x)

Where: - Ft(x) is the prediction of the ensemble at iteration t. - Ft−1(x) is the prediction of the ensemble at iteration t−1. - ht(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 treespecific parameters, learning rate, depth of trees, regularization terms, and other settings that affect the boosting process and model complexity.

4.3. Data Flow Diagrams:

4.3.1. DFD Level 0:

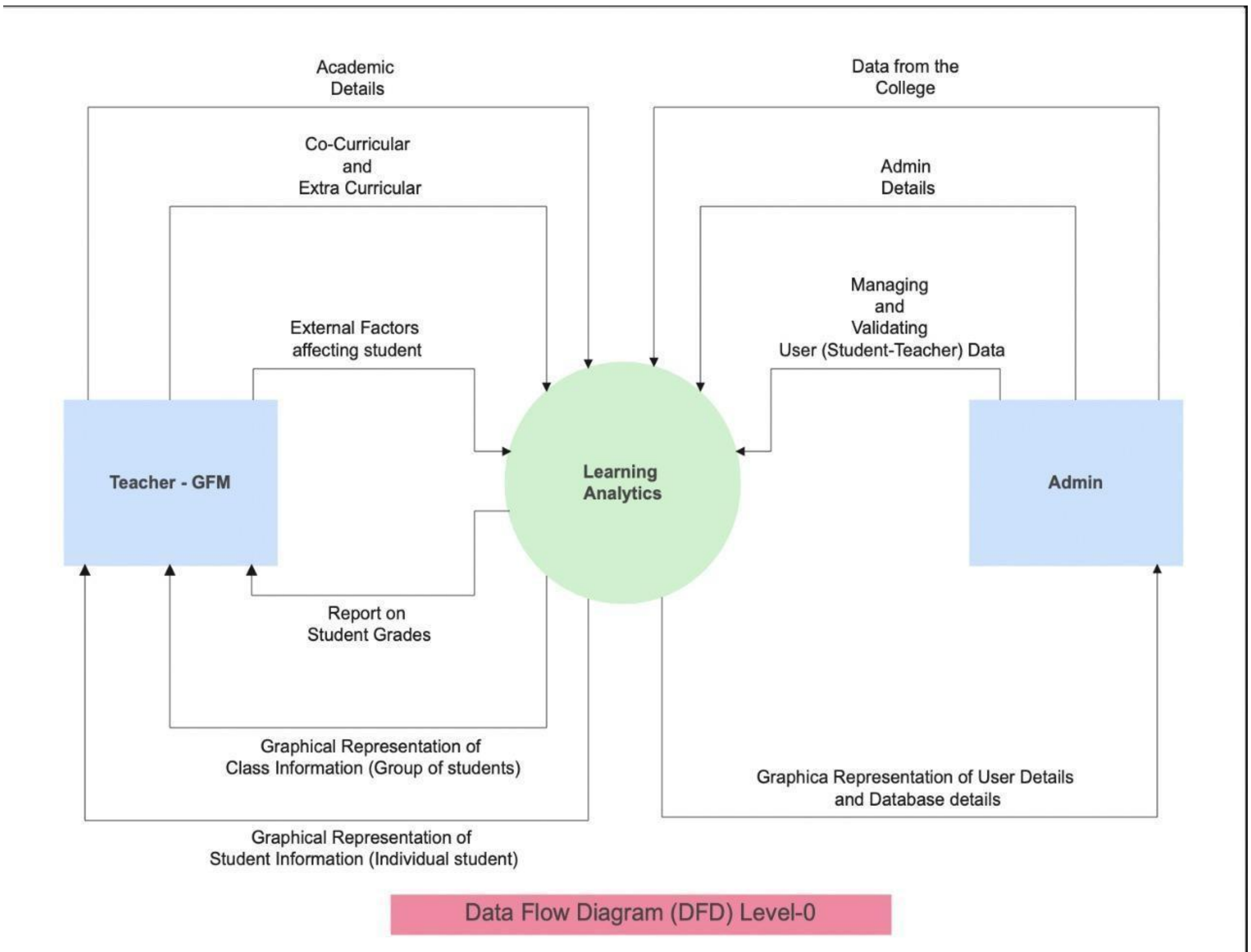


Fig: DFD Level 0 Diagram

4.3.2. DFD Level 1:

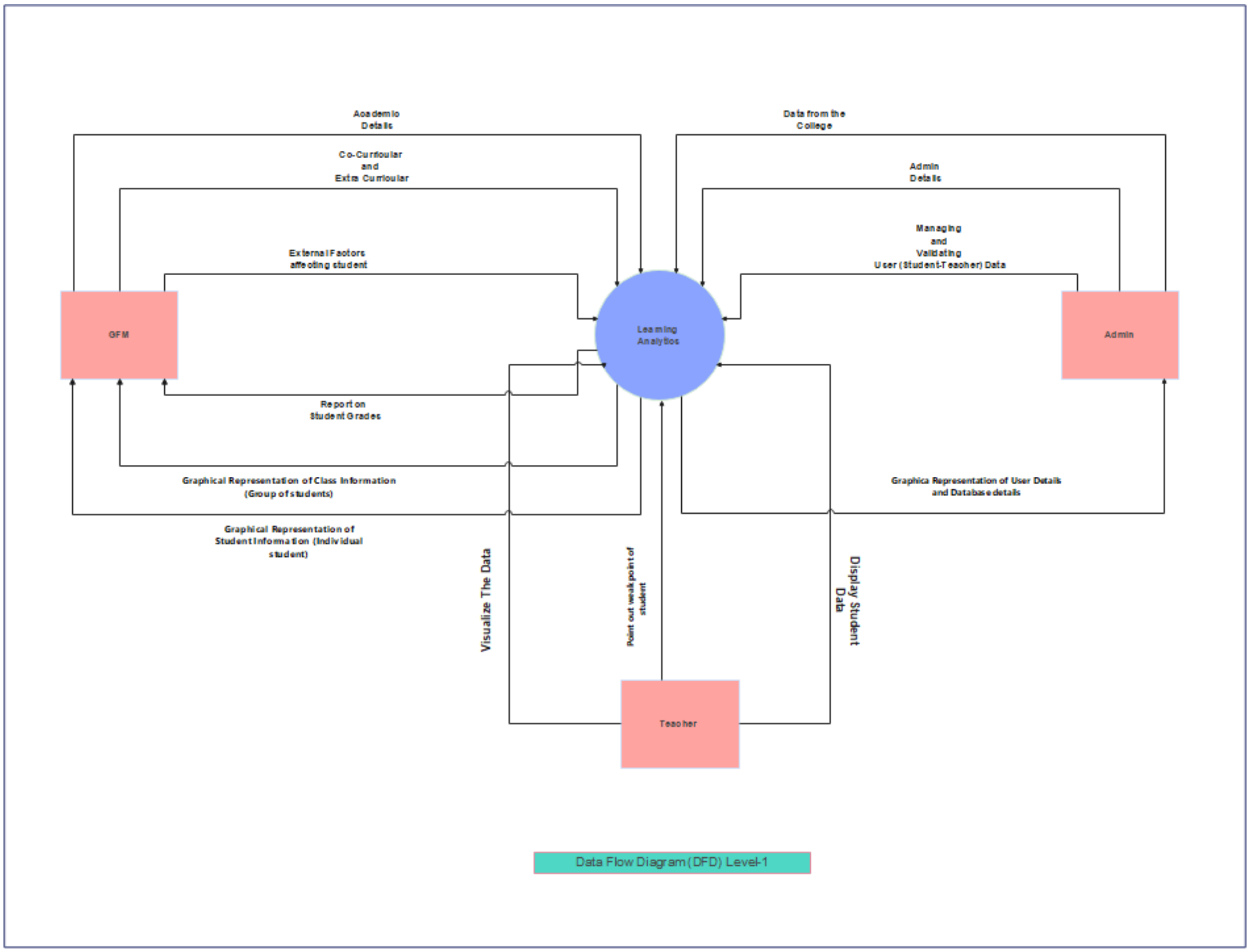


Fig: DFD Level 1

4.4. **Entity Relationship Diagram**:

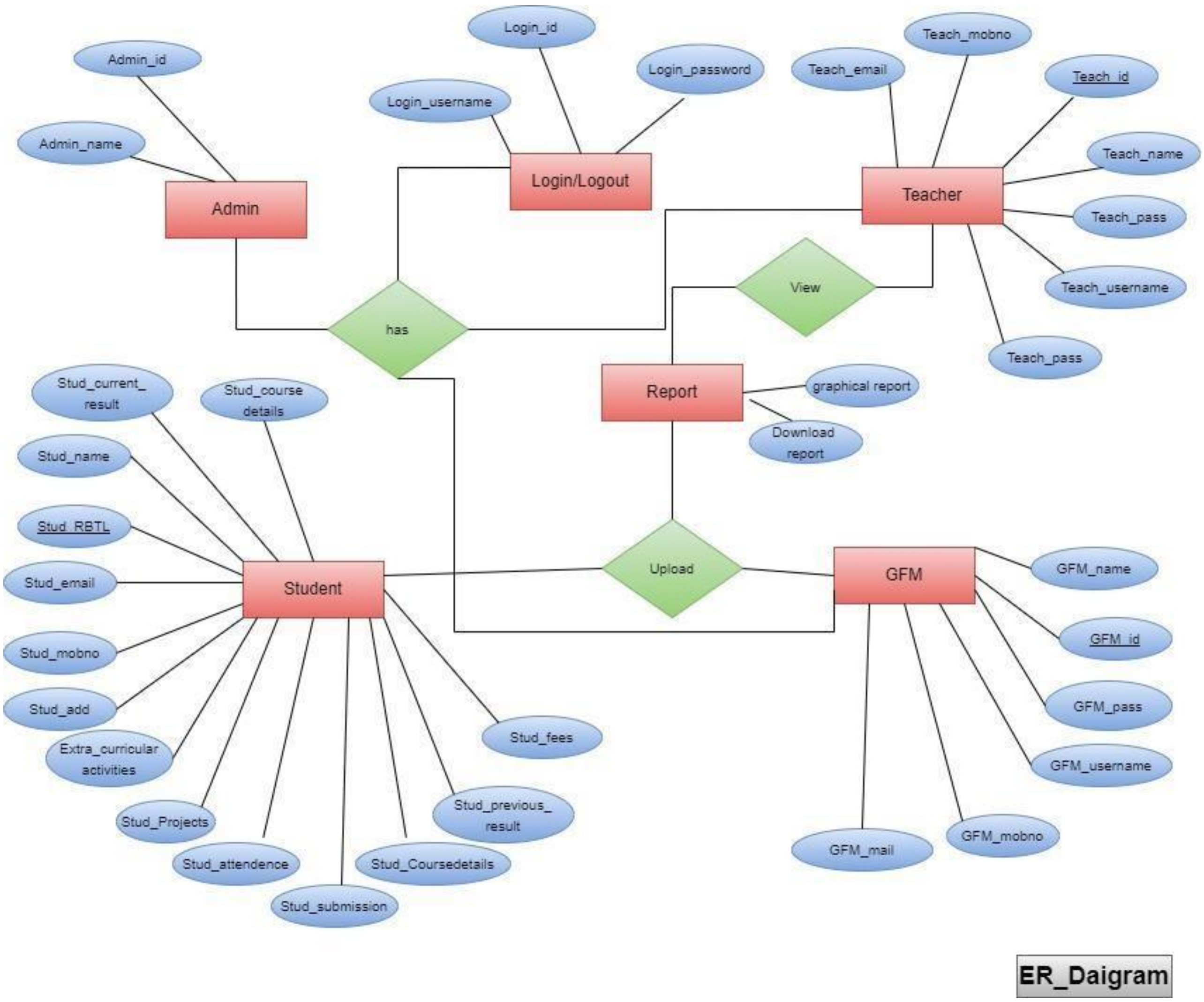


Fig: ER Diagram

4.5. UML Diagram:

4.5.1 Use case Diagram:

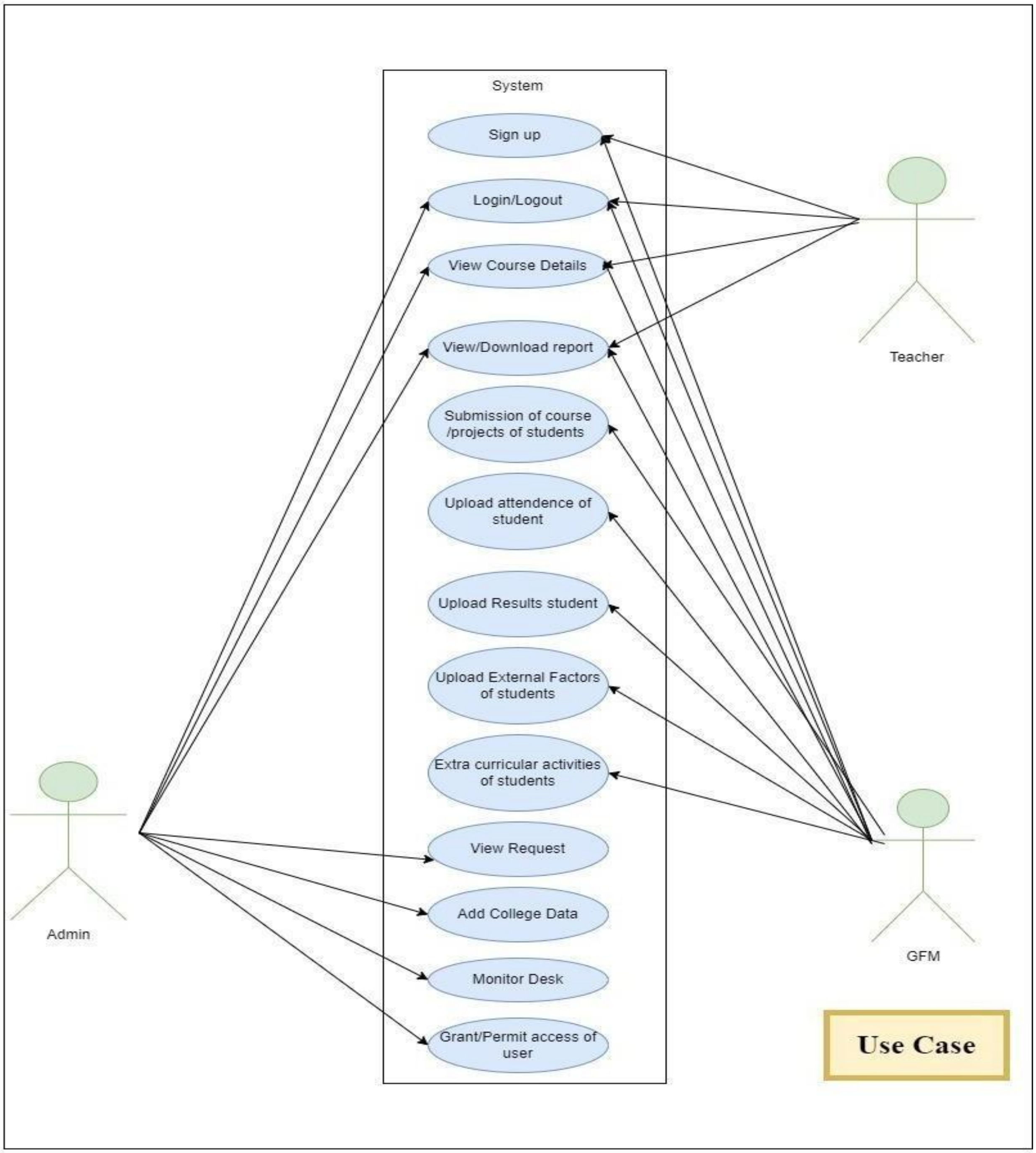


Fig: Use Case Diagram

4.5.2. Structure Chart Diagram:

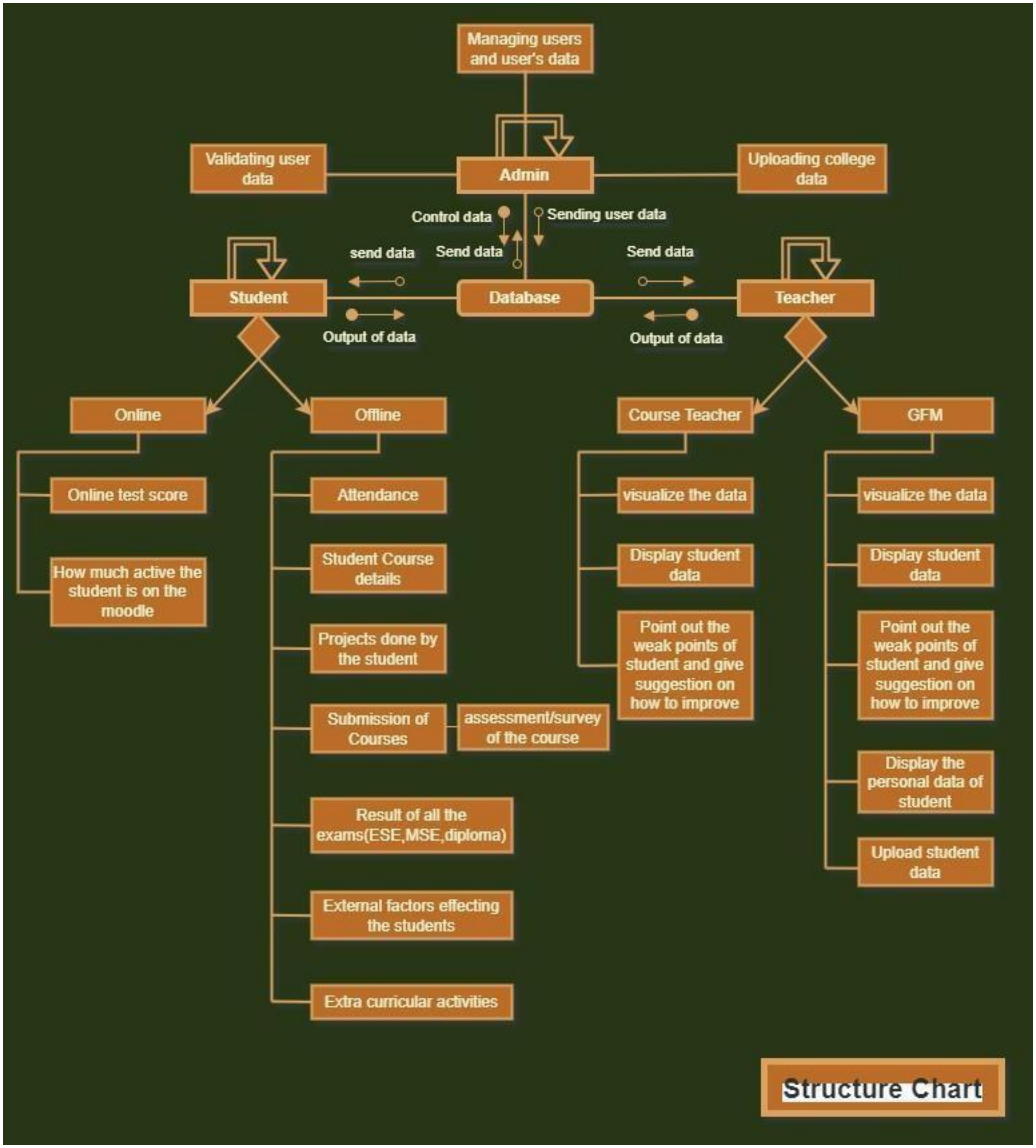


Fig: State chart diagram.

4.5.3. State Transition Diagram:

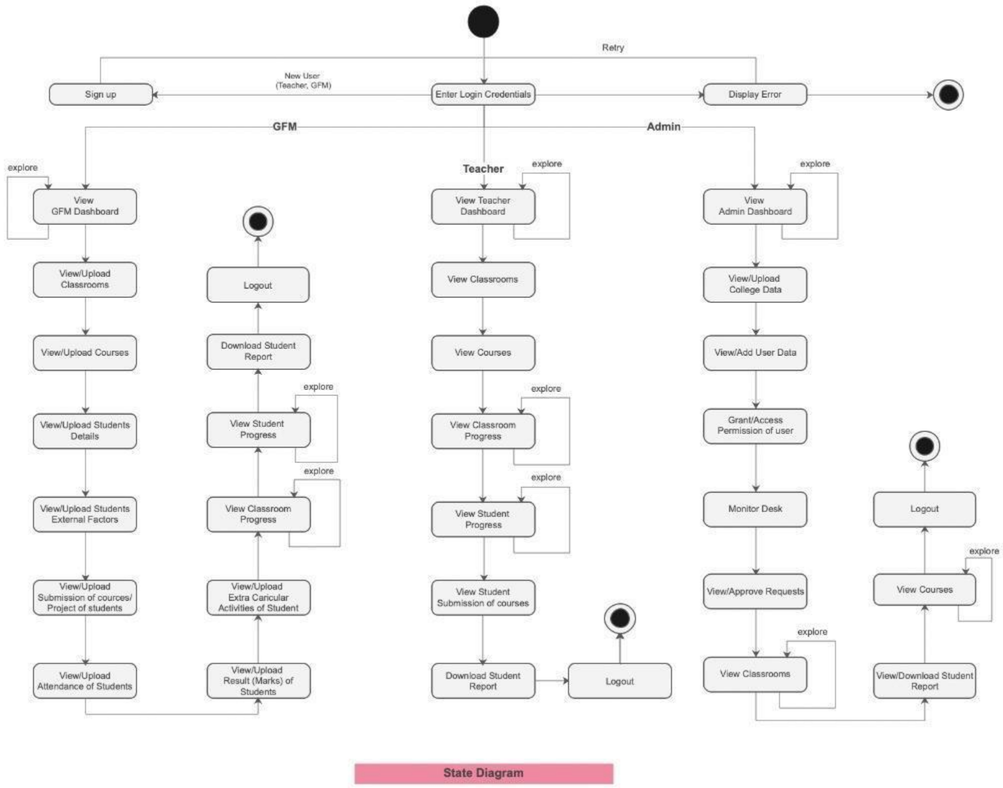


Fig: State transition diagram.

4.5.4. Sequence Diagram:

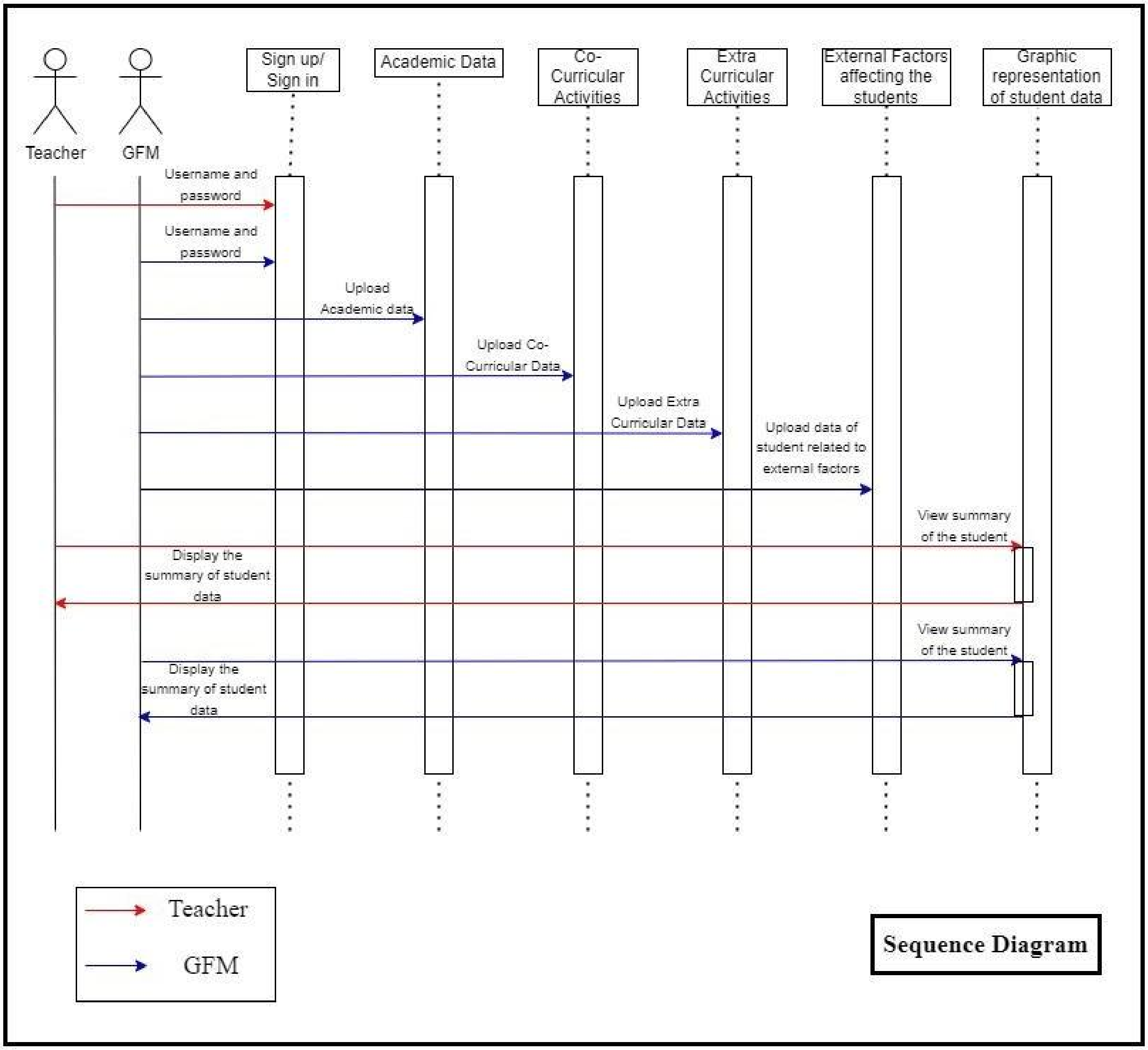


Fig: Sequence Diagram

4.5.5 Class Diagram:

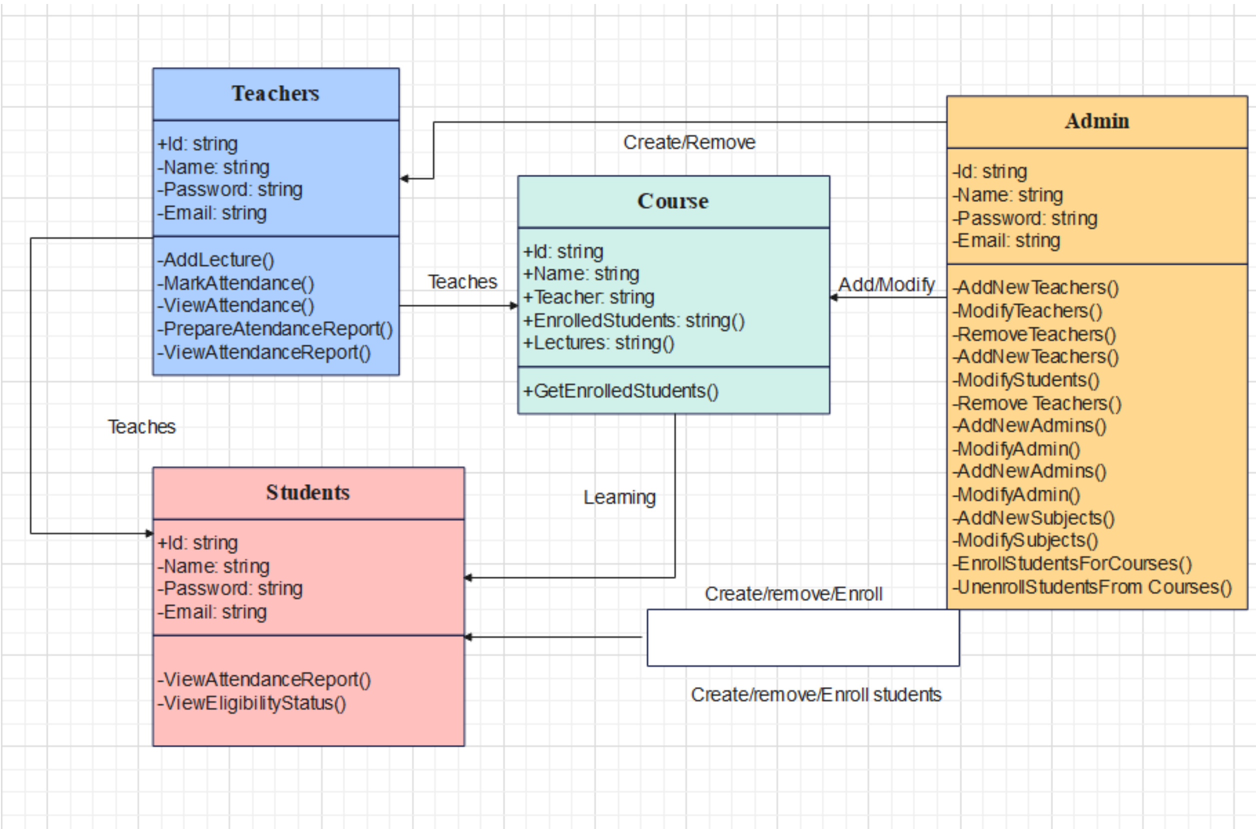


Fig: Class diagram

4.6. Project Schedule and Timeline Chart :

Phase	**Tasks**
Project Initiation Phase	- Define project objectives, scope, and requirements - Identify stakeholders and their roles - Set up project management tools and communication channels
Research and Data Collection	- Gather relevant datasets for training and testing - Conduct exploratory data analysis - Preprocess and clean the data
Machine Learning Model Development	Random Forest Model: - Perform feature selection and engineering - Split the data into training and validation sets - Train the Random Forest model - Tune hyperparameters - Evaluate model performance
	Decision Tree Model: - Perform feature selection and engineering - Split the data into training and validation sets - Train the Decision Tree model - Tune hyperparameters - Evaluate model performance
	SVC Model: - Perform feature selection and engineering - Split the data into training and validation sets - Train the SVC model - Tune hyperparameters - Evaluate model performance
Web Development	- Design the website layout and user interface using HTML and CSS - Set up the development environment and install necessary tools - Create React components for different sections of the website - Implement routing and navigation using React Router - Integrate machine learning models into the web application
Testing and Quality Assurance	- Perform unit testing for individual web components - Conduct integration testing - Validate the accuracy and performance of the machine learning models - Identify and fix bugs or issues
User Interface Refinement	- Gather user feedback and conduct usability testing - Incorporate user feedback to improve website design and user experience - Optimize website responsiveness and load times
Deployment and Launch	- Set up hosting environment and deploy the web application - Conduct final testing in the production environment - Configure domain and SSL certificate if necessary - Perform final checks and ensure proper functioning
Monitoring and Maintenance	- Monitor web application performance, stability, and security - Implement logging and analytics - Regularly update and maintain the machine learning models - Address bugs and user feedback promptly
Project Closure	- Conduct project review and document lessons learned- Obtain stakeholder sign-off on project completion - Archive project documentation, code, and datasets

4.7 Team Organization:

Team Member	Role	Task assigned	Work Accomplished
Shubham Asbe	Project Lead/back-end developer	Project planning, coordination, and communication/Data collection and Analysis	Project planning, coordination, and communication .Developed project schedule, facilitated team meetings
Akanksha Lugade	Back-end developer/documentation	Report making/presentation planning/Data cleaning	Documentation like report, ppt etc.
Yash More	Back-end developer/Tester	Data collection and preprocessing/ identify bugs	Conducted test cases, identified and reported bugs
Dipali Bhalerao	Designer/Front-end developer	User interface design and mockup creation/Frontend development	Created wireframes, UI mockups, and style guide, Coding
Anuradha Partudkar	Font-end developer/Tester	Frontend development **/** Testing and QA	Coding, Testing and quality assurance

CHAPTER V

PROJECT IMPLEMENTATION

05. Project Implementation

5.1 Overview Of Project Modules :

1) **Admin Module :** Admin is a person who has the responsibility of managing the team and providing daily support as well as keeping the ongoing operations of an learning system. In other words, this employee is the one who usually deals with all over educational data.

Admin has the following role:

- Validating User data: In this role admin validate the user data is correct or not.
- Uploading college data: In this module, admin helps to upload the all over college data. They keep records and reports up to date.
- Database: Creating and maintaining database standards and policies. Supporting database design, creation, and testing activities.

2) **Student Module:**

Online Module: Online module is divided into further two modules:-

- Online test score: This module will track and review the online score of the student.
- Activity of student on moodle: This module will show and summarize the usage of moodle.
- Offline Module: offline module is divided into 7 sub modules:-
- Attendance: Track the attendance of individual student as we as the whole class and give the summary of it.
- Student course details: Track the students progress in the course and how is he/she performing in a particular course in a particular semester.
- Projects done by the student: Track the projects done by the student and the different languages and framework used by the students in those projects.
- Submission of courses: Track the submission details of each course in a particular semester and will also track the assessment and survey reports of the students.

- Result of all Exams: Track and summarize the result marks of all the exams, up till current semester.
- External factors affecting the students: Monitor the external factors(family issue, personal problems) affecting the academic of the student.
- Extra Curricular activities: Track the participation of the student in different activities excluding academic.(Ex. Clubs, competitions)

3) **Teacher Module (+ GFM module):** Teacher module is divided into five sub-modules.

- Visualize the information: Visualize all of the class data so that GFM can see how the class is improving and where students are struggling.
- Display student data: To display specific student data in which the GFM will be able to see the previous semester marks and current semester marks, as well as his subject internal grades, which will assist the instructor in analyzing the students weaknesses.
- Student weakness & Recommendations: After showing all of the students data to the GFM, the system will analyze the data and point out the students weak spot or where the student is trailing behind, as well as make suggestions to help the GFM advise the student on the weak point.
- Display the students personal data: In This module, we will display the students personal details such as family background, prior school, previous college, his/her weak areas, his/her strong areas, locate, family details, and student fees.
- Upload student data: In this Module, the GFM will be able to upload the data of a specific student in order to show student information and analyze the data.

5.2 Tools and Technologies Used:

1. Python:

Known for its readability and simplicity, Python is a high-level, versatile programming language. Because of its vast library and framework selection and ease of use, it has become extremely popular among developers. Multiple programming paradigms, such as procedural, object-oriented, and functional programming, are supported by Python.

2.HTML:

The common markup language used to create the content and structure of web pages is called HTML. It offers a collection of pre-made attributes and tags that specify the elements and how they appear on a webpage. Important attributes of HTML include:

5 **CSS:** The visual representation of HTML and XML documents is described using the stylesheet language CSS. It specifies the arrangement, color scheme, typeface, spacing, and other visual components of how elements should be shown.

6 **Streamlit:**

Streamlit is an open-source Python application framework. It speeds up the process of developing web apps for machine learning and data science. Major Python libraries like Scikit-Learn, Keras, PyTorch, SymPy (latex), NumPy, pandas, Matplotlib, and others are compatible with it. Callbacks are not required with Streamlit because widgets are handled like variables. Computation pipelines are made simpler and faster by data caching. Streamlit automatically deploys the application through the shared link and monitors any updates to the linked Git repository.

Dataset :

	full_name	prn_number	roll_number	age	gender	Day_scholar	department	year	division	cgpa	sgpa	10th_percentage	12th_percentage	certification_platform	paid_or_unpaid_member	clubs_joined	avg_time_on_social_media	social_media	Fast_slow_learner
2	shruti atul nadgauda	rbt21cs005	cs2105	19	female	0	computer	sy	a	8.1	8.1	90	85	udemy	1	3	2	youtube	0
3	samarth akash patil	rbt21cs011	cs2111	19	male	1	computer	sy	a	8.9	9.04	87	90	udemy	1	1	2	instagram	1
4	alisha akbar tamboli	rbt21cs066	cs2165	20	female	0	computer	sy	a	9.57	9.59	93.8	98	udemy	0	1	1	instagram	1
5	pawar parmeshvar ramchandra	rbt20cs016	cs3106	20	male	0	computer	ty	a	8.74	8.4	95.8	74.92	udemy	0	2	1	youtube	1
6	shreya pranath panicker	rbt20cs132	cs3148	20	female	1	computer	ty	a	9	9	92.8	90.77	udemy	0	2	0.5	youtube	1
7	swarada gade	rbt21cs048	cs2147	20	female	1	computer	sy	a	9.11	9.43	90.2	90.2	udemy	1	1	4	instagram	1
8	ankita babasaheb kamble	rbtl20cs006	cs2279	22	female	1	computer	be	a	8.7	8.7	80.4	0	coursera	0	0	1	youtube	0
9	vaishnavi pawar	rbtl20cs003	cs2203	21	female	1	computer	be	a	9.74	9.75	88	0	other	0	0	3	youtube	1

5.3 Algorithm Details:

1. Random Forest: An ensemble learning algorithm called Random Forest uses several decision trees combined to generate predictions. Regression and classification tasks are its main applications. To get the final result, the algorithm generates a large number of decision trees and aggregates their predictions.

Essential elements of Random Forest:

- Ensemble learning: To increase accuracy and decrease overfitting, Random Forest aggregates the predictions of several decision trees.
- Random feature selection: To increase diversity and decrease correlation between trees, every decision tree in the forest is trained on a random subset of features.
- Bootstrap aggregating (bagging): To ensure that every tree has a slightly different training set, Random Forest samples the training data with replacement to create distinct subsets for each tree.

Random forest

```
[ ] from sklearn.impute import SimpleImputer

    # Replace missing values with the mean
    imputer = SimpleImputer(strategy='mean')
    X_train_imputed = imputer.fit_transform(X_train)

    # Train the model
    rfe = RandomForestClassifier(n_estimators=500,random_state=42)
    rfe.fit(X_train_imputed, y_train)

    # Replace missing values with the mean in the test set
    X_test_imputed = imputer.transform(X_test)

    # Evaluate the model on the test set
    y_pred = rfe.predict(X_test_imputed)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy}")

    Accuracy: 0.7297297297297297
```

2. XGBoost: The highly effective and performant gradient boosting algorithm XGBoost is well-known. It is frequently applied to problems involving ranking, regression, and classification.

Highlights of XGBoost:

• Gradient boosting: XGBoost is an ensemble learning method that sequentially combines weak prediction models, most commonly decision trees.

• Regularization and optimization: To reduce overfitting and enhance generalization, XGBoost uses regularization, tree pruning, and column subsampling.

XG Boost

```
import xgboost as xgb
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.metrics import accuracy_score

# Load the dataset
data = load_breast_cancer()
X = data.data
y = data.target

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create an instance of the SimpleImputer class
imputer = SimpleImputer(strategy='median')

# Fit and transform the imputer on the training data
X_train_imputed = imputer.fit_transform(X_train)

# Transform the imputer on the test data
X_test_imputed = imputer.transform(X_test)

# Create a new XGBoost classifier
xgb_model = xgb.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, random_state=42)

# Fit the model on the imputed training data
xgb_model.fit(X_train_imputed, y_train)

# Predict on the imputed test data
y_pred = xgb_model.predict(X_test_imputed)

# Calculate accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9649122807017544
```

3.Naïve Bayes: The Naive Bayes algorithm is a probabilistic classification method that relies on the conditional independence of features and the Bayes theorem. Spam filtering and text classification are two common uses for it.

Essential elements of Naive Bayes

• Bayes' theorem: Using the input features as a starting point, Naive Bayes determines the posterior probability of a class.

• Conditional independence assumption: To make the computation of probabilities easier, Naive Bayes makes the assumption that the features are conditionally independent of one another.

• Feature probability estimation: Using the training data, Naive Bayes calculates the probability distributions of the features for each class.

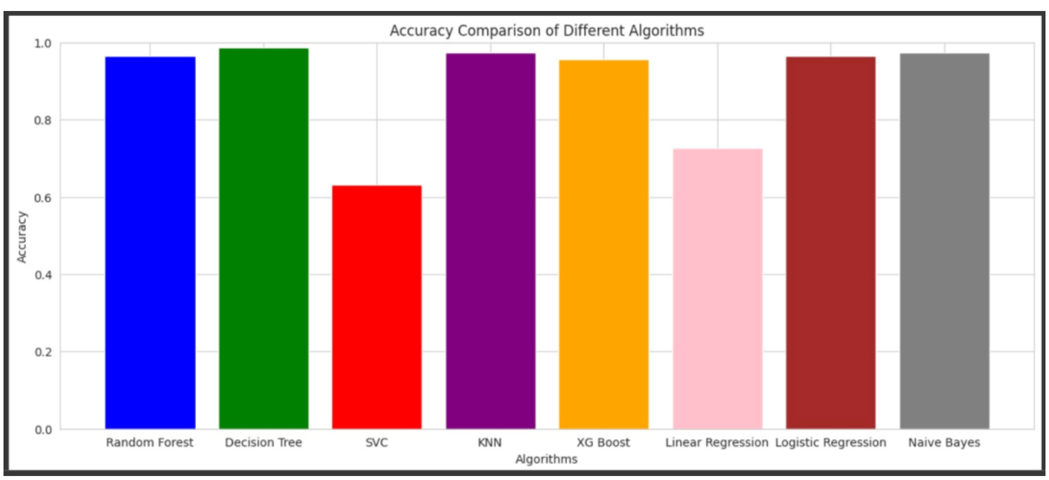
• Easy to use and effective: Naive Bayes requires a minimal quantity of training data and is a computationally efficient method.

• Text classification applicability: Naive Bayes performs especially well on text classification tasks like sentiment analysis.

Naive Bayes

```
[ ]  from sklearn.naive_bayes import GaussianNB

     # Create a new Naive Bayes model
     nb_model = GaussianNB()

     # Fit the model on the imputed training data
     nb_model.fit(X_train_imputed, y_train)

     # Predict on the imputed test data
     y_pred_nb = nb_model.predict(X_test_imputed)

     # Calculate accuracy score
     accuracy_nb = accuracy_score(y_test, y_pred_nb)
     print("Accuracy (Naive Bayes):", accuracy_nb)

     Accuracy (Naive Bayes): 0.9736842105263158
```

Accuracy Chart of all algorithams:



CHAPTER VI

SOFTWARE TESTING

06. Software Testing

6.1 Type of Testing:

- **Unit Testing:**
  Because a portion of this system was a GUI-based web portal. Unit testing has been handled successfully in our system. Every module received the test data in all respects and produced the intended results. Every module has been tested and found to be operational.

- **Interface Testing:**
  Verifying that there are no hiccups in the communication between the webserver and the app server is crucial. It is important to test the software, hardware, network, and database compatibility to ensure that all of the interactions function as a single unit. It is recommended to test the two primary interfaces of the web server, which are the application server and database server interface, for any errors or exceptions.

- **Security Testing:**
  Due to the increased susceptibility of today's cyber world to threats and vulnerabilities, businesses' top concerns are website availability and customer data security. Any kind of website security breach could result in negative effects like a decline in customer confidence, legal troubles, or even worse effects on their brand. Therefore, to make sure that your website and web apps are safe from attacks and vulnerabilities, you can use a certified team of ethical hackers that are connected to independent testing service providers.

- **Performance Testing:**

  The other most important factor for your websites and web applications is that they should deliver flawless performance even under loads. Effective web load testing and web stress testing should be taken up by next-gen performance testing provider to ensure your websites deliver great user experience even when numerous users access the same page.

6.2 Test Cases and Test Result:

Test Case Type	Description	Test Step	Excepted Result	Status
Login	Verify successful login with valid credentials.	1. Navigate to the login page. 2. Enter valid username and password. 3. Click on the login button. 4. Verify that the user is logged in.	User should be successfully logged in. The system should redirect to the user's dashboard	Pass
Upload Data (CSV)	Test data upload functionality using CSV file.	1. Navigate to the "Upload Data" section. 2. Select a CSV file for upload. 3. Click on the upload button. 4. Verify that the uploaded data is reflected in the system.	The system should provide an option to upload data. The uploaded data should be processed without errors, and a success message should be displayed.	Pass
Upload Data (Excel)	Test data upload functionality using Excel file.	1. Navigate to the "Upload Data" section. 2. Select an Excel file for upload. 3. Click on the upload button. 4. Verify that the uploaded data is reflected in the system.	The system should provide an option to upload data. The uploaded data should be processed without errors, and a success message should be displayed.	Pass
Upload Data Privilege Check (GFM)	Test data upload privilege check (GFM).	1. Attempt to upload data with a non-GFM user. 2. Log in with a user having the privilege "GFM". 3. Repeat the data upload process. 4. Verify that the uploaded data is reflected in the system.	The system should deny access and display an error message for non-GFM users. Users with the privilege "GFM" should be able to upload data, and the uploaded data should be reflected in the system without errors.	Pass
Search Non-Existent Student	Test the system's response when a user tries to search for a student data that is not present in the database.	1. Navigate to the search section. 2. Enter the details of a non-existent student (e.g., a non-existent student ID or name). 3. Click on the search button.	The system should display a clear error message indicating that the student data is not found in the database. The user should be informed that the searched student does not exist.	Pass

Test Case Type	Description	Test Step	Excepted Result	Status
Functionality	Test the functionality of core features and use cases.	Check if data is stored correctly in the database and retrieved accurately.	Data Should be stored in database and working correctly.	Pass
Security	Verify that user authentication and authorization mechanisms are functioning correctly.	Validate that user inputs are properly validated.	Authentication and Authorization functionality shoud be working properly without any error.	Pass
Usability	Evaluate the ease of use and intuitiveness of the user interface.	Test the user journey from start to finish and ensure it is logical and straightforward.	Validate that error messages are clear and helpful to users.	Pass
Compatibility	Test the website on different browsers (e.g., Chrome, Firefox, Safari, Edge) and versions.	Verify that the website works well on different operating systems (e.g., Windows, macOS, Linux).	Validate that the website should be compatible with different versions of external dependencies.	Pass
Performance	Check the system's performance by simulating multiple users accessing the application simultaneously.	Measure the system's response time under normal and peak load conditions.	Validate that the system should maintains an acceptable response time even during heavy loads.	Pass

CHAPTER VII

RESULTS

07. Results

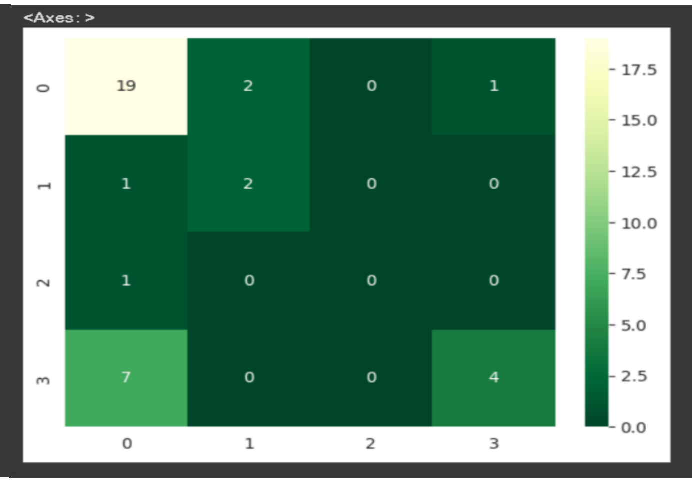
7.1 Outcomes:

- **Improved Data Visualization and Analysis:**
  - Teachers can easily access and analyze individual student performance, class-level trends, and comparative insights.
  - Visual representations, such as charts, graphs, and tables, help teachers identifypatterns and areas for improvement.
- **Deep Learning Integration for Recommendations:**
  - Deep learning algorithms were successfully integrated into the dashboard to provide key recommendations for performance improvement.
  - By analyzing student data, the deep learning models generate personalized suggestions and interventions based on individual strengths and weaknesses.
- **Enhanced Student Performance:**
  - The implementation of the teacher-facing dashboard and deep learning-basedrecommendations has positively impacted student performance.
  - Teachers have reported improved understanding of individual student needs,allowing them to provide targeted support and interventions.
  - Students have shown increased engagement and motivation as they receive personalized guidance for improving their academic performance.
- **Empowered Teachers:**
  - Teachers can easily identify struggling students, track progress, and implement effective interventions based on the provided recommendations.
  - This has resulted in more effective and personalized teaching approaches, ultimatelyleading to improved student outcomes.

Confusion Matrix for Different Algorithms used in Project:

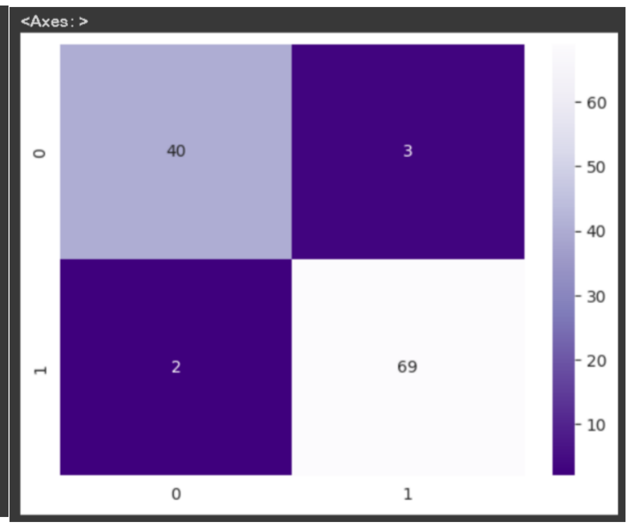
Random Forest:

	precision	recall	f1-score	support
a	0.68	0.86	0.76	22
b	0.50	0.67	0.57	3
na	0.00	0.00	0.00	1
s	0.80	0.36	0.50	11
accuracy			0.68	37
macro avg	0.49	0.47	0.46	37
weighted avg	0.68	0.68	0.65	37



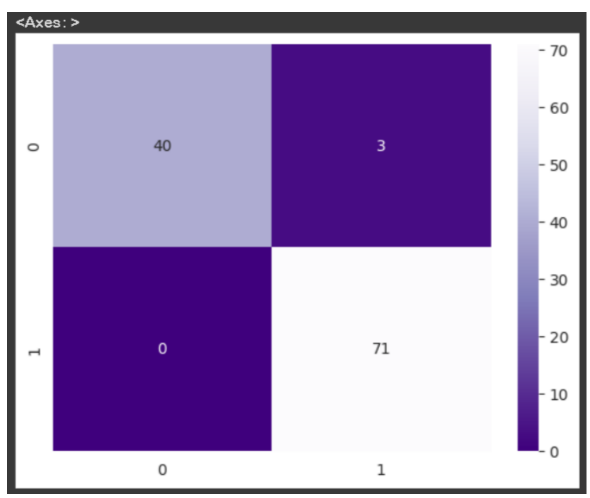
XGBoost:

	precision	recall	f1-score	support
0	0.95	0.93	0.94	43
1	0.96	0.97	0.97	71
accuracy			0.96	114
macro avg	0.96	0.95	0.95	114
weighted avg	0.96	0.96	0.96	114



Naive Bayes:

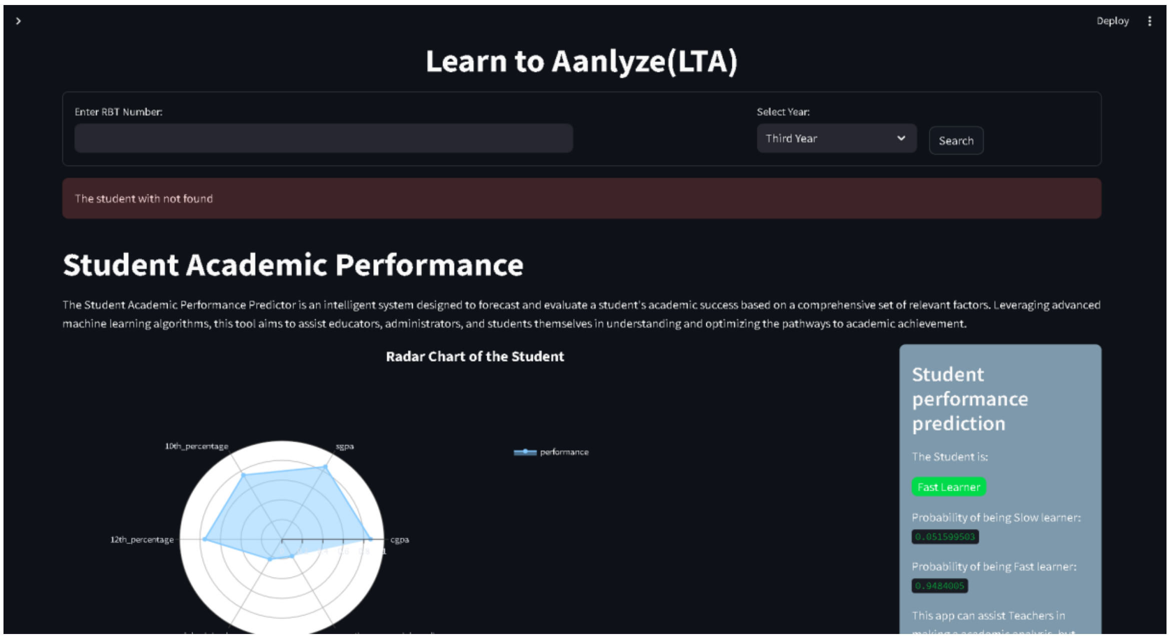
	precision	recall	f1-score	support
0	1.00	0.93	0.96	43
1	0.96	1.00	0.98	71
accuracy			0.97	114
macro avg	0.98	0.97	0.97	114
weighted avg	0.97	0.97	0.97	114

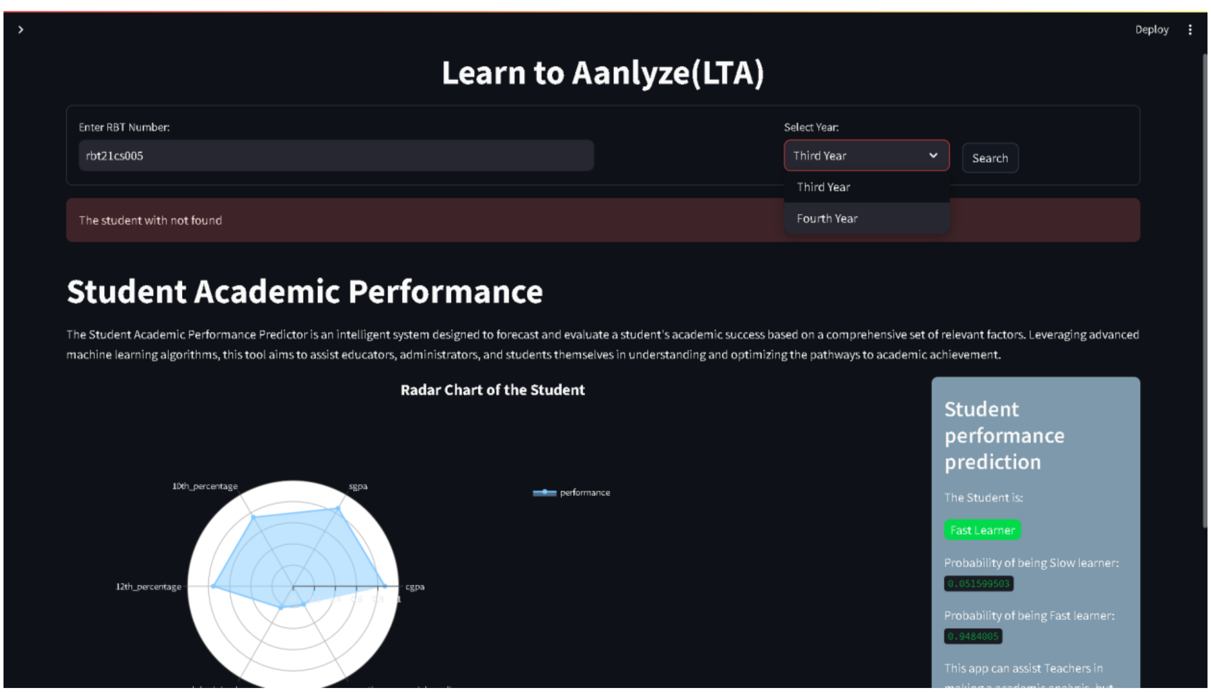


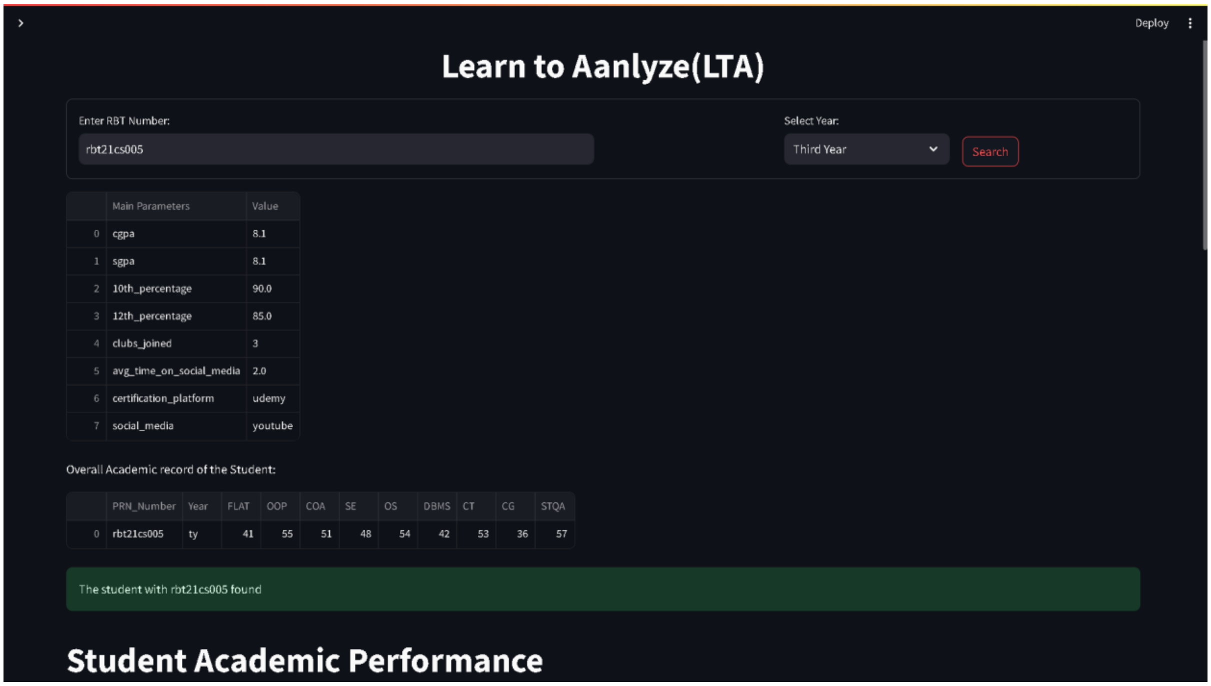
The confusion matrix shows how well our algorithms classify data. It's like a report card—tells us where the model gets things right (true positives and negatives) and where it slips up (false positives and negatives). This breakdown helps us measure accuracy, tweak the model, and figure out which algorithm works best for our project.

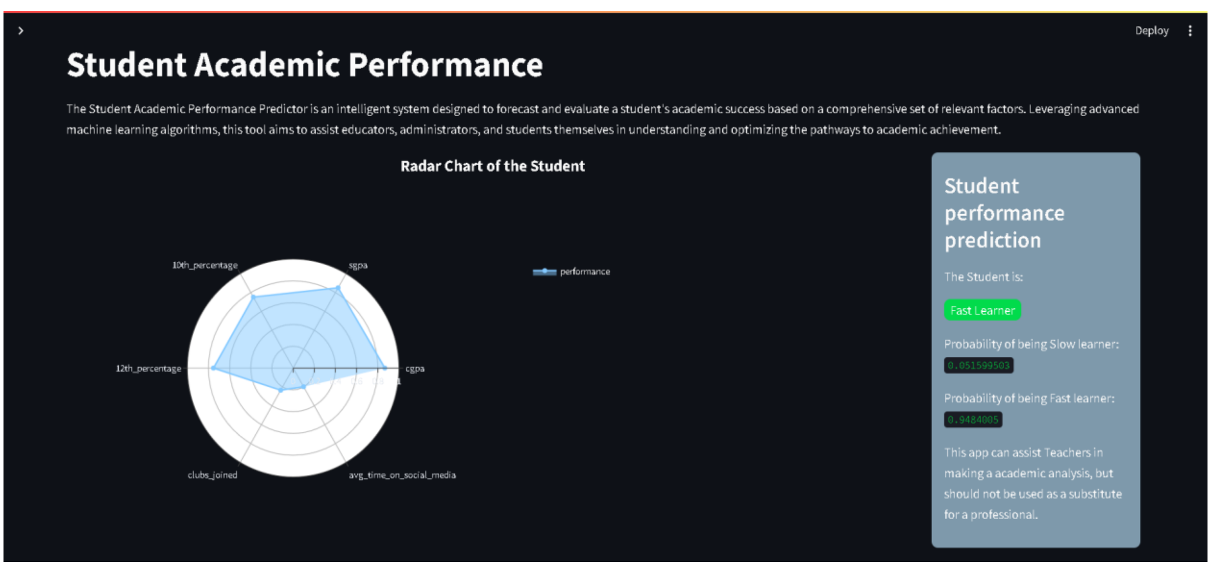
.

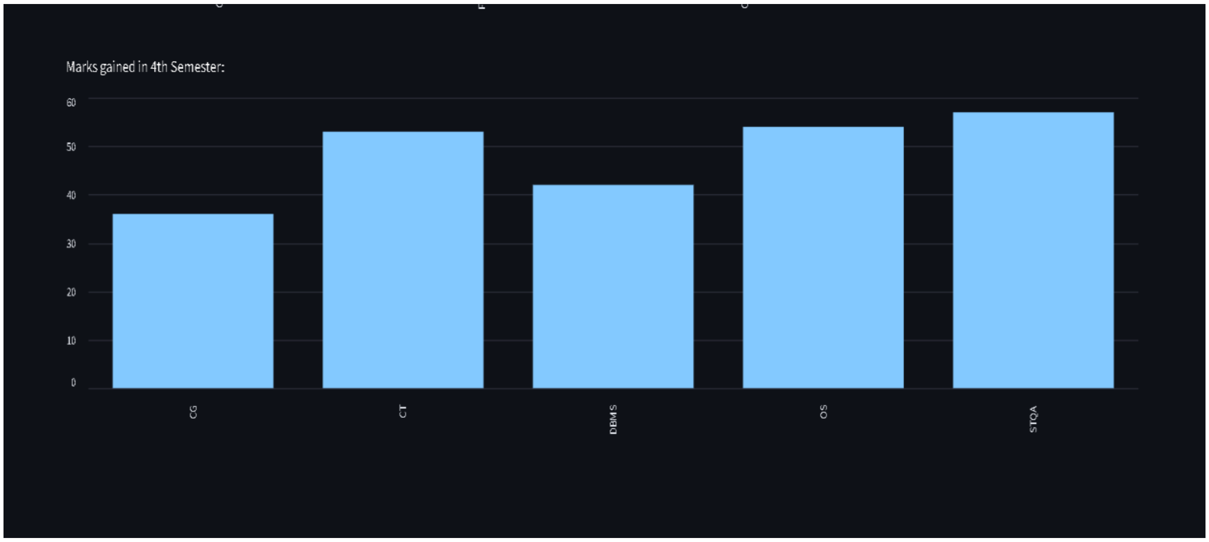
7.2 Screenshots :






Deploy
Learn to Aanlyze(LTA)
Enter RBT Number:
rbt21cs005
Select Year:
Third Year
Search
Main Parameters | Value
0 cgpa 8.1
1 sgpa 8.1
2 10th_percentage 90.0
3 12th_percentage 85.0
4 clubs_joined 3
5 avg_time_on_social_media 2.0
6 certification_platform udemy
7 social_media youtube
Overall Academic record of the Student:
PRN_Number Year FLAT OOP COA SE OS DBMS CT CG STQA
0 rbt21cs005 ty 41 55 51 48 54 42 53 36 57
The student with rbt21cs005 found
Student Academic Performance


Deploy
Student Academic Performance
The Student Academic Performance Predictor is an intelligent system designed to forecast and evaluate a student's academic success based on a comprehensive set of relevant factors. Leveraging advanced machine learning algorithms, this tool aims to assist educators, administrators, and students themselves in understanding and optimizing the pathways to academic achievement.
Radar Chart of the Student
10th_percentage
sgpa
12th_percentage
cgpa
clubs_joined
avg_time_on_social_media
performance
Student performance prediction
The Student is:
Fast Learner
Probability of being Slow learner:
0.051599503
Probability of being Fast learner:
0.9484005
This app can assist Teachers in making a academic analysis, but should not be used as a substitute for a professional.


Marks gained in 4th Semester:
60
50
40
30
20
10
0
CG
CT
DBMS
OS
STQA


Deploy
Marks gained in Second Year
Marks gained in 3rd Semester:
55
50
45
40
35
30
25
20
15
10
5
0
COA
FLAT
OOP
SE

CHAPTER VIII
CONCLUSION

8 Conclusion

This study delved into crafting a teacher-facing dashboard to enhance classroom collaborations in higher education, revealing how educators utilized dashboard data for actionable insights. It highlighted a direct link between teachers' actions and improved student participation. However, it uncovered that teachers felt they missed crucial moments during collaborative sessions due to juggling knowledge-focused and social aspects of real-time learning. To address this, the paper proposes a four-dimensional checklist for LMS dashboard development, aiming to guide researchers and tech developers. It emphasizes the intricate teacher-student interactions and pedagogical needs. Additionally, the study's insights underscore both the promises and challenges of integrating technology to bridge the student-teacher gap, emphasizing the necessity for seamless incorporation of these innovations into education for truly impactful learning experiences.

8.1 Future Work

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 ac complishments. 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.

8.2Applications :

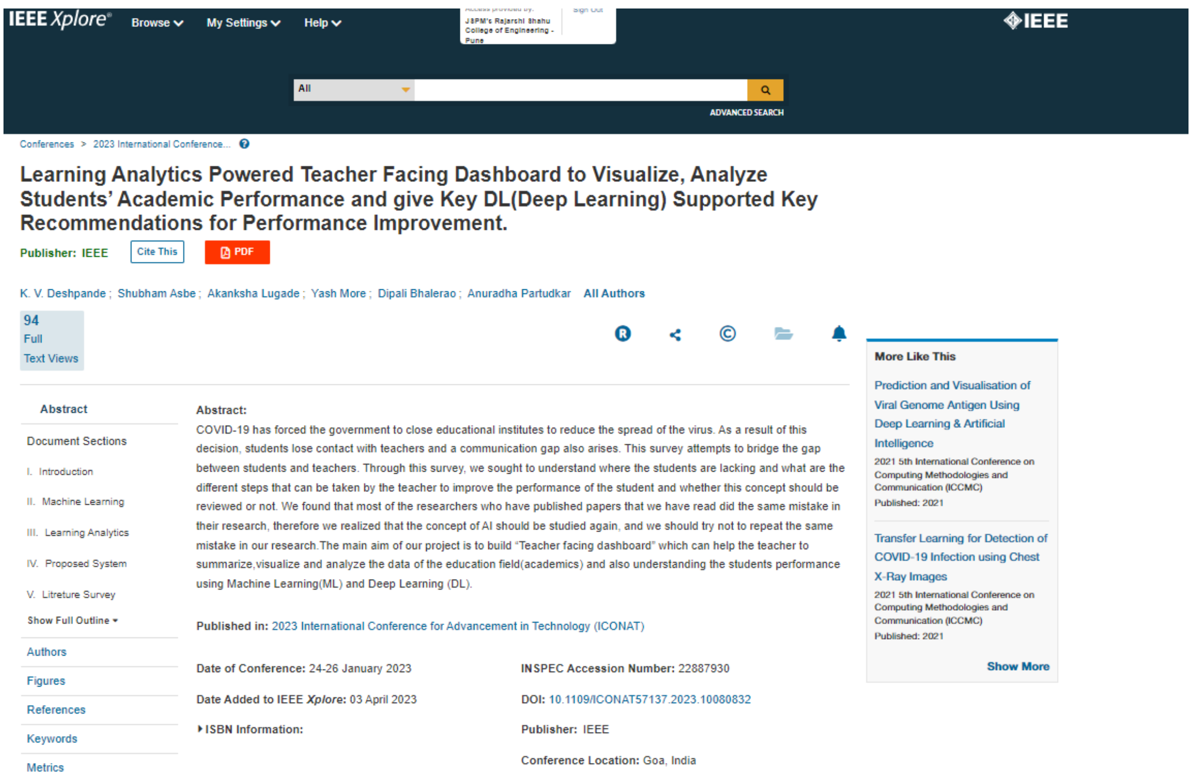
a) Educational Institutions:
b) Teacher Empowerment:
c) Student Performance Enhancement:
d) Curriculum Enhancement:
e) Educational Policy Development:
f) Parental Involvement:
g) Deep Learning Integration:
h) Research and Development:

9 APPENDIX – A

- **Details of paper publication**:

1. **<u>Name of the conference</u>**: IEEE|2023 Iternational Conference for Advancement in Technology (ICONAT)

2. **<u>Acceptance Email</u> :**



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Learning Analytics Powered Teacher Facing Dashboard to Visualize, Analyze Students' Academic Performance and give Key DL(Deep Learning) Supported Key Recommendations for Performance Improvement.

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K. V. Deshpande ; Shubham Asbe ; Akanksha Lugade ; Yash More ; Dipali Bhalerao ; Anuradha Partudkar **All Authors**

94 Full Text Views

Abstract

Document Sections

I. Introduction

II. Machine Learning

III. Learning Analytics

IV. Proposed System

V. Litreture Survey

Show Full Outline

Authors

Figures

References

Keywords

Metrics

Abstract:
COVID-19 has forced the government to close educational institutes to reduce the spread of the virus. As a result of this decision, students lose contact with teachers and a communication gap also arises. This survey attempts to bridge the gap between students and teachers. Through this survey, we sought to understand where the students are lacking and what are the different steps that can be taken by the teacher to improve the performance of the student and whether this concept should be reviewed or not. We found that most of the researchers who have published papers that we have read did the same mistake in their research, therefore we realized that the concept of AI should be studied again, and we should try not to repeat the same mistake in our research.The main aim of our project is to build "Teacher facing dashboard" which can help the teacher to summarize,visualize and analyze the data of the education field(academics) and also understanding the students performance using Machine Learning(ML) and Deep Learning (DL).

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3. Survey Paper

2023 International Conference for Advancement in Technology (ICONAT)
Goa, India. Jan 24-26, 2023

Learning Analytics Powered Teacher Facing Dashboard to Visualize, Analyze Students' Academic Performance and give Key DL(Deep Learning) Supported Key Recommendations for Performance Improvement.

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2023 International Conference for Advancement in Technology (ICONAT) | 978-1-6654-7517-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICONAT57137.2023.10080832

***Abstract*—COVID-19 has forced the government to close educational institutes to reduce the spread of the virus. As a result of this decision, students lose contact with teachers and a communication gap also arises. This survey attempts to bridge the gap between students and teachers.**

Through this survey, we sought to understand where the students are lacking and what are the different steps that can be taken by the teacher to improve the performance of the student and whether this concept should be reviewed or not. We found that most of the researchers who have published papers that we have read did the same mistake in their research, therefore we realized that the concept of AI should be studied again, and we should try not to repeat the same mistake in our research.The main aim of our project is to build "Teacher facing dashboard" which can help the teacher to summarize,visualize and analyze the data of the education field(academics) and also understanding the students performance using Machine Learning(ML) and Deep Learning (DL).

***Index Terms*—teacher facing dashboard, learning analytics, students, teachers, visualize, analyze, education field, machine learning, deep learning.**

I. Introduction

To comprehend and optimize learning experiences, learning analytics systems use and analyse behavioural and interaction data from students. Applications for learning analytics are used. serves a variety of uses at educational institutions, including student's performance tracking tools, learning platforms for college students, and teaching systems for teachers educational consultants. known early warning systems, Dashboards examine educational data to identify underachievers facilitating timely interventions by teachers or advisers for students. Learning Analytics is gaining popularity (LA) has expanded quickly among educational institutions (HEIs) across the globe in recent years. Data will be harnessed by LA to enhance the learning process and, by extension, the contexts in which it unfolds. With a strong emphasis on educators and students, LA has a lot of opportunity to address educational issues. Higher education institutions (HEIs) are facing a growing desire to live, exhibit, and enhance performance. As a result, learning analytics becomes a feasible alternative for resolving issues with student achievement, development, and attrition. Learning analytics, as contrasted to educational data acquisition and academic analytics, is focused on resolving educational challenges, utilising decision making, and enhancing learning. Data cannot accurately represent an individual's identity, interests, or values because they are

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1

not objective entities. These characteristics are, nevertheless, frequently assigned to data in the age of enormous data. Data provide misleading representations of individuals based on their interaction with technologies, significantly limiting them to representations made up of only a few pieces. More and more learning platforms are being utilized in education as online teaching and learning are becoming more commonplace. Academic data and digital learning information are expanding quickly. It has become difficult to transform educational data into meaningful information and knowledge, which has an impact on both students' academic achievement and teachers' favored teaching approaches due to decisions about educational management and resource allocation. Additionally, much research on learning analytics is required to aid the growing trend of intelligentizing learning settings. Although learning analytics (LA) have the ability to support teachers in their daily work, their adoption has not been fully embraced due to the limited participation of teachers as co-designers of l.a. systems and interventions. Because of this, teacher-facing dashboards are necessary for determining if students truly understand what is being taught as well as for their overall evaluation. Learning analytics systems employ and analyse student behavioural and interaction data to comprehend and enhance learning experiences. Applications for learning analytics are used in academic institutions for a variety of purposes, including platforms for college students and instructors to learn from as well as solutions for educational advisors to monitor student performance. Early detection systems and dashboards analyse educational data to identify underperformers and give instructors and academic counsellors the chance to intervene in as soon as feasible. Learning analytics (LA) has seen a dramatic increase in acceptance among academic institutions (HEIs) all over the world in recent years. Data will be utilised by LA to improve learning and, consequently, the environments in which it occurs. LA has several opportunities to address educational concerns because of the strong emphasis on educators and students. Major applications, like LA visualization, analysis of scholars' trace data, and large-scale feedback, which support various course modalities, including blended and online courses and employ a variety of materials, including textual data and trace data, serve to illustrate this concept. Living, displaying, and performing better within the context of universities of higher education is becoming highly significant (HEIs). As a result, learning analytics is now a practical solution to issues relating to student development, performance, and attrition. In opposition to academics analysis and data processing for education, learning analytics is concentrated on resolving educational problems. use people's judgments while promoting learning. Since identity, interests, and values are not objective entities, data cannot accurately reflect them. Nevertheless, in the era of huge data, these traits are frequently applied to information. Data give incomplete representations of individuals based on their interactions with technologies, significantly limiting them to portraits composed of only a few parts. As online learning and teaching become more prevalent, more learning platforms are being implemented in education. Academic data and knowledge about digital learning are growing swiftly. Due to judgments on educational administration and resource allocation, it has become challenging to transform educational data into relevant knowledge and information, which affects both students' learning results and teachers' preferred teaching styles. Additionally, the most recent advancement in learning environments' intelligence necessitates a thorough examination of learning analytics. Although learning analytics (LA) have the potential to aid teachers in their day-to-day work, their adoption has not been fully embraced because instructors have had limited access to the tools and practices that were co-designed with learning analytics. Teacher-facing dashboards are important to monitor students' overall performance and assess if they are actually understanding what is being taught.

II. Machine Learning

Humans have the capacity to learn from their experiences in a variety of ways. In the real world, we also have computers or other equipment that operates in accordance with our commands. Can a machine learn from prior data and experiences in the same manner that a person does? Machine learning is used in this situation. Artificial intelligence (AI) is a sort of machine learning that enables programmes to forecast outcomes more correctly without having to be explicitly programmed to do so. Machine learning algorithms are those that forecast future events based on historical data. Recommendation engines frequently use machine learning, in which computers automatically learn by analysing historical data. For creating mathematical models and making predictions based on past data, many algorithms are utilised. It is capable of a wide range of functions, including picture identification, speech recognition, email filtering, auto-tagging on Facebook, recommendation systems, and more. Additionally, the software is used to automate business processes (BPA), do predictive maintenance, and detect fraud, spam, and malware threats..

Classification of Machine Learning

Machine learning can be classified into three types:

1) Supervised instruction
2) Learning without supervision
3) Reward-based learning

1)Supervised instruction:

A machine learning system is trained using sample labelled data through the process of supervised learning, and then it predicts its output using that information. The system creates a model with labelled data to learn about each dataset after training and processing the datasets are finished. The model is then put to the test using sample data to see if it can accurately predict the outcome. The end outcome of supervised learning is an output map. When a student is learning while being supervised by a teacher, this is referred to as supervised learning.

There are two other groups of algorithms for supervised methods:

- Classification algorithms

- Regression algorithms

2)Learning without supervision

When a machine learns without being closely watched, this is known as unsupervised learning. The algorithm must operate independently while the machine is fed data that has not been labelled, classified, or categorised in order to train it. Unsupervised learning does not have a preconceived result; instead, the incoming data is restructured into new features or a collection of objects with related patterns. It takes a lot of data to find insightful information.

Two types of algorithms can be used in unsupervised classification:

- Clustering algorithms
- Association algorithms

3)Reward-based learning

Rewarding the learner for each appropriate activity and punishing the learner for each inappropriate action comprise the reinforcement approach. The learner automatically raises its performance as a result of this feedback. Reinforcement learning involves an agent interacting with and exploring its environment. The agent must perform better if it wants to earn the most reward points.

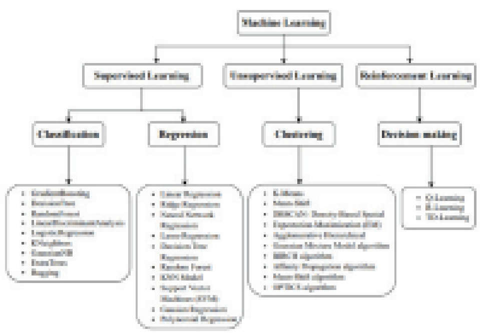

Figure: Types of Machine learning

How does machine learning works?

Machine learning algorithms work by analyzing and identifying patterns in datasets, then using this information to make better predictions.
Humans learn and improve this way as well. For better assessment of a situation, we consider our past experiences whenever we make a decision. To predict or make decisions, machine learning models analyze historical data. Ultimately, machine learning is an AI application that allows a machine to learn from data on its own.
Math is at the core of machine learning. All machine learning algorithms revolve around a mathematical function that can be altered. In other words, machine learning also uses mathematics during the learning process.

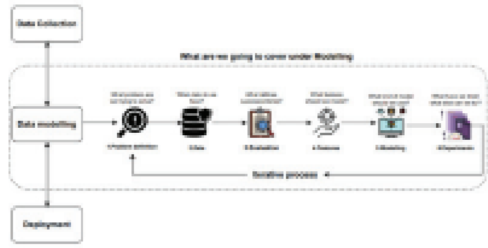

Figure: How the machine learning works

III. Learning Analytics

Even though the field is still expanding, the definition of LA (Learning analytics) from 2011 states that this general definition includes personalising learning and the environment in which it takes place as well as measuring, gathering, analysing, and reporting data about learning and its contexts. Learning analytics has expanded both academically and commercially during the past ten years.In the study of learning analytics, the interdisciplinary fields of learning (educational research, learning sciences, assessment), analytics (statistics, visualisation, computer/data sciences, artificial intelligence), and human-centered design (usability design, participatory design, and sociotechnical systems thinking) come together.

Types of learning analytics

1) Descriptive analytics
2) Diagnostic analytics
3) Predictive analytics
4) Descriptive analytics

1) Descriptive Analytics: Analyse the past

Understands trends and evaluative metrics through data aggregation and data mining. Most statistics are used to analyse past data and include:

- Student satisfaction and graduate surveys gather feedback from students
- Data-driven process of analysing data at all stages of the student lifecycle, from admissions to orientations, to enrolments, to pastoral care, study support, exams, and graduations.

2) Diagnostic Analytics: why did it happen

By using advanced techniques such as drill-down, data discovery, data mining, and correlation, data or content is analysed to answer "Why did it happen?":

- Data analysis for the purpose of improving key performance indicators at all levels throughout the organization
- Design metrics based on analysis of patterns
- analysing effective strategies for ensuring equity of student access

- Metrics for improving student engagement in learning management systems

3) Predictive Analytics: understanding the future

By combining historical data to identify patterns, applying statistical models and algorithms to predict trends and capturing relationships between various data sets, this program identifies:

- Implementation of Staff Dashboards to assist in detecting areas of improvement through the prediction of student numbers and cohort mobility

4)Prescriptive Analytics: advise on possible outcomes

It does more than describe and predict, recommending one or more options based on the combination of machine learning, algorithms, business rules, and computational models, such as:

- A focus on courses/subjects where small changes could make a big difference on engagement, feedback, and outcomes
- Data visualization via specific tools to provide teachers with a visual snapshot of students' enrolment, program grade, results, and survey feedback at the program/degree level

IV. Proposed System

The proposed system uses e-learning system and excel sheet to collect teaching and learning activities from the teacher of each individual student. The collected data are immediately analyzed to provide feedback to the teacher. For example, the teacher can check which students are good at which subject and where the majority of the class is lacking using the preview achievement graph. The teacher can easily grasp student's status and whether or not students are able to progress well or not.

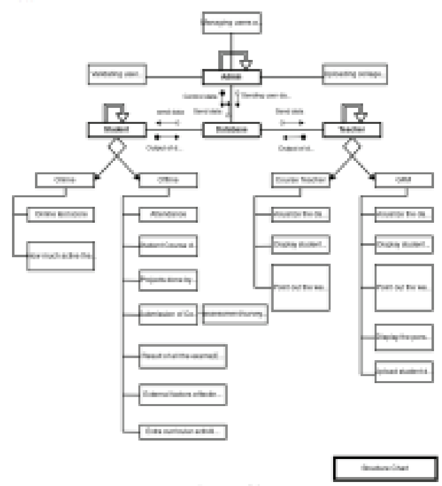

Figure: Structure Chart

Student Module

The student module will be divided into 2 modules: 1)Online Module 2)Offline Module

1)Online module will have 2 sub-module:- a)Online test score This module will track and review the online score of the student b)Activity of Student on moodle This module will show and summarize the usage of moodle

2)Offline module will have 7 sub-modules:- a)Attendance Track the attendance of individual student as we as the whole class and give the summary of it. b)Student course details Track the students progress in the course and how is he/she performing in a perticular course in a particular semester. c)Project done by the student Track the projects done by the student and the different langauages and framework used by the students in those projects d)submission of courses Track the submission details of each course in a particular semester and will also track the assessment and survey reports of the students. e)Result of all the Exams(ESE adn MSE) Track and summarize the result marks of all the exams, up till current semester f)External factors effecting the students Monitor the external factors(family issue, personal problems) affecting the academic of the student g)Extra curricular actitvities Track the participation of the student in different activities excluding academic.(Ex:-clubs,competitions)

Teacher Module

The teacher module will be split into two modules. Course GFM Module and Teacher Module

While the course instructor is separated into two modules

1)Visualize the data: Visualize all of the class data so that the instructor can see how the class is improving and where students are struggling.

2)Display Student Data: To display specific student data in which the teacher will be able to see the previous semester marks and current semester marks, as well as his/her subject internal marks, which will assist the instructor in analysing the student's weaknesses.

3)Student Weakness Suggestions: After showing all of the student's data to the instructor, the system will analyse the data and bring out the student's weak spot.

Another module we have is the GFM Module: GFM Module is broken into five sections: 1) Visualize the information: Visualize all of the class data so that GFM can see how the class is improving and where students are struggling.

2)Display Student Data: To display specific student data in which the GFM will be able to see the previous semester marks and current semester marks, as well as his subject internal grades, which will assist the instructor in analysing the student's weaknesses.

3)Student Weakness Recommendations: After showing all of the student's data to the GFM, the system will analyse the data and point out the student's weak spot or where the student is trailing behind, as well as make suggestions to help the GFM advise the student on the weak point.

4)Display the student's personal data: In this module, we will display the student's personal details such as family background, prior school, previous college, his/her weak areas, his/her strong areas, locale, family details, and student fees.

5)Upload student data: In this module, the GFM will be able to upload the data of a specific student in order to show student information and analyse the data.

Admin Module

Admin Admin is a person who has the responsibility of managing the team and providing daily support as well as keeping the ongoing operations of an learning system. In other words, this employee is the one who usually deals with all over educational data.

Admin has the following role

1.validating User Data In this role admin validate the user data is correct or not

2.Uploading college data In this module admin helps to upload the all over college data. They Keep records and reports up to date.

3. Database Creating and maintaining database standards and policies. Supporting database design, creation, and testing activities.

V. Litreture Survey

Gašević–Dragan , Tsai– Yi-Sha , Drachsler–Hendrik They concentrated on three primary areas, specifically 1. Analysis of data from a learning scenario using Naive Bayes, neural networks, decision trees, and clustering. 2. Presentation and visualisation 3. Corrective actions based on data analysis. The outcome demonstrates that "social infrastructure" and "technological infrastructure" are essential to an institution's potential for learning analytics[2022].

Teo Susnjak, Gomathy Suganya Ramaswami and Anuradha MathraniTheir study had theoretical as well as practical ramifications; they found that the first LAD to do so was a single display that included descriptive, predictive, and data-driven prescriptive analytics. Priority is given to identifying obstacles to LAD projects, followed by an analysis of the advantages and disadvantages of current LADS. they demonstrated a dashboard that is currently being used at a trials institute[2022].

Sanjay Manocha and Pankaj Saini, The issues that educators face today include information security, improper options, and inefficient ways to collect, access, or preserve information, the focus is on innovative growth strategies in India's higher education[2022].

Leeuwen Anouschka van, D Stephanie. 4Teasley@12, Friend Alyssa Wise, The system that was built was a student and teacher facing dashboard to establish tranparency between teacher and student, it discussed few aspects such as theoritical models[2022].

Leah P. Macfadyen, The expanding collection of research examining the difficulties in implementing systemic change using LA in intricate educational environments is updated and summarised in this chapter. The most promising framework for institutional LA implementations—the SHEILA framework—is used in work outlining its application[2022].

Alhusna Nupiah, Walter McCulley, Tao He, Library research is defined as research that uses library data from books as its subject matter. The author examines and evaluates the data found in literature related to the issues examined in this study. The majority of data sources are found in books or other written materials such as journals, periodicals, newspapers, bulletins, and so on.

Jia Du, Wei Pan, This study looked into the impact of social and psychological factors on energy conservation practises. Amos 23.0 and SPSS 22.0, both written in computer-aided multiscientific techniques, were the two main pieces of software used. A new variable called "personal moral standard" has been added to the Theory of Planned Behavior (TPB) model. According to the TPB hypothesis, males in dormitories exhibit more behavioural variance and behavioural intention than females. The findings will aid in the promotion of energy-saving activities by providing a better understanding of residential student behaviour[2022].

Yi-Shan Tsai , Vitomir Kovanovi ́c , Dragan Ga ̌sevi ́c, We investigate the influence of major factors on the adoption of LA using ENA analysis, and we further investigate these relationships by extracting interviews categorized under recurring themes. A quantitative ethnographic method is mainly based on culture to show how an enormous amount of information is transformed into valuable information[2021].

Rogers-Kaliisa, Anders-Kluge Anders- I. Mørch-, We researched how existing LA frameworks can help educators manage such challenges in enabling the orchestration of LA adaptation at the academic level. Information gathering, research procedure, data verification, data processing, and presentation are indeed the frameworks currently in use to tackle issues that come with utilizing LA[2021].

Jean-Marc Dewaele Chengchen Li, Both pro and con feelings of joy and boredom were revealed toward being regulators of students' evaluations of their instructors' passion, with dullness behaving as a negative mediator. It is crucial to comprehend the literature on education, psychology, ISLA, as well as the research that integrates emotional and psychological factors[2021].

Jelena Jovanovi ́c, Mohammed Saqr, Sre ́cko Joksimovi ́c, Dragan Ga ̌sevi ́,The study looked at different key factors that contribute towards how students behaved when learning online, including activity levels and regularity indicators. The survey's objective was to examine how educational situations affect academic performance[2021].

Catherine Mooney and Brett A. Becker, This system basically provides an learning environment for all students which is considered as the primary responsibility, the system basically measures the students 'Sense of Belonging' or which is also termed as 'belongingness' . The data was collected from Human Research Ethics Committee, the responses was collected using google forms[2021].

Jia-Hua-Zhang1*, Ye-Xing-Zhang, Qin-Zou and Sen-Huang, This study was basically based on an online course on the moodle platform. which offered different ways of teachings like online and offline. It basically counted 22 classess and approximately 1088 learners. [2021].

Elias,The study's findings indicate that the LA can only succeed if efforts are made to develop a LA cultural activity in HEI. Students like leading seminars, involving students in events, and taking on extra responsibilities wherever they can[2021].

QAZDAR Aimad, QASSIMI Sara , HASSIDI Oussama , HAFIDI Meriem ,Hassan El ABDELWAHED, Melk Youssef , The data set was completed by using the course gradebook, which allows teachers to view, edit, and categorise grades. It included the date, time, name of the student, completed activities, and additional information about the action. Connectivity, Acquisition, Productivity, Interactivity, and Reactivity are the KPIs. Indicators were used in the study to forecast student performance and identify at-risk students. It also aims to create a system of recommendations that will assist students in passing exams without failing[2021].

Jose A.Ruiperez-Valientea,SherifHalawab, RachelSla-maa,JustinReich Comparing regional and global MOOC learning in arab world they used decision tree.After comparing they realised that a regional MOOC providers play very different role than global providers[2020].

S Ranjeeeth,T.P.Latechoumi,P.Victer Paul In this paper auther used Decision tree, SVM support vector machine, DA Discriminant analysis, ANN (Artificial Neural network).This research can help student to keep them more engaged and improve their success. Their are 30 courses of application like STEM(Science, Technology, engineering math) has, 20

Abeer Qushou In this surevey paper auther didi the study to verify the factors related to students' behavioral and intention to use Mobile-learning which is based on technology accepetence model. For collect the student opinion or the data related to mobile-learning auther was design the self Questionaries.This survey indicate the result that student(67.3advanced level[2020].

Geng Xuewang , Xu Yufan ,Chen Li , Ogata,Atsushi Shimada Hiroaki,amada Masanori Y Auther did the study of 7 weeks of learning logs in DLMR.Auther checks the result based on correlation examination of Z-score in between behavior of teacher and student also there performance this examination shows the result that only statistically significant result less than the significance value[2020].

Dirk Ifenthaler, Jane Yin-Kim Yau They suggested that we take advantage of the body of knowledge in learning analytics by designing large-scale longitudinal or quasi-experimental investigations. using a variety of machine learning algorithms, including classification systems, decision trees, vector machines, logistic regression, and binary logistic regression[2020].

Bertrand Schneider, Joseph Reilly, Iulian Radu They created a course curriculum so that other instructors at other universities might teach non-technical courses as well.This survey aims to make practitioners aware of the potentials and constraints rather than turning them into data mining gurus.They can therefore act as a kind of intermediary between stakeholders and the educational system. By involving teachers and educators in the design of learning analytics and educational data mining tools, the researchers seek to hasten beneficial change in formal and informal learning contexts[2020].

Rienties-Bart ,Køhler-Henrik Simonsen-and-Herodotou, Christothea In order to realize the full potential of AIED, CSCL, EDM, and LA, these authors establish potential boundaries and synergies between these four fields and take into account how a combination of interdisciplinary research approaches can be done. The significant difference between AIED, CSCL, EDM, and LA is somewhat fuzzy[2020].

Purwoningsih Tuti, B Harry . Santoso, x A. Hasibuan Purwoningsih, Evaluating the students taking part in online eLearning activities at universities with ODL systems was the aim of this study. In the context of learning, techniques like machine learning and exploratory data analysis are used to extract knowledge from different forms of data. Support vector machine (SVM) classification was proven to be a reliable approach for determining student learning level from e-Learning data with profile information[2020].

Natercia-Valle, Pavlo-Antonenko, Kara-Dawson, Anne-Corinne-Huggins-Manley, The findings of the study indicated that there is indeed a contradiction between designing and evaluating LADs. The problem with LADs is that their design and evaluation are not in sync. To provide a deeper understanding and optimisation of learning, learning analytics consists of four main components: (a) measurement, (b) gathering, (c) analysis, and (d) reporting of the information related to the learners and their settings[2020].

Reet Kasepalu, Although there are many existing system for teachers, but there exists a problem transferring the findings reached by researchers into actual class room practice, which is solved by this system. Four types of teachers were differentiated as for cluster analysis such as reflecting observer, Novice Assessor, Potiential user and experienced practitioner which is done using K-means clustering algorithm[2020].

Kyle M. L. Jones, Andrew Asher, Abigail Goben, Michael R ,Perry, Dorothea Salo, Kristin A. Briney, M. Brooke Robertshaw, Semistructured interviews are used in this study to learn about students' perceptions and understanding of privacy. To comprehend the research process, it also employs the naturalistic paradigm and the social constructivist framework. Significant gaps in student knowledge and nuanced attitudes toward privacy have been discovered by researchers. Over 100 students from eight different universities in the United States were interviewed about their experiences with data ownership, informed consent, trust, transparency, and other issues that universities must address.[2020].

Bart-Rienties , Henrik-Køhler-Simonsen and Christothea Herodotou, In this research, the author introduces (MILA) as a Moodle (LMS) interactive (LA) that can analyse both Moodle categories and (SCORM) tracking data. This study's conclusion is that MILA's interactive visualisations provide useful data about courses, including learning materials and student behaviour.[2019].

Billy Tak-ming Wong, Kam Cheong Li[14]imply that learning analytics interventions have improved student learning and helped identify problems and challenges students experience before they become at risk. They also imply the possibility of expanding the techniques' purview to accommodate a larger range of objectives. By providing examples, they demonstrate how institutional data can be used to support various types of learning practises. personalised recommendations, learning data visualisation individualised report on academic performance/progress individualised assignments/assessments social contact[2019].

Kyle M. L. Jones Two things are recommended by the authors. 1) The learner will be more worried about how their organisation uses their private information; 2) They will acquire strong information control Learning analytics address current privacy concerns and They also recommend that if colleges and universities discover their work to be more helpful than they already are, the current system should be reviewed. Their work may be profitable or valuable to several institutions[2019].

Aline de Campos, Sílvio César Cazella, The improvement of an individualized learning framework powered by an analytics platform is developed in this study. We aim to enhance the performance by providing prescriptive analysis and a technology solution that is distinctive and more ambitious than others, integrated with Cognitive Computing resources. This study's objective is to ascertain how Cognitive Computing might be utilised to enhance the Learning Analytics process in higher education[2019].

Araujo Laecio Costa, Vieira Marlo das Santos e ,Souza do Nascimento Lais Salvador, x Jose do Nascimento Amorim, Rocha This system basically does the evalution of scholor behaviour within the LMS, to check the educational objectives achieved by him/her. The methodology used was LAS and SapeS[2019].

Justian Knobbout and Esther van der Stappen, We conducted a systematic review of the existing literature on learning analytics interventions to examine how it operationalizes affected learning. The goal of learning interventions made possible by learning technologies is to enhance learning.[2019].

VI. Conclusion

According to the papers cited on learning analytics, the main focus is on how students should enhance their academics with the help of learning analytics; where teachers fall short in imparting their information to students using their old ways; and how students' success is affected by external elements that he/she may experience in everyday life. To address these difficulties, we plan to create a machine learning module that would gather, analyse, and report learner data for both students and teachers. This will aid students in improving their development by assisting them with the concepts they are missing, as well as directing teachers' attention to the areas where a student is falling behind and the causes for it. The teacher feedback dashboard will assist the instructor in getting to know the student better and identifying areas where the student is falling behind, allowing the teacher to improve that aspect of the student's performance.

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4.Certificates

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