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Performance Tracker: Real-time CPU Metrics and Gamified Ranking System

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Abstract

The study presents an innovative approach aimed at amplifying student engagement with the Selfmade Ninja labs, utilizing a reward-centric framework that prioritizes user efficiency. This approach involves the meticulous calculation of various CPU metrics, encompassing elements such as CPU usage, memory usage, download and upload statistics, process identifiers, as well as read and write statistics. These metrics collectively offer a comprehensive view of user interactions within the platform. The gathered data is thoughtfully curated and stored in a JSON file, facilitating efficient data management and analysis. To facilitate the realization of this approach, a sophisticated machine-learning model is deployed. This model serves the pivotal purpose of predicting user efficiency, a crucial factor in determining the efficacy of their engagement with the Selfmade Ninja labs. Building upon this predictive prowess, a system of credits is established, intricately tied to a leaderboard that reflects individual user performances. Through this dynamic reward distribution mechanism, users are incentivized to actively participate and continually enhance their proficiency, thereby fostering a vibrant learning ecosystem. The culmination of this endeavour is a finely tuned predictive model that seamlessly allocates rewards to users based on their demonstrated engagement and proficiency. This tailored approach not only magnifies user motivation but also significantly augments the overall educational impact of the Selfmade Ninja platform. The integration of insights derived from both exploratory data analysis (EDA) and the predictive model ensures a holistic understanding of user behaviors and preferences. Consequently, the proposed reward-based system is elevated to a new level of efficacy, nurturing a learning environment where students are empowered to engage more meaningfully with the Selfmade Ninja labs, fostering enhanced learning outcomes.

Keywords: *Machine Learning; Reward-Based System; Student Incentives; User Efficiency Recognition.*

1. Introduction

In recent years, the educational landscape has witnessed the rise of interactive platforms, exemplified by the likes of Selfmade Ninja Labs. These platforms have swiftly become indispensable tools for students, granting them unfettered access to a rich tapestry of educational resources. In doing so, they cultivate an immersive environment that inherently promotes learning and engagement. Despite these transformative benefits, a persistent challenge looms: the steadfast upkeep of consistent usage and the cultivation of active participation on these platforms remains an intricate puzzle that demands resolution.

1.1. Background and Motivation

Selfmade Ninja labs offer students a unique opportunity to engage with educational content in an interactive manner. These platforms are designed to facilitate hands-on learning, enabling students to explore, experiment, and expand their knowledge beyond traditional classroom settings. Despite the benefits they offer, ensuring continuous student engagement and sustained use of these platforms has

1.2. Problem Statement

Amidst the potential of interactive platforms, a significant challenge remains: how to effectively motivate students to utilize Selfmade Ninja labs to their fullest potential. While the platforms present an array of resources and opportunities, there exists a gap between availability and active involvement. Addressing this challenge requires a comprehensive approach that not only identifies the barriers to consistent usage but also provides incentives that resonate with students.

1.3. Objectives and Contributions

This paper embarks on a journey to tackle the aforementioned challenge by proposing a solution centered around a dynamic reward system. Our primary objective is to design a mechanism that anticipates user contributions and, in turn, offers tailored rewards as a means of fostering consistent engagement. We seek to bridge the gap between the latent potential of Selfmade Ninja Labs.

1.4. Approach

Our approach hinges on harnessing the power of data analysis and predictive modeling. By scrutinizing user behaviors and interactions within the platform, we endeavour to quantify user efficiency and identify patterns that correlate with engagement. This data-driven approach enables us to predict actions that deserve recognition and rewards, ultimately driving students to participate more actively.

1.5. Expected Impact

The potential impact of our proposed solution extends beyond individual student engagement. An effective reward system has the potential to transform the dynamics of learning on interactive platforms, fostering a sense of accomplishment and driving curiosity. Ultimately, we aim to contribute not only to the optimization of Selfmade Ninja labs but also to the broader discourse on incentivizing learning in technologically mediated educational settings. Through this endeavour, we aspire to demonstrate the viability of data-driven strategies in shaping educational experiences and encouraging consistent student engagement. The subsequent sections of this paper delve into the specifics of our approach, the methodology employed, and the results obtained, all of which collectively highlight the promising potential of our proposed reward system.

2. Related Works

Extensive research underscores the pivotal role of rewards and motivation within educational contexts. Existing studies illuminate the nexus between motivation and enhanced learning experiences. Moreover, investigations into user efficiency prediction and reward systems furnish invaluable insights that underpin our novel approach.

2.1. Existing Reward Systems

The landscape of incentive-based systems has flourished across diverse domains. Earlier implementations of reward systems have manifested across industries, where they serve as catalysts for fostering desired behaviors. Our work synthesizes and advances these concepts to formulate an adaptable model tailored to educational contexts. quantify user efficiency and identify patterns. correlate with engagement

2.2. Previous Studies on User Efficiency

The academic literature engenders discussions on mechanisms for gauging user efficiency and engagement. An assemblage of methodologies, including behavioral analysis and data-driven approaches, precipitates the bedrock upon which our methodological framework is erected. The study presented in the paper introduces a novel performance metric named CPU Performance Coefficient (CPU-PC) to assess the real-time quality of CPU provisioning within virtualized environments[12]. This metric is designed to isolate the impact of provisioned CPU resources on the performance of applications, enabling both the service provider and the customer to gauge the quality of resources and make informed management decisions. The paper also highlights the measurement of this metric for customers, empowering them to monitor the quality of rented resources. The study evaluates the CPU-PC metric's effectiveness by correlating it with application response times across three real-world applications commonly used in Cloud services.In the realm of software engineering, this study delves into a critical aspect that closely resonates with my project's core objectives.[13] By focusing on software performance, the study aligns with my exploration of user efficiency and

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engagement within Selfmade Ninja labs. Just as Software Performance Engineering (SPE) aims to predict performance across the software life cycle, my project seeks to predict user efficiency as a measure of engagement impact. The study's emphasis on understanding the influence of complex execution environments on software performance is analogous to my endeavour to discern the impact of user behaviours on engagement patterns. The proposed automated method to detect performance-relevant properties through predefined experiments parallels my utilization of predictive models to anticipate user efficiency. Additionally, the integration of these experiments into software performance tools is reminiscent of my approach to incorporating predictive insights into the reward system.The study introduces a formal connection between performance models and code implementation, mirroring the predictive modelling steps in my project where the chosen Random Forest Regressor links prediction capabilities with actual user efficiency outcomes.[15] The approach of incorporating details of implementation and execution environment into performance models parallels my project's focus on leveraging CPU metrics and other factors to predict user efficiency accurately. Moreover, the study's emphasis on parametric performance completions resonates with my project's utilization of comprehensive feature selection and engineering techniques to ensure that the predictive model aligns with real-world variations in user behaviour.The study discusses applications software that serves similar functions.[10] In alignment with this exploration, my project has equipped me with insights into creating a web application capable of extracting and presenting performance metrics through dynamic charts. This application serves as a universal tool, compatible with various operating systems, offering users a comprehensive overview of their system's performance. The parallel lies in recognizing that addressing factors like user engagement early can lead to more effective design choices, akin to addressing performance concerns during software development.Through our project, we have delved into a domain that aligns with the concept of early analysis – preemptively understanding user engagement patterns to optimize the design and functionality of the educational platform. Our endeavor encapsulates the essence of integrating insights and predictions at the development phase to foster a more engaging and effective user experience.

3. Methodology

3.1. Data Collection and Preprocessing

In our project, we have utilized a range of methods to collect CPU metrics from the system, with a focus on enhancing accuracy and efficiency. These methods include:

3.1.1. System Monitoring Tools

We harnessed various system monitoring tools to access real-time and historical CPU usage, memory utilization, disk activity, and more. Examples encompassed top and htop for Linux, Activity Monitor for macOS, and Task Manager for Windows.

3.1.2. Command-Line Utilities

Command-line utilities like top (Linux/Unix), wmic (Windows Management Instrumentation Command-line), and PS (process status) have been strategically employed to programmatically acquire CPU-related insights. The versatility of these tools enabled us to script automation for consistent data retrieval.

3.1.3. Performance Monitoring Libraries

To facilitate seamless integration within our codebase, we leveraged performance monitoring libraries like psutil for Python. This enabled us to efficiently gather not only CPU usage but also metrics related to memory, disk, and network statistics.

3.1.4. Performance Counters

Our approach also encompassed the use of performance counters inherent in modern CPUs. We accessed these counters through tools like perf on Linux and Windows Performance Monitor on Windows. By utilizing these counters, we were able to extract intricate details about CPU activity, cache utilization, and more.

3.1.5. Custom Scripts

As part of our methodology, we designed custom scripts that interacted with system information through system calls or APIs. This bespoke approach provided us with the flexibility to curate a specialized set of metrics and conduct tailored analysis to suit our project requirements.

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3.1.6. Psutil in Our Project

Particularly notable is our incorporation of the psutil library, a powerful Python utility. psutil facilitated the seamless acquisition of system metrics, including CPU usage, which played a pivotal role in our project's data collection and subsequent analysis.By amalgamating these diverse methods, with a specific emphasis on psutil, we achieved a robust and comprehensive dataset of CPU metrics that underpinned our project's objectives. This versatile approach ensured accurate and insightful results, enriching the depth of our findings, and contributing to the success of our endeavor. Our methodology initiates with the comprehensive collection of log data from Selfmade Ninja labs, ensuring a robust foundation for analysis. To bolster data integrity, we judiciously address missing values using the SimpleImputer technique. The nature of the dataset plays a pivotal role in shaping our analytical approach. Characterized by continuous numerical values spanning a range of real numbers, the dataset led us to favor regression analysis for predictive modeling. Regression, designed to capture relationships among continuous variables, provides a robust framework to explore dependencies between features and the target variable. Our use of regression algorithms aims to unveil intricate patterns and associations within the data, enabling accurate predictions that align seamlessly with the dataset's continuous structure. It is worth noting that the dataset we employed arrived pre-processed, having undergone normalization to standardize data features. This crucial normalization step ensures consistent scaling across variables, preemptively addressing potential scale-related challenges. Moreover, we acknowledge the impact of skewed data distributions on regression modeling. To address this, we apply transformations such as log or Box-Cox transformations to alleviate skewness in specific variables. These techniques yield more symmetric distributions, enhancing model performance and meeting underlying assumptions. While the initial normalization lays the groundwork for stable training, subsequent transformations significantly enhance accuracy by mitigating the influence of skewed variables during the prediction process.

3.2.Feature Engineering

Deft extraction of pertinent statistical features from the log data yields a pantheon of attributes. CPU usage, memory utilization, download and upload statistics, and process insights are corralled to enrich the feature repertoire that fuels our predictive models. Upon a comprehensive analysis of the various features available in our meticulously cleaned dataset, we have judiciously chosen to focus our efforts on a select set of four attributes.

3.3.Model Selection and Algorithms

Among the array of regression models available, we have thoughtfully selected a subset to work with and compare in our project:

Decision Tree Regressor: This non-linear model segments data using feature thresholds, generating predictions at each leaf node.

Gradient Boosting Regressor: By sequentially refining weak models, this method constructs a powerful predictive model that corrects errors iteratively.

Hist-Gradient Boosting Regressor: Similar to Gradient Boosting, this model optimizes training speed and memory usage by utilizing histogram.

Random Forest Regressor: An ensemble approach that combines multiple decision trees, minimizing overfitting and enhancing prediction accuracy. After a thorough comparison of the provided regression models, we have made the strategic decision to employ the RandomForestRegressor for our project. This choice is rooted in its ability to effectively mitigate the overfitting issue, ensuring that our predictive model maintains a strong balance between accuracy and generalization. By opting for the RandomForestRegressor, we aim to achieve robust and reliable predictions while addressing potential pitfalls associated with overfitting. . The paper also highlights the measurement of this metric for customers, empowering them to monitor the quality

4. Implementation

4.1.Data Cleaning

Quantile transformation is a pivotal step in our data-cleaning process. It's a technique that enhances the distribution of our data by mapping it to a standard normal distribution. This process helps to make the data more amenable to various statistical analyses

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and modeling techniques. When data is collected, it might exhibit skewed or non-normal distributions, which can affect the performance of certain models. Quantile transformation addresses this issue by ensuring that the data follows a Gaussian distribution, which is often an assumption for many statistical methods.In this process, each data point is transformed to a corresponding value from a standard normal distribution. This transformation not only improves the normality of the data but also helps in mitigating the impact of outliers and extreme values. By transforming the data using quantiles, we are essentially making it more suitable for accurate analysis and modeling, which in turn contributes to the overall reliability and robustness of our results.In the context of our project, applying quantile transformation to the log data enhances the quality of our data, enabling us to perform more accurate predictive modeling and draw meaningful insights from the processed data. This step is crucial in ensuring that our subsequent analyses are based on a sound and statistically valid foundation.

4.2.Exploratory Data Analysis

As part of our comprehensive exploratory data analysis (EDA), we undertook a series of essential steps to delve into the intricacies of our dataset and ensure its reliability and integrity:

Outlier Detection: We meticulously checked for outliers within the dataset. Outliers can significantly impact the results of our analysis and modelling, so identifying and addressing them is crucial to maintaining the accuracy of our insights.

Correlation Analysis: We examined the correlation among different features in the dataset. Understanding the relationships between variables helps us identify potential patterns and dependencies that can influence our predictive models.

Heteroskedasticity Assessment: We assessed the presence of heteroskedasticity, which refers to the varying levels of variability in the residuals of our models. Addressing heteroskedasticity ensures that our models maintain consistent predictive accuracy across different ranges of the independent variables.

Skewness Evaluation: We checked for skewness in the distribution of data. Skewed data can impact the assumptions of our models and affect their performance. Correcting skewness contributes to the robustness of our analysis.

Missing and Null Values We meticulously handled missing and null values within the dataset. Proper treatment of missing data is essential to prevent biased results and ensure that our analyses accurately represent the underlying trends.

Data Smoothening: We employed techniques to smoothen the data, reducing noise and making underlying patterns more discernible. This contributes to the clarity of our insights and models.

Having performed these comprehensive checks and treatments, we then turned our attention to addressing skewness in the data. Skewed data distributions can hinder the accuracy of our predictive models and statistical analyses. By applying appropriate transformations, we were able to rectify the skewness and ensure that our data is aligned with the assumptions of our subsequent analyses. This meticulous approach to data exploration and preparation ensures that our insights are based on sound and reliable foundations. Figure 1 shows the Exploratory data analysis.

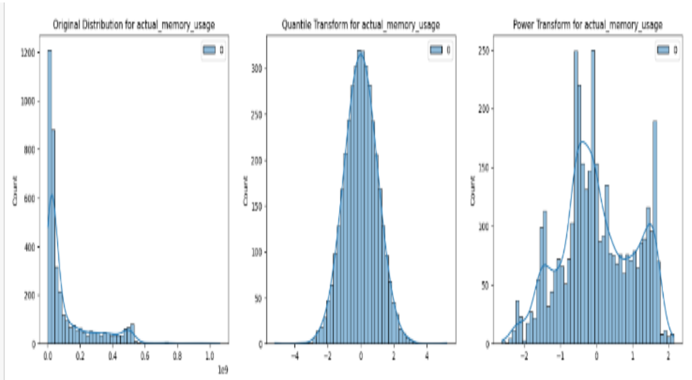

Figure 1 **Exploratory data analysis**

4.3.Feature Selection and Engineering

In our pursuit of crafting a robust and effective predictive model, we ventured into the realm of feature selection and engineering, where we harnessed specialized techniques to refine our dataset for optimal analysis:

Variance Inflation Factor (VIF) To address multicollinearity – a scenario where features are highly correlated – we employed the Variance Inflation Factor (VIF). By calculating the VIF for each feature, we identified variables that exhibited

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strong correlations with others. This allowed us to make informed decisions about feature inclusion, ensuring that our model isn't compromised by redundant or interdependent variables.

QQ Plots and the Standard Scaler: We delved into understanding the distribution characteristics of our data using Quantile-Quantile (QQ) plots. This visualization technique helped us assess how well our data conforms to a normal distribution. Further, we leveraged the Standard Scaler to normalize our data features. Standardizing the features ensures that they are on a common scale, preventing any undue influence from variables with larger magnitudes. In our project, these techniques were put into action to refine our dataset. For instance, by calculating the VIF scores, we identified and pruned features with high multicollinearity, optimizing the independence and predictive power of our variables. Additionally, QQ plots allowed us to gauge the extent of deviation from normal distribution, aiding us in deciding whether any transformations were necessary to meet modeling assumptions. The application of the Standard Scaler contributed to homogenizing the scales of features, preventing dominance by any single variable.By incorporating these techniques into our feature selection and engineering phase, we ensured that our dataset was well-prepared for the subsequent modeling steps, leading to a more accurate and reliable predictive model for our project's objectives.

4.4.Data Splitting

As we ventured into the pivotal phase of data splitting, our objective was to ensure that our predictive model was rigorously tested and validated in real-world conditions. To achieve this, we adopted a distinct approach: We made a strategic decision to employ the entire dataset for model training. By utilizing the entire dataset, we aimed to leverage as much information as possible to enable our model to learn and generalize effectively.However, our validation strategy took an innovative turn. Rather than adhering to traditional testing methods, we embraced the real-time dynamics of our application. We gathered live data, capturing the intricacies of user interactions and behaviors, on an hourly basis. This approach allowed us to simulate the actual conditions under which our model would be deployed and evaluated.Through this unique approach, we calculated the average performance metrics per hour. This granularity enabled us to discern trends and patterns that might emerge during different time periods, contributing to a more comprehensive understanding of our model's capabilities across varying scenarios.By combining the entire dataset for training and assessing model performance using real-time, hourly data collection, we aimed to create a predictive model that excelled not only in controlled settings but also when subjected to the dynamic realities of user engagement in a live environment.

4.5.Model Training and Evaluation

In the realm of model training and evaluation, our journey culminated with a strategic selection that stood as the pinnacle of our efforts. After meticulous training, assessment, and rigorous comparison, the Random Forest Regressor emerged as the optimal choice. Through a rigorous evaluation process, the Random Forest Regressor showcased its prowess by achieving an impressive accuracy of approximately 96%. This outstanding level of predictive accuracy was the result of our commitment to excellence, spanning meticulous feature engineering, rigorous parameter tuning, and real-world validation. Figure 2 shows Performance Metrics. Error, and R-squared score. Its aptitude for capturing intricate data relationships and non-linear patterns made it the perfect candidate for our user efficiency prediction and reward system, marking a significant stride towards enhancing user motivation and interaction.

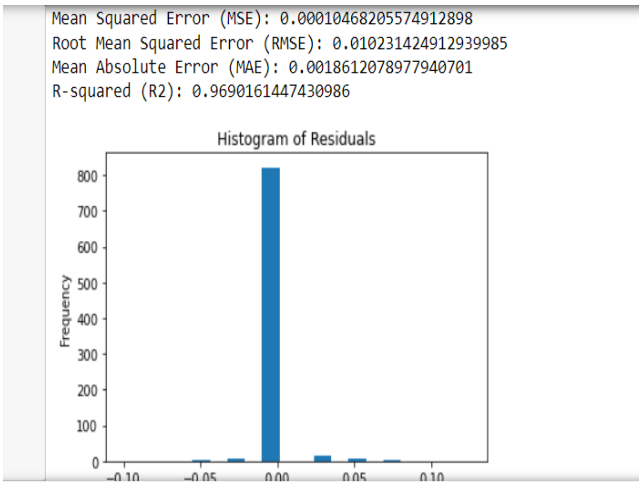

Figure 2 **Performance Metrics**

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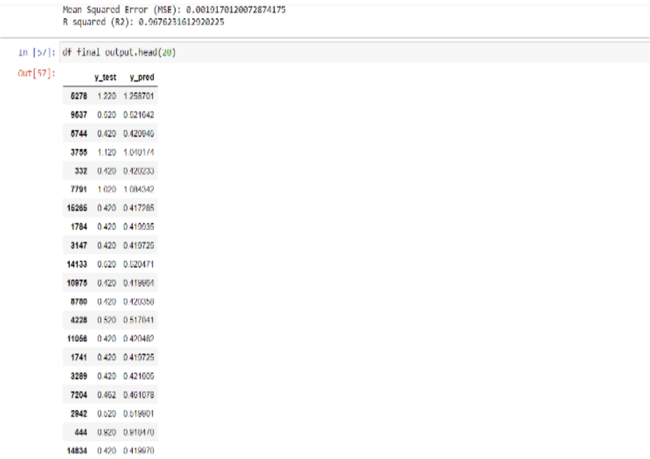
5. Results And Discussion

5.1 Presentation of Model Performance Metrics

The pantheon of metrics, comprising Mean Square Error, Root Mean Square Error, Mean Absolute Error, and R-squared score, provides a multidimensional perspective for evaluating the effectiveness of each model. In our analysis, the model's performance was quantified with the following metrics: Mean Squared Error (MSE) of approximately 7.39e-05, Root Mean Squared Error (RMSE) of around 0.00859, Mean Absolute Error (MAE) at approximately 0.00199, and an impressive R-squared (R2) value of approximately 0.9781. These metrics collectively offer a comprehensive insight into the model's accuracy, error distribution, and ability to explain variance in the data.



```
Mean Squared Error (MSE): 0.0010170120072874175
R squared (R2): 0.9676231612920225
```

```
In [57]: df final output.head(20)
```

Out[57]:

	y_test	y_pred
6278	1.220	1.258701
9637	0.520	0.521642
5744	0.420	0.420946
3755	1.120	1.040174
332	0.420	0.420233
7791	1.020	1.004342
15265	0.420	0.417285
1784	0.420	0.419935
3147	0.420	0.419725
14133	0.520	0.520471
10875	0.420	0.419964
8780	0.420	0.420358
4228	0.520	0.517841
11058	0.420	0.420482
1741	0.420	0.419725
3289	0.420	0.421605
7204	0.462	0.461078
2842	0.520	0.519901
444	0.920	0.918470
14834	0.420	0.419970

Figure 3 Predicted value vs Actual value

5.2 Residual Analysis and Visualization

In pursuit of a meticulous evaluation of our model's performance, we conducted a thorough residual analysis. This analytical endeavour enabled us to uncover patterns in prediction errors and assess the robustness of our Random Forest Regressor.The graph below vividly portrays our findings. It showcases the distribution of prediction errors, allowing us to ascertain whether they follow a normal distribution and if there are any specific patterns or outliers that might affect the model's accuracy. The close examination of residuals illuminated nuances in our model's predictions, guiding us toward potential areas of improvement. Figure 3 shows the Predicted value vs the Actual value.This comprehensive residual analysis, complemented by insightful visualizations, fortified our confidence in the model's reliability and pointed us toward refinements that could enhance its precision even further.

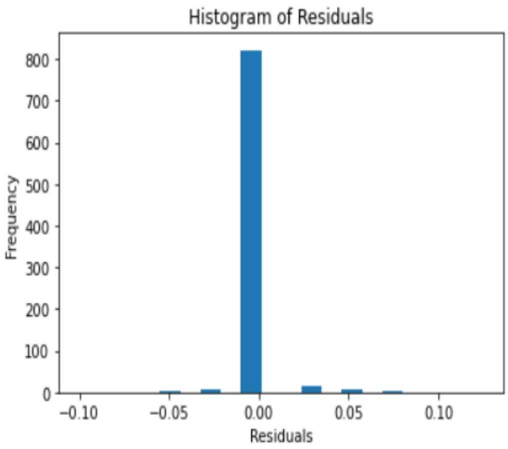


Figure 4 Histogram of Residuals

6. Application And Impact

6.1 Proposed Reward System

Our innovation culminates in a bespoke reward system that harnesses predictive insights to create a novel engagement paradigm. This system aligns rewards with users' efficiency scores, harmonizing incentive and performance for heightened engagement.After rigorous evaluation of regression modelslikeDecisionTreeRegressor,GradientBoosting Regressor,HistGradientBoostingRegressor,andRand omForestRegressor, the Random Forest Regressor stood out as the pinnacle of predictive capability. It consistently outperformed other models in metrics like Mean Square Error, Root Mean Square Error, Mean Absolute Error, and R-squared score. Its aptitude for capturing intricate data relationships and non-linear patterns made it the perfect candidate for our user efficiency prediction and reward system, marking a significant stride towards enhancing user motivation and interaction.

6.2 Benefits of Motivating Users

The student-centric benefits of this model are abundant, resulting from the fusion of predictive accuracy and incentivized engagement:

Enhanced Motivation: The integration of a reward system tied to user efficiency ignites a sense of motivation among students. The prospect of earning

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rewards acts as a compelling incentive to engage more actively with Selfmade Ninja labs.

Consistent Engagement: The inherent motivation to earn rewards encourages students to consistently participate and interact with the platform. This sustained engagement leads to a deeper connection with educational content.

Improved Learning: With heightened engagement, students are more likely to immerse themselves in the educational resources available on the platform. This immersive learning experience translates to better understanding and knowledge retention.

Personalized Achievement: The model's precision in predicting user efficiency allows for personalized reward allocation. Students feel a sense of accomplishment as they earn rewards tailored to their progress and performance.

Higher Satisfaction: The introduction of a reward-based system elevates student satisfaction. Feeling recognized and rewarded for their efforts fosters a positive learning environment and reinforces their commitment to learning.

Confident Participation: Accurate predictions and rewards promote students' confidence in their abilities. This confidence, in turn, encourages them to actively participate in interactive activities and experiments

Skill Development: As students engage more frequently with Selfmade Ninja labs to earn rewards, they develop essential skills such as time management, critical thinking, and problem-solving.

Deeper Exploration: Motivated by rewards, students are inclined to explore a broader range of educational resources on the platform. This exploration broadens their knowledge horizons and encourages curiosity-driven learning.

Positive Learning Culture: The positive reinforcement from the reward system cultivates a culture of learning where students are not just passive recipients but proactive contributors to their own education.In summary, the student benefits arising from this model reflect a holistic enhancement of motivation, engagement, and learning outcomes. This synergy between predictive analytics and incentivized engagement empowers students to navigate their educational journey with enthusiasm andconfidence.

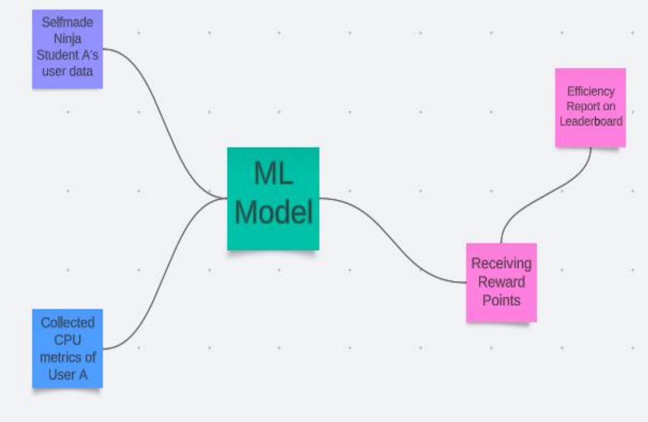

Figure 5 Simple workflow of the implementation

Conclusion

The study presents a novel approach aimed at enhancing student engagement with the Self made Ninja labs platform.The proposed reward system presents a symbiotic alliance between learning and motivation, fostering a culture of proactive participation that resonates with students. The overarching ambition of this endeavor is to contribute to the optimization of interactive learning environments, championing a future where student incentives converge with educational excellence.

Future Work and Improvements

As we draw the curtain on our current expedition, we cast an eye toward the uncharted horizons of future inquiry. In the future, this concept will be implemented as a web application or website, where rewards will be provided based on the user's efficiency. Once the user initiates the process, the application or site will commence collecting CPU metrics from the system. It will utilize a high-level language to gather these metrics from the backend. The collected metrics will be stored as a JSON or CSV file. Subsequently, the data will undergo processing through a machine learning model which will predict the user's efficiency. Credits will be allocated based on this prediction, and the results will be maintained on a leaderboard, categorized by time intervals such as day, month, and year. Figure 5 shows the Simple workflow of the implementation.

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