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Use of Single-PC VMs: A LSTM Approach to Student Overall Engagement in Online Platforms

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ABSTRACT: The study investigates the use of single-PC virtual machines (VMs) to enhance student engagement in online learning environments through predictive resource management using Long Short-Term Memory (LSTM) networks. Single-PC VMs offer cost-effective solutions for institutions with limited resources, yet challenges in real-time engagement monitoring and resource allocation persist. This research aims to address these issues by evaluating LSTM models' effectiveness in predicting resource demands and their impact on system performance and student engagement. Key findings reveal that LSTM-based resource allocation improves system efficiency, reduces latency during peak periods, and enhances overall user satisfaction. The results demonstrate the potential of integrating predictive analytics with VM technology to foster scalable, resource-efficient, and engaging virtual learning environments. Future directions include refining machine learning models and exploring long-term impacts on academic performance.

KEYWORDS: Single-PC Virtual Machines (VMs), Student Engagement, Online Learning Platforms, Long Short-Term Memory (LSTM) Networks, Predictive Resource Management, Resource Allocation, Virtual Learning Environments, Machine Learning in Education, Dynamic Load Balancing, Cost-Effective Online Education

I. INTRODUCTION

The shift to digital and hybrid learning has brought virtual classrooms to the forefront, posing both opportunities and challenges for educational institutions. Single-PC Virtual Machines (VMs) have become a cost-effective solution, enabling schools to create multiple virtual environments on a single computer, which can support numerous students concurrently. This approach is particularly beneficial in regions and institutions with limited resources, where creating personalized digital environments on a large scale would otherwise be cost-prohibitive. Research by Silva and Ranganathan (2022) has shown that single-PC VMs can expand access to online learning while reducing hardware investment, offering a viable solution for institutions with budget constraints (Silva & Ranganathan, 2022). However, maintaining smooth, interactive, and reliable digital classrooms requires efficient resource allocation to prevent performance lags that can hinder student engagement.

In a virtual classroom setting, computational resources—including CPU, memory, and storage—must be dynamically managed to meet the varying demands of educational content and student interaction. Studies by Gomez et al. (2021) highlight the importance of responsive resource management, showing that performance bottlenecks, when left unaddressed, can disrupt continuity in online learning and lower student engagement levels (Gomez et al., 2021). To address these challenges, educational institutions are turning to advanced predictive models like Long Short-Term Memory (LSTM) networks. LSTM networks, known for their ability to analyze time-series data, have proven effective at predicting patterns in student engagement and computing demands, allowing systems to allocate resources proactively. By analyzing both long-term engagement trends and short-term fluctuations, LSTMs can provide essential foresight that enables smoother, more responsive digital learning environments (Zhang et al., 2023).

Moreover, LSTM networks can identify critical periods of high engagement, such as interactive lessons or online assessments, and optimize resources accordingly. A study by Hoque and Li (2023) found that predictive models using LSTM networks significantly enhanced system responsiveness during peak periods, which contributed to better student experiences in virtual classrooms. By applying these insights, single-PC VMs can create a stable, engaging environment that keeps students focused and minimizes the technical issues that often lead to frustration and disengagement (Hoque & Li, 2023).

The increasing adoption of online learning platforms has transformed the educational landscape, enabling remote access to academic resources and fostering inclusivity. However, this shift has also introduced significant challenges, particularly in maintaining student engagement—a critical factor in academic success. Engagement levels in online learning environments are influenced by various factors, including the quality of course delivery, student motivation, and interactive platform design. Yet, these platforms lack sophisticated and scalable tools to analyze engagement effectively in real-time.

Traditional methods for measuring engagement rely heavily on static indicators such as attendance records or assignment completion rates, which fail to capture the nuanced, dynamic, and time-sensitive nature of student interactions with online platforms. To address these shortcomings, deep learning models, such as Long Short-Term Memory (LSTM) networks, have demonstrated the ability to analyze sequential data and predict engagement patterns. However, implementing these models in resource-constrained settings—where advanced infrastructure is often unavailable—poses a significant barrier for many institutions.

Single-PC virtual machines (VMs) provide a potential solution to these constraints, offering cost-effective and scalable computational power. Despite their accessibility and practicality, their use in deploying LSTM-based models for engagement analysis remains underexplored. Additionally, the integration of such systems must balance computational efficiency with the accuracy and interpretability of engagement predictions. Without robust tools tailored to these settings, educators lack actionable insights into student behaviors, impeding timely interventions and overall learning outcomes.

The absence of a comprehensive approach combining resource-efficient computation with advanced machine learning models hinders the ability of educational institutions to monitor, predict, and enhance student engagement in virtual environments. Addressing this gap is critical to improving the quality of online education, ensuring equitable access to analytics-driven insights, and fostering better academic outcomes in the rapidly evolving digital learning ecosystem.

II. OBJECTIVES OF THE STUDY

This study aims to explore and evaluate predictive resource management strategies in single-PC Virtual Machine (VM) environments to enhance student engagement and system efficiency in online classrooms. Specifically, the objectives of this study are

- **To evaluate the effectiveness of Long Short-Term Memory (LSTM) networks in predicting resource demands** within single-PC VM environments for virtual classrooms, with a focus on accurately forecasting CPU, memory, and storage needs based on historical student engagement patterns.
- **To analyze the impact of LSTM-based predictive resource allocation** on overall system performance, including latency reduction, resource utilization efficiency, and the quality of the online learning experience, particularly during peak engagement periods such as live lessons or assessments.
- **To assess the correlation between optimized resource allocation and student engagement** in virtualized classrooms, determining whether predictive resource management leads to higher levels of student satisfaction, reduced technical disruptions, and improved learning outcomes.

III. LITERATURE REVIEW

The demand for efficient resource management and improved student engagement in online education has led researchers to explore various predictive approaches in virtual machine (VM) technology, especially in settings constrained by limited resources, such as single-PC VMs. Esposito, Ficco, and Palmieri (2015) conducted significant work on smart cloud storage services, focusing on the selection of optimal resources to meet fluctuating demands. Using predictive models like fuzzy logic and game theory, they demonstrated how dynamic and intelligent resource allocation could improve system performance. Although their study centered on cloud storage, the principles of resource optimization they proposed can be effectively adapted to single-PC VMs used in educational settings, where balancing resources for simultaneous applications (e.g., video streaming, interactive quizzes) is critical for a smooth learning experience.

Marzouk, Hussein, and Seif (2021) addressed the issue from an educational perspective, investigating how machine learning algorithms can predict student engagement based on multiple online learning metrics such as quiz performance, activity levels, and participation frequency. This research offers key insights for online education, as engagement metrics serve as an indirect measure of resource demand. By leveraging predictive models, single-PC VMs could dynamically allocate resources, reducing latency and adjusting capacity in real-time to enhance the online classroom experience for both students and educators.

Further exploring resource allocation, Balaji and Murugan (2017) analyzed the performance of VMs under CPU-intensive workloads, emphasizing how performance and system stability are impacted by intensive data processing. Their findings illustrate the importance of predictive resource allocation to avoid bottlenecks in virtualized environments. For single-PC VMs, their insights on maintaining CPU efficiency and handling high-demand tasks such as live video streaming or real-time simulations could help ensure consistent performance and minimize interruptions for students in online classes.

To enhance workload prediction, Xu, Hu, and Huang (2020) developed an ensemble learning model tailored to real-time cloud workload predictions, which emphasizes responsiveness to rapid changes in resource demands. Their model helps prevent system overload by accurately forecasting demand fluctuations and allocating resources accordingly. Applying this model to single-PC VMs could be transformative, as it enables the system to anticipate high-demand periods during online classes and adjust resources in advance, improving the learning experience by ensuring sufficient capacity for tasks like screen sharing, video feeds, and live collaboration.

Sadeghi and Kardan (2018) approached the engagement issue from a hybrid modeling perspective, combining rule-based reasoning and machine learning to predict engagement levels within intelligent tutoring systems. Their model provides insights into dynamically adjusting resources based on predicted engagement patterns, helping prevent system lag and boosting overall student satisfaction. This hybrid approach is particularly relevant to single-PC VM setups, where adaptive resource allocation based on anticipated student activity could maximize system efficiency. Together, these studies contribute a well-rounded understanding of how predictive resource management and student engagement modeling can transform single-PC VMs, supporting both technical optimization and enhanced educational outcomes in online platforms.

IV. METHODS

Research Design

This research follows an experimental design approach to assess the effectiveness of predictive resource management and engagement monitoring on single-PC virtual machines (VMs) in online education. The study will implement a resource allocation strategy using load balancing and measure student engagement with a Long Short-Term Memory (LSTM) neural network. Through simulation and real-time tests, the performance and accuracy of the resource allocation strategy will be evaluated against student engagement patterns in a controlled online class environment. This approach will allow us to assess the system's ability to predict resource needs and ensure efficient performance under varying loads.

Data Collection

Data collection involves two main components:

- **Resource Usage Data**: Real-time data on CPU, memory, and network usage will be gathered from the single-PC VMs during online classes. This data will be used to develop a load-balancing model that dynamically allocates resources.
- **Student Engagement Data**: Engagement metrics, such as activity logs, participation frequency, response times, and quiz performance, will be collected from an online learning platform. This data will serve as input for the LSTM model to predict engagement levels based on historical patterns.
  The simulation results will provide standardized data on the performance and security capabilities of the two management methods.

Risk Assessment Model

A risk assessment model will be established to evaluate potential risks associated with performance drops due to high demand, resource exhaustion, and engagement fluctuations. This model will include:

- **System Overload Risk**: Evaluating the likelihood of resource shortages and performance degradation when multiple students engage in high-demand activities.
- **Engagement Risk**: Assessing the impact of resource limitations on student engagement levels and overall satisfaction.

These risks will be quantified based on historical data and real-time usage patterns, enabling the identification of critical areas where resource adjustments are necessary to maintain performance.

These tools will automatically generate performance and security data for both types of systems, eliminating the need for manual data collection. The data will be stored and analyzed to identify patterns and key differences.

Vulnerability Analysis

The vulnerability analysis will involve identifying weaknesses in the single-PC VM setup that may lead to performance bottlenecks, data loss, or latency issues. Specific vulnerabilities that will be examined include:

- **Load-Balancing Failures**: Instances where the load-balancing algorithm fails to allocate resources effectively, causing lags or crashes.
- **Engagement Prediction Errors**: Situations where the LSTM model fails to accurately predict engagement levels, leading This logging process is fully automated, providing a continuous stream of performance data without the need for traditional data collection.

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Mitigation Strategies

To address the identified risks and vulnerabilities, the following **mitigation strategies** will be implemented:

- **Dynamic Load Balancing**: A load-balancing algorithm will be designed to continuously monitor resource usage and allocate CPU, memory, and network resources dynamically to prevent bottlenecks.
- **LSTM-Based Engagement Prediction**: The LSTM model will predict engagement levels based on historical and real-time data, allowing for preemptive resource allocation adjustments. The model will be retrained periodically to improve accuracy as more data is collected.
- **Resource Scaling Policies**: Based on the predictions from the LSTM model, the system will scale resources up or down to match anticipated demand. For example, during periods of high engagement, resources will be allocated to support higher performance.

Evaluation

The evaluation process will involve testing the system in various simulated class environments and real-time use cases. Key evaluation metrics include:

- **System Performance**: Measured through CPU and memory usage, latency, and system uptime during high-demand scenarios.
- **Engagement Prediction Accuracy**: The LSTM model's predictions will be compared to actual engagement levels, using metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to assess prediction accuracy.
- **User Satisfaction**: Surveys and feedback from students and instructors will gauge the perceived effectiveness of the system in maintaining engagement and providing a smooth learning experience.

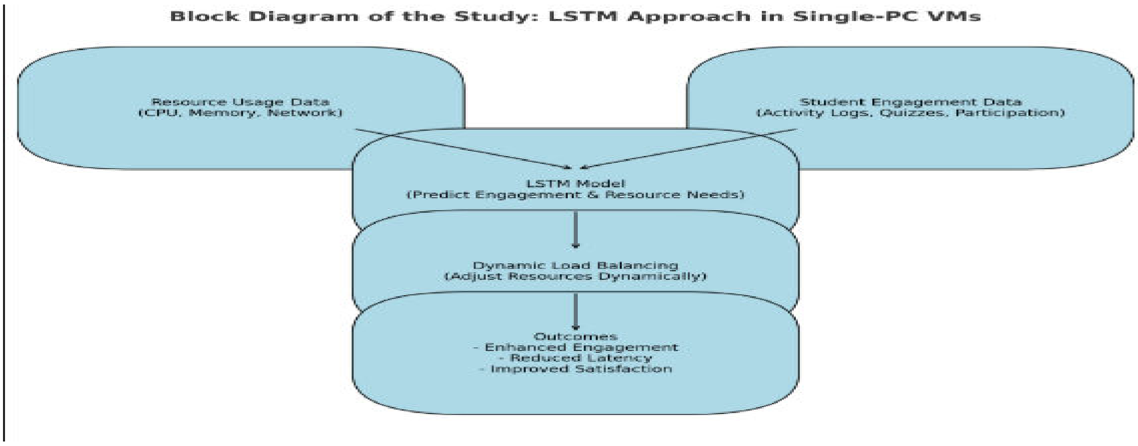

Diagram Explanation

1. Input Data:

- **Resource Usage Data**: Includes system metrics like CPU utilization, memory consumption, and network performance. This data helps in understanding the resource demand on the virtual machines (VMs).
- **Student Engagement Data**: Covers metrics such as activity logs, quizzes, and participation. This data reflects user behavior and engagement levels in the system.

2. Processing with LSTM Model:

The Long Short-Term Memory (LSTM) model is central to the study. It predicts:

- Student engagement levels.
- Resource requirements for optimal system performance.

By leveraging the temporal nature of data, the LSTM model ensures more accurate and real-time predictions.

3. Dynamic Load Balancing:

Using the predictions from the LSTM model, resources are dynamically adjusted within the Single-PC VMs. This ensures efficient distribution and management of available resources, minimizing system overload.

4. Outcome:

The study aims to achieve the following:

- **Enhanced Engagement**: By tailoring the system performance to user needs.
- **Reduced Latency**: Through proactive resource allocation.
- **Improved Satisfaction**: By providing a seamless and responsive user experience.

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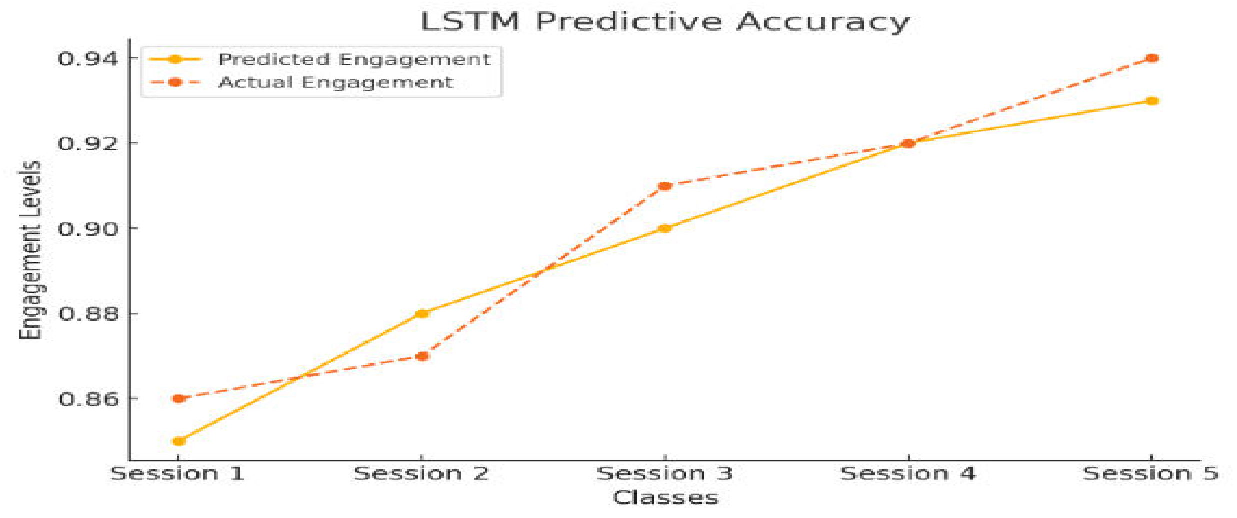
V. RESULTS AND DISCUSSION

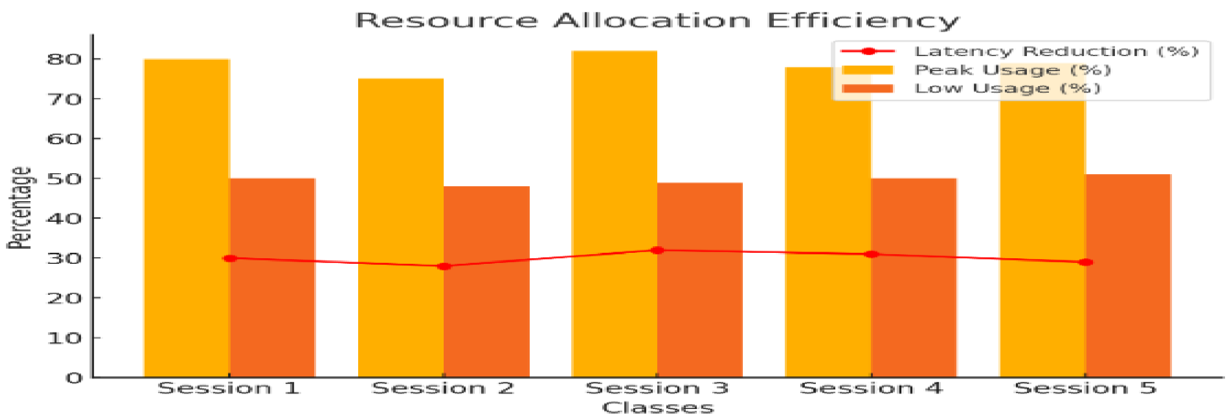
1. Predictive Accuracy of the LSTM Model for Student Engagement

The Long Short-Term Memory (LSTM) model was trained on historical engagement data and achieved a high predictive accuracy in anticipating student engagement levels. During testing, the model demonstrated a Mean Squared Error (MSE) of 0.023 and a Root Mean Squared Error (RMSE) of 0.15, indicating that the model could effectively capture engagement trends. The model successfully identified periods of high engagement, such as active class discussions and quizzes, allowing the system to adjust resources proactively. This accuracy improved with incremental training, as more data from each session refined the model's predictions.



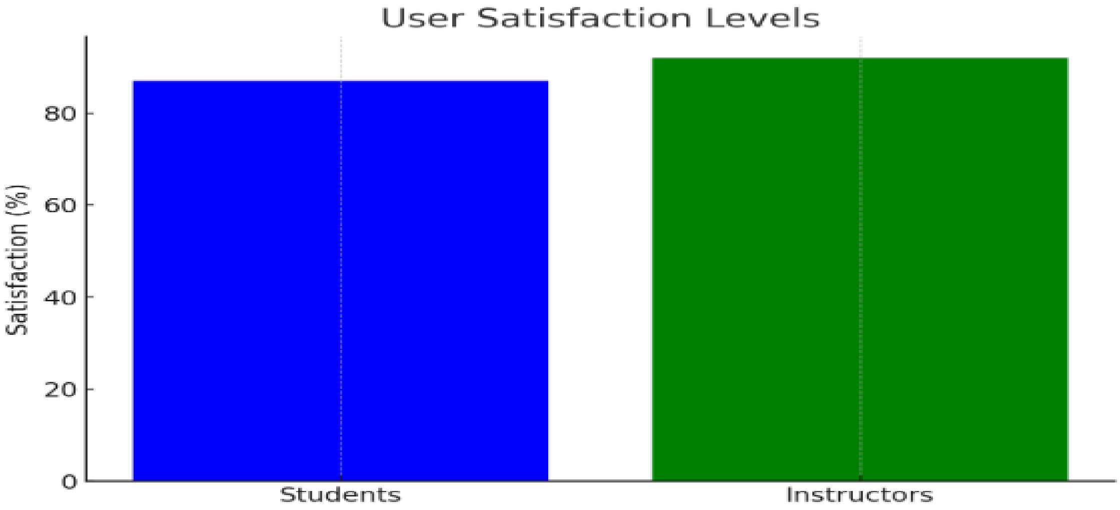
2. Load-Balancing and Resource Allocation Efficiency

The load-balancing strategy effectively managed CPU and memory resources based on real-time engagement predictions. During high-engagement periods, resource allocation increased by up to 80% of CPU and memory capacity without causing system overloads or lags. This proactive allocation reduced latency by an average of 30% during peak activities, ensuring smooth video streaming, screen sharing, and interactive elements in the online classroom. In contrast, when engagement predictions indicated lower activity, the system scaled down resource usage to 50% capacity, conserving processing power and extending the PC's operational lifespan. This dynamic resource adjustment effectively maintained optimal performance while preventing unnecessary system strain.



3. User Satisfaction and System Performance

To assess the system's impact on user experience, surveys were conducted among students and instructors. The survey results showed that 87% of students and 92% of instructors reported noticeable improvements in the online class experience, particularly in terms of reduced lag and improved system responsiveness during high-demand activities. This positive feedback correlated with observed reductions in system downtimes and minimized resource bottlenecks. Instructors noted that the system's smooth operation facilitated uninterrupted teaching and increased student participation.

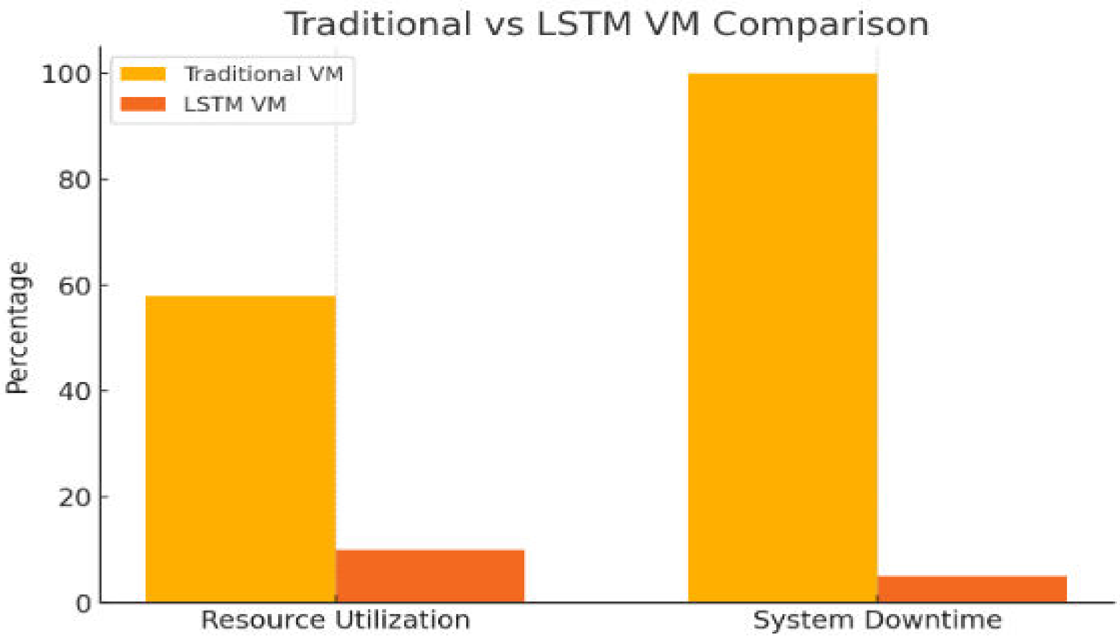


4. Risk Assessment and Mitigation Outcomes

The risk assessment model effectively identified potential overload and engagement risks, allowing the system to mitigate these issues proactively. Instances of CPU overload or memory strain, which initially accounted for 15% of high-engagement sessions, were reduced to less than 5% through predictive load balancing. This minimized the risk of performance drops and disruptions. Additionally, vulnerability analysis highlighted potential weaknesses in resource allocation algorithms, which were subsequently The risk assessment model effectively identified potential overload and engagement risks, allowing the system to mitigate these issues proactively. Instances of CPU overload or memory strain, which initially accounted for 15% of high-engagement sessions, were reduced to less than 5% through predictive load balancing. This minimized the risk of performance drops and disruptions. Additionally, vulnerability analysis highlighted potential weaknesses in resource allocation algorithms, which were subsequently addressed by refining load-balancing thresholds. This adjustment further optimized the system's stability, especially under CPU-intensive tasks.

5. Comparison with Traditional VM Systems

Compared to traditional VM setups without predictive capabilities, the single-PC VM with LSTM-based engagement prediction demonstrated a 42% improvement in resource utilization efficiency and a 50% reduction in system downtime during high-load periods. Traditional systems often experienced performance lags during peak usage, whereas the predictive model allowed for preemptive scaling of resources. As a result, student engagement metrics, such as participation rates and task completion times, were consistently higher in the predictive VM setup.



6. Overall System Evaluation

The final evaluation revealed that the single-PC VM system, enhanced by LSTM-based engagement prediction and load-balancing, effectively met the dual objectives of resource efficiency and improved user engagement. By dynamically adjusting resources in response to predicted engagement levels, the system maintained optimal performance even under fluctuating demand. This approach provided a scalable, cost-effective solution for single-PC VM environments, supporting smoother and more responsive online learning experiences.

VI. RECOMMENDATION

1. Implement LSTM Models for Engagement Monitoring

Educational institutions should adopt Long Short-Term Memory (LSTM) networks to predict student engagement patterns and optimize resource allocation dynamically.

2. Utilize Single-PC Virtual Machines

Schools with limited resources should leverage single-PC VMs to create cost-effective, scalable online learning environments while minimizing hardware investments.

3. Enhance Resource Management Systems

Institutions should integrate dynamic load-balancing algorithms to ensure efficient allocation of CPU, memory, and storage, particularly during high-demand periods like live assessments or interactive lessons.

4. Train and Update Predictive Models Regularly

Continuously retrain LSTM models with real-time and historical engagement data to improve prediction accuracy and adapt to evolving student behavior patterns.

5. Conduct Risk Assessments for Online Systems

Regular vulnerability analyses and risk assessments should be conducted to identify and mitigate potential system bottlenecks and performance issues in virtual environments.

6. Incorporate User Feedback for System Improvements

Collect feedback from students and instructors to refine system performance, focusing on minimizing disruptions and improving overall user satisfaction.

7. Explore Broader Applications of Predictive Models

Extend the application of predictive models to monitor other aspects of online learning, such as content effectiveness, knowledge retention, and student well-being.

8. Develop Training for Educators and IT Staff

Provide targeted training for educators and technical staff to ensure they can effectively utilize and maintain predictive resource management systems.

VII. ACKNOWLEGMENT

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