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ARTIFICIAL INTELLIGENCE ENHANCED PERSONALIZED ONLINE LEARNING PLATFORM

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Abstract
Personalized e-learning systems powered by AI represent a transformative approach to education. These systems aim to revolutionize traditional learning by tailoring the experience for individual students. By leveraging AI, data analytics, and natural language processing, these systems dynamically adjust learning paths, conduct assessments, and provide immediate feed-back. This reshapes the educational paradigm. Personalized e-learning systems create interactive and collaborative learning environments. This promotes engagement between peers and sharing of knowledge. By encouraging natural language interactions and social learning, these systems enhance the effectiveness of instruction and deepen understanding. The research emphasizes the need to customize learning to cater to diverse student needs, considering their skills, speed, and learning styles. Through exploring intelligent tutoring systems, adaptive learning methodologies, and self-regulated learning principles, the paper elucidates the complexities of personalized education. These AI-powered e-learning systems hold the potential to revolutionize the way we learn and educate ourselves.
Keywords: Adaptive Deadline, Self-Regulated Learning, Deep Learning, Machine Learning.

I. Introduction

In the fast-changing world of education, technology has opened up new possibilities for innovation and change. E-learning platforms have become a crucial part of modern education. The COVID-19 pandemic has further increased the demand for flexible, accessible, and personalized learning. To meet this growing demand, educational institutions and tech companies are increasingly using Artificial Intelligence (AI) to transform e-learning.

AI holds great promise in the field of online learning. It can enhance teaching efficiency, personalize learning experiences, and improve student success. By using machine learning, natural language processing, and data analysis, AI-powered online learning systems can adapt to individual student needs. They can provide real-time feedback and deliver customized content. This adaptability and personalization are crucial for addressing the varied learning styles, preferences, and abilities of students. This helps increase engagement and improves knowledge retention.

Traditional e-learning has its limitations, mainly due to the static and uniform instructional delivery. Conventional systems tend to offer a one-size-fits-all approach, with prepackaged content and standardized assessments that do not cater to the diverse learning needs and preferences of students. When learning environments are too strict, it can lead students to feel bored, annoyed, and ultimately, less successful in their studies, as they have difficulty connecting with the information or seeing its significance. Additionally, traditional online learning platforms often do not have ways to give immediate feedback or adjust to individual needs, which makes it harder for them to offer help.

When designing personalized e-learning systems, we aim to overcome the limitations of traditional models by using AI to develop dynamic, adaptive, and student-centered environments. By utilizing machine learning and natural language processing, our goal is to customize learning experiences for each student based on their individual characteristics like learning style, pace, and skill level. Using personalized assessments, progress tracking, and real-time feedback, we aim to offer specialized instruction and assistance, creating a more stimulating, efficient, and inclusive learning environment

for all students. Our method emphasizes personalized learning paths, interactive involvement, and ongoing enhancement, empowering students to take control of their education and reach their maximum potential.

Our research paper aims to explore how AI can enhance online learning. We plan to create a web app that uses AI to personalize the learning experience. The app will have features like user authentication, a dashboard, social learning tools, gamification, recommendations, analytics, accessibility options, and mobile integration. These components will work together to provide a dynamic and adaptable e-learning environment. The goal is to cater to diverse learner needs, encourage collaboration and engagement, and drive continuous improvement in the learning process.

By taking on this project, we hope to add to the discussion around AI in education. We want to provide insights into how AI can revolutionize e-learning and shape the future of education. Through a detailed look at our proposed web app design and its parts, we'll show how AI can improve the quality, accessibility, and inclusiveness of online learning. We believe our research can help create new e-learning solutions that empower learners, teachers, and schools to succeed in the digital age.

II. Literature

The M. Murtaza et al. [1] talks about the personalized online learning system that combines knowledge tracing, recommendation systems, and adaptability based on each learner's abilities. It highlights the importance of adaptivity, continuous assessments, detailed data collection, and personalized advice to create a learning environment that caters to a wide range of learner needs and preferences. By making use of AI technology, the system adjusts content recommendations by analyzing individual learner data, promoting continuous improvement and engagement. The paper focuses on different algorithms necessary for achieving these goals, such as Bayesian Knowledge Tracing (BKT), Deep Knowledge Tracing (DKT), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and the Attention Mechanism in Transformers, notably employed in Attentive Knowledge Tracing (AKT) to achieve these goals. These AI algorithms are crucial for adapting learning paths in real-time, offering customized suggestions, and improving the overall quality of the personalized online learning journey.

The Pogorskiy et al. [2] investigates how helpful a virtual learning assistant is for improving self-regulatory skills in online learners, with the goal of addressing issues like low completion rates and lack of support. However, there are some limitations in the study, such as a high dropout rate among participants, which may impact the overall applicability of the results. Additionally, it is important to enhance the accuracy and amount of data collected to improve analysis techniques and gain a better understanding of how effective the intervention is. To reduce dropout rates, suggested strategies include administering short surveys and having students do self-assessments on a weekly basis.

Tapalova et al. [6] dives into how AI can totally change education, making it more tailored to each student's needs. It talks about the cool things AI can do, like personalizing learning, adapting to students' progress, and revamping teaching methods. It explains AI lingo like machine learning and deep learning and how they are shaking up every industry, not just education. Plus, it shows how AI helps students learn better, giving them feedback and making learning more engaging. The paper also mentions how AI tools are used in teaching psychology, focusing on students' needs. But there are some big worries about AI in education, like privacy issues and unfairness. Thankfully, there are groups trying to make rules to keep AI in check, making sure it's fair and safe for everyone involved.

AI is changing education by making learning more personalized and efficient for students as mentioned in Chen et al. [7]. It stresses the need to think about ethical concerns while using AI in education. While the study does not have hard numbers to prove AI's effectiveness in schools, it still suggests that more research is needed. The paper suggests ways universities can use AI tools to improve their programs. It explores how AI is being used in education, from robots in classrooms to online learning systems. It discusses various AI technologies like machine learning and data mining and how they're used to personalize learning and improve teaching. The paper shows how AI helps with administrative tasks like grading and curriculum development, and how it enhances the overall learning experience.

Overall, AI is seen as a game-changer in education, improving efficiency, quality of instruction, and personalized learning. The study concludes that AI has had a significant impact on education, making administrative tasks easier, improving teaching quality, and enhancing learning experiences.
In Dr Ronilo G. Berondo et al. [8] talks about how AI is being used in education, with a focus on research from China, India, and the US. It shows that China is leading in the number of publications, India is focused on supplementary systems, and the US has a wide range of applications across educational fields. The importance of AI in customizing education is emphasized, with discussions on student-focused learning solutions and adapting to individual learning styles and habits. Algorithms like machine learning models, natural language processing, and data mining play crucial roles and can be used in our project. These algorithms help in providing personalized feedback, recommending content, and identifying learning patterns. Incorporating features such as adaptive learning paths, customized study materials, and real-time assessment based on individual progress can further improve the effectiveness of the e-learning platform, making the learning experience more engaging and tailored for users.
The research on using artificial intelligence for tailored learning in education highlights the significant impact AI can have in improving learning outcomes. By utilizing a comprehensive methodology that includes surveys, interviews, observations, and assessments, the study uncovered impressive findings. Initial assessment scores showed a worrying average of 60%, with the majority of students performing below the average. However, after the implementation of AI, post-assessment scores showed a notable increase to 80% [9]. The information collected from interviews with students supported these results, showing a clear preference for AI-driven personalized learning compared to traditional approaches because of its interactive and successful characteristics. These findings not only confirm the benefits of AI in improving student learning results but also offer valuable guidance for our project. As we create our customized online learning system with the help of machine learning and AI, we can use this data to create adaptive learning programs, smart tutoring platforms, and rigorous evaluation tools that enhance student involvement and achievements. Furthermore, it is important to include ethical factors, as emphasized in the research, to maintain the credibility and trust of our platform. By following these findings and approaches, we strive to develop an innovative e-learning environment that inspires students and transforms the field of education.

III. Methodology

Proposed System Architecture: -
The Key Elements of the system in the Fig. 4.1 include:
Machine Learning Model: The machine learning model is a key part of personalization. It uses algorithms to analyze user data and do the following tasks:
1. Deadline Prediction: Predict deadlines for completing courses, taking into account the user's progress and learning speed. 2. Test Result Prediction: Forecast potential test results by looking at the user's past performance and current level of knowledge. 3.Personalized Feedback Generation: Provide personalized feedback that is customized to the user's performance on assessments.
Scheduler: The scheduler component utilizes deadlines estimated by the ML model to organize tasks, mainly focusing on scheduling periodic tests during the learning process.
Database: The database acts as a central hub where all system-related data is stored, such as user information, question sets, test outcomes, feedback produced by the ML model, and other pertinent details for the platform.
User Interface/API: This part allows users to easily engage with the system. Users are able to view course content, complete tests, and get individual feedback that is tailored to their progress.

3.1 Proposed System Workflow

The system works continuously to customize the learning journey:
User Data Acquisition: The User Model collects information on the student's progress and current course section.

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Deadline Prediction & Test Scheduling: The ML model uses this data to predict deadlines for completing the course and anticipate test results. The Scheduler then schedules regular tests based on these deadlines.

Test Delivery: The Test Model retrieves question sets tailored to the user's progress, ensuring they are aligned with the current learning section. Students take the scheduled tests, and their results are stored within the Database.

Personalized Feedback Generation: Based on the test results, the ML model generates personalized feedback for the student. This feedback may highlight areas of strength, identify weaknesses requiring further study, or offer additional resources for targeted improvement. This cyclical process fosters a personalized learning experience by continuously adapting deadlines, feedback, and potential areas of focus based on each student's performance.

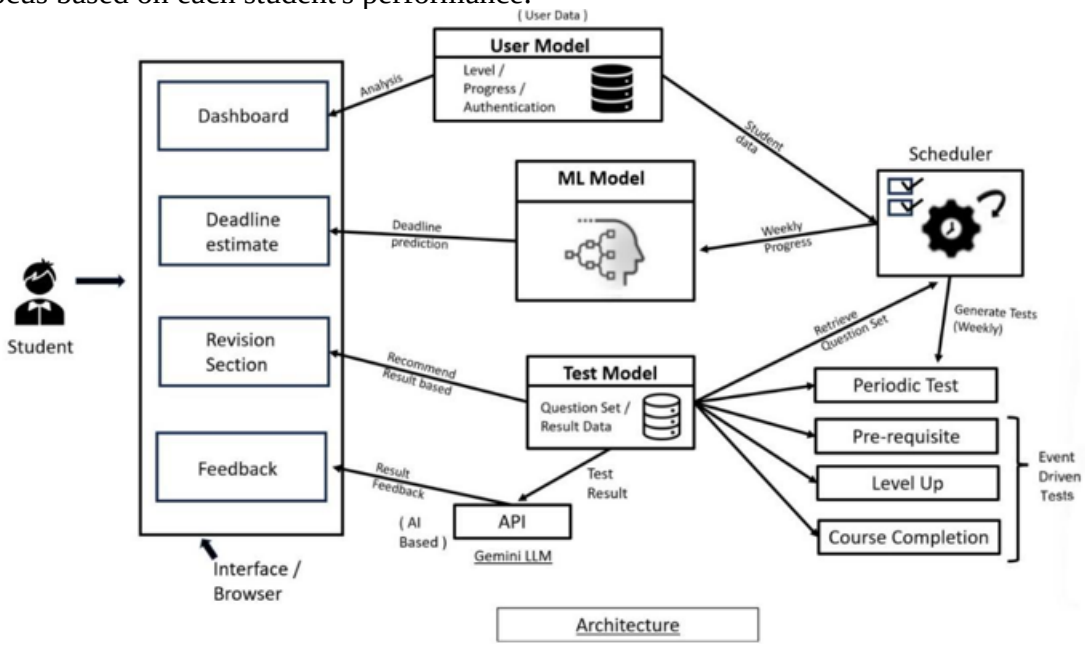

Fig. 4.1 Proposed System Architecture

3.2 Data Acquisition and Deadline Prediction in our system

In this part we describe how we collect data and predict deadlines, in our e-learning system that prioritizes meeting deadlines. Our approach involves using two schedulers to track user activity on a weekly basis.

Daily Scheduler: This scheduler is responsible, for collecting user activity information on a basis. This information may consist of:

Daily logins and the time spent on the platform.

Progress status of quizzes, knowledge assessments or specific learning sections.

User engagement with materials, such as viewed videos, read articles or completed exercises.

Data Processing: The obtained daily data goes through the following processing stages:

Daily Module Completion: The system computes the gap between the number of sections completed today and those completed yesterday. This variance indicates the users section completion rate. The outcome is then saved in a specialized database table for assessment.

Days Since Course Commencement: The system calculates and maintains the number of days passed since the user started the course. This information is also stored in the database, for computations.

3.2.1 Weekly data aggregation

Weekly Scheduler: This planner works on a schedule. Carries out the following tasks:

Average Daily Module Completion: The system collects information, on daily module completions from the database and computes the average number of modules finished per day in the previous week.

Feature Generation: Based on the accumulated data, the system generates the following features for the ML model:
Days Passed: Total number of days elapsed since the course began.
Modules Left: Total number of modules remaining to be completed in the course.
Total Modules Completed: Total number of modules completed by the user to date.
Average Modules Per Day: Average number of modules completed per day over the past week.

3.2.2 Deadline prediction

The information obtained is used to train a machine learning model known as a Random Forest Regression model. This model analyzes past data to forecast how many more days a user will need to finish the course (Estimated Completion Time).
Estimated Deadline Calculation: The system forecasts how many days it will take to complete the course, which is then added to the user's start date to determine when they are likely to finish. This calculation gives an estimate of the deadline for that user to complete the course. The projected deadline is revised every week according to the most recent information and forecasts generated by the machine learning algorithm.
During our study, we used a data-driven method to predict when personalized e-learning courses would be finished by students. We relied on the Random Forest Regression algorithm, a powerful ensemble learning technique widely recognized for its adaptability and success with intricate datasets.
To start, we collected important information such as how many modules were in the course, when the student began their learning journey, and how many modules they complete each day. Using this information, we created new data points like the total days passed since the course began and the average number of modules completed daily. Following that, we divided the data into two parts - one for training our model and the other for testing its accuracy. Then, we created a Random Forest Regression model and used the training data to train it. The features included the total days elapsed and the average number of modules completed per day, while the target variable was the number of remaining modules to be completed. We assessed the model's performance by measuring the Mean Squared Error to validate its predictive capability. In the end, we used AI to calculate how long it would take for a student to finish their courses. By combining this estimate with their start date, we were able to determine when they would likely complete the online course. This approach lets us predict completion dates more accurately for each student, making e-learning more personalized and efficient. The results of our analysis indicate significant variations in the prediction accuracy among the different machine learning models.

IV. Results and Discussion

Performance Evaluation Metrics:
The results of our analysis indicate significant variations in the prediction accuracy among the different machine learning models.
Linear Regression: The model achieved a training R2 score of 0.976 and a testing R2 score of 0.957, indicating high accuracy in predicting project completion deadlines. However, the model displayed higher MAE and RMSE values compared to other models.
SVM Regression: The SVM Regression model exhibited lower prediction accuracy with a training R2 score of 0.035 and a testing R2 score of 0.286. This indicates that the model struggled to generalize well to unseen data and showed higher errors in predicting project deadlines.
Random Forest Regression: The Random Forest Regression model outperformed the other models with a training R2 score of 0.998 and a testing R2 score of 0.989. The model demonstrated superior accuracy in predicting project completion deadlines and exhibited lower MAE and RMSE values, indicating better generalization and robustness.
Based on our findings, the Random Forest Regression model emerges as the most effective approach for predicting project completion deadlines with high accuracy and reliability. The model's ability to handle complex relationships within the data and mitigate overfitting makes it a suitable choice for

deadline prediction in project management scenarios. Further research could explore ensemble methods and deep learning techniques to enhance prediction accuracy and robustness.

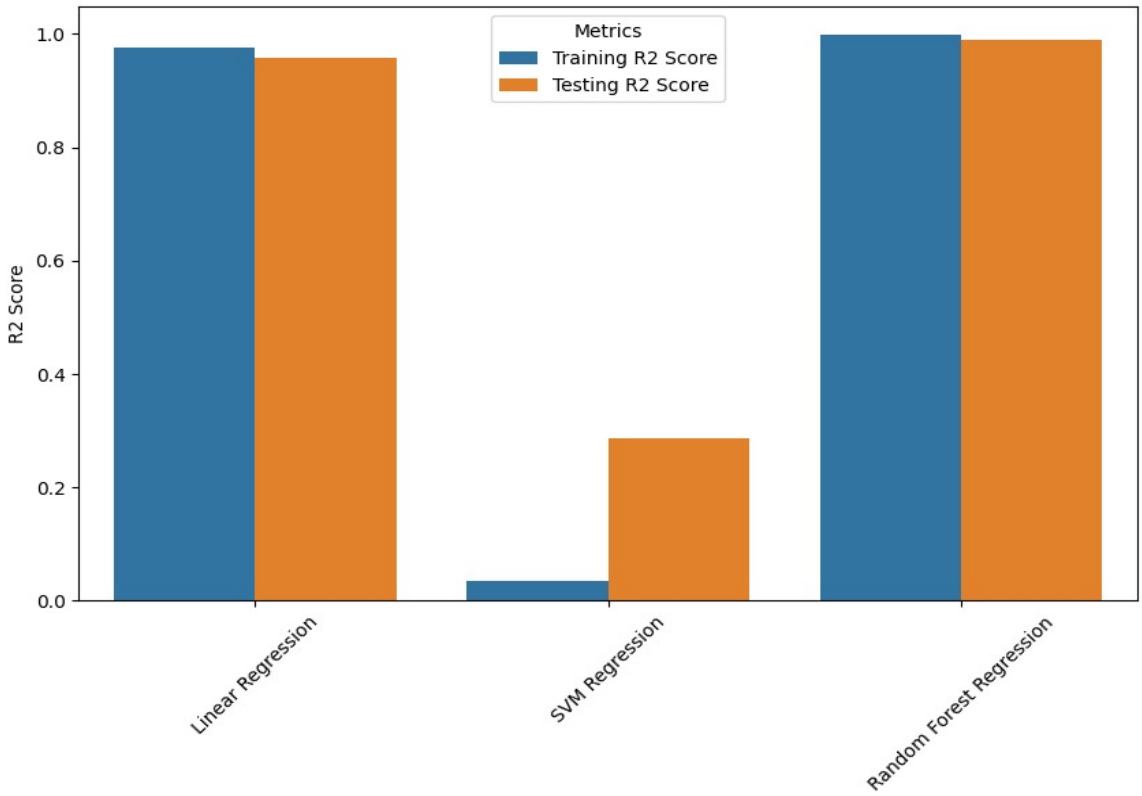

Fig. 5.1 Performance of Different ML Models based on R2 Score

In assessing the efficiency of our Random Forest regression model, we employed several standard performance metrics:

Performance Measures	Training	Testing
MAE	0.1827355623100303	0.4271186440677966
RMSE	0.3318444094973322	0.6464762266222062
R2 Score	0.9981796178068154	0.9895105801848909

Table 5.1 Tabular representation of performance metrics

1. Mean Absolute Error (MAE): The MAE gauges the average absolute variance between the predicted and actual values. A lower MAE signifies a superior model performance.
2. Root Mean Squared Error (RMSE): RMSE computes the square root of the mean of squared difference between predicted and actual values. It penalizes larger errors more severely than MAE.
3. R-squared (R2) Score: The R2 score indicates the proportion of variance in the dependent variable predictable from the independent variables. A score closer to 1 denotes a better model fit.

Learning curve for Random Forest Regression model:

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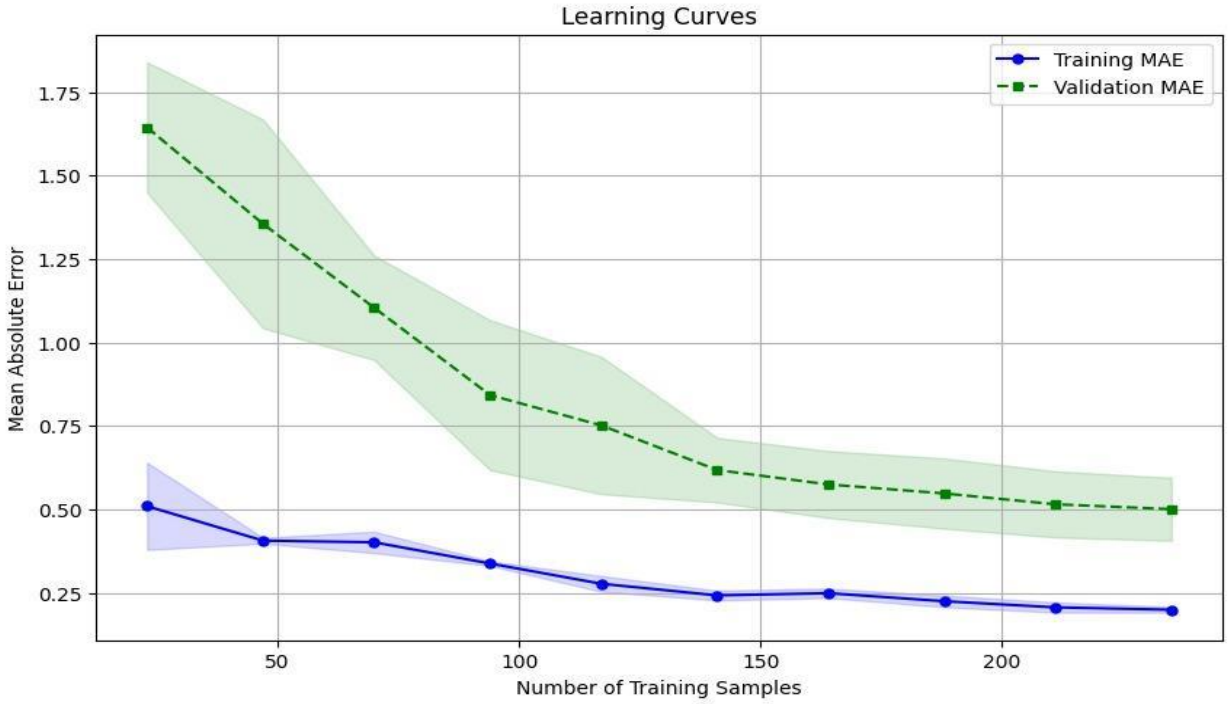

Fig. 5.2 Showing Results of Random Forest Regression for Mean Absolute Deviation Method

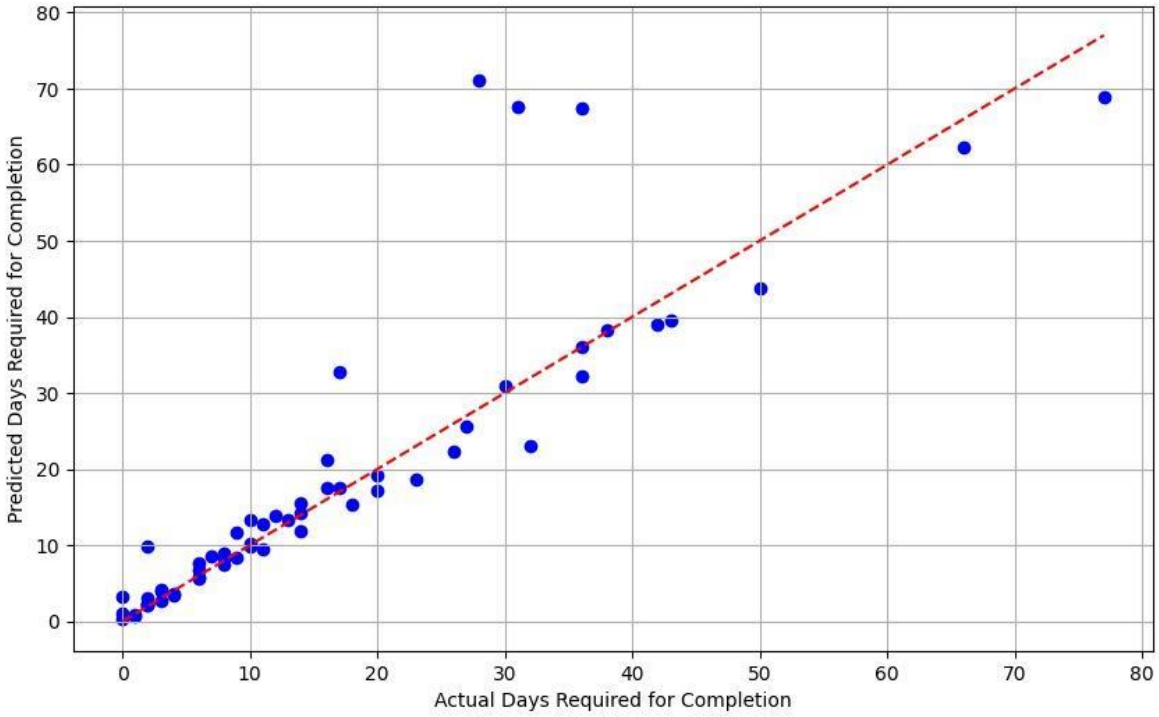

Fig. 5.3 Showing Analysis of Predicted Days Vs Actual Days

Interpretation and Analysis:

Our Random Forest Regression model demonstrates commendable performance, exhibiting high R2 scores approaching unity and minimal MAE and RMSE values with remarkable accuracy and robustness in predicting project deadlines. With training and testing R2 scores nearing perfection at 0.998 and 0.989, respectively, and Notably, Random Forest Regression achieved significantly lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values compared to other models. With lower error rates than its counterparts, Random Forest Regression emerges as the preferred choice for accurate and reliable project deadline predictions.

V. Conclusion

This study demonstrated the significant impact that personalized e-learning platforms, especially when combined with Artificial Intelligence and Machine Learning, can have on education. Our Research shows the potential for transforming education, particularly in the fields of Machine Learning and Artificial Intelligence. By leveraging Machine Learning Algorithms such as Random Forest Regression, we have shown that personalized e-learning platform can predict the deadlines more efficiently and robustly. We have seen promising results in our model my integrating Machine Learning algorithms. This shows the potential for better interpretability and performance compared to traditional methods.

By embracing adaptability, customization and individualization these systems can open up opportunities, for learners, around the globe. Our project aims to use AIs capabilities to build a learning setting that is personalized, dynamic, responsive and supports learning. Furthermore, with the advancements, in Artificial Intelligence and machine learning we expect improvements in optimization algorithms that will boost the scalability and effectiveness of our models.

Our research underscores the significance of adopting technologies, like Artificial Intelligence to enhance personalized e learning. By pushing the limits of innovation and exploration we can discover avenues, for tailoring and improving education.

In the realm of exploration one interesting direction to delve into is the creation of learning settings that replicate real life situations and foster active participation through interactive simulations and role play activities. By infusing elements of gaming into the learning process we can design flexible experiences that cater to preferences and learning approaches ultimately enhancing comprehension and retention of educational material.

Moreover, the incorporation of Artificial intelligence (AI) and machine learning (ML) algorithms presents opportunities, for customized gaming experiences. Leveraging analytics and predictive modeling our platform has the ability to dynamically adapt game components and content in response, to user interactions, preferences and performance metrics. This ensures a personalized and interactive learning journey tailored to each learner.

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