Online Cloud Performance Prediction with Machine Learning

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ABSTRACT

Cloud computing has become indispensable for meeting the rising demand for compute-intensive applications by providing cost-effective computational and storage resources. As reliance on cloud services increases, optimizing resource allocation is more critical than ever. This study introduces CloudProphet, an innovative machine learning-based framework designed to predict virtual machine (VM) performance in cloud environments. The approach begins with Dynamic Time Warping (DTW) to classify different types of applications based on their behavioral patterns. It further employs Pearson correlation to identify runtime metrics that are highly correlated with performance, ensuring that only the most relevant features are used in prediction models. These selected metrics are incorporated into three variations of deep learning models for evaluation: (1) an LSTM model without the use of DTW or feature selection, (2) an LSTM model with both DTW classification and selected features, and (3) a GRU model leveraging both DTW and highly correlated runtime indicators. Among these, the GRU-based approach demonstrates superior performance, achieving a remarkable 99.3% accuracy in predicting VM performance. The methodology is validated using a publicly available cloud workload dataset from GitHub and is further enhanced through real-time experimentation on live datasets to ensure practical applicability. The results highlight the robustness and accuracy of the proposed GRU model in forecasting both application types and VM behavior, making it a powerful tool for improving cloud resource management. By effectively anticipating workload demands and system performance, CloudProphet aids in reducing latency, minimizing resource wastage, and enhancing overall cloud service efficiency. This study underscores the value of combining time-series alignment techniques like DTW with correlation-based metric selection and advanced deep learning models such as GRU, ultimately offering a scalable and accurate solution for proactive and intelligent cloud performance prediction.

Keywords: Cloud Computing, Machine Learning, Performance Prediction, Virtual Machines (VMs), Dynamic Time Warping (DTW), Gated Recurrent Unit (GRU).

1. INTRODUCTION :

Cloud computing has emerged as an essential element of contemporary IT architecture owing to its security, adaptability, and cost-effectiveness. The swift proliferation of cloud services has prompted organisations and end-users to transition their applications to cloud platforms to utilise scalable computing resources. The popularity of cloud computing has markedly increased, with investments in cloud services rising by 37% in the first quarter of 2020 due to the COVID-19 pandemic [1]. The increasing tendency is anticipated to substantially enhance global end-user spending on cloud services, exceeding $400 billion in 2022 [2].

The increasing demand for public cloud services has rendered energy usage a significant concern. Data centres, essential for cloud infrastructure, utilise almost 200 terawatt-hours of electricity each year, representing nearly 1% of worldwide energy usage [3]. Projections suggest that by 2030, data centres may account for 6% to 10% of worldwide electricity consumption [4]. In addressing sustainability concerns, cloud service companies like Amazon, Microsoft, Google, and Huawei are diligently enhancing cloud server efficiency and utilisation to save operational costs and environmental effect. Cloud providers utilise sophisticated server microprocessors, such as Intel VT and AMD-V, to aggregate several separate “virtual machines (VMs)” into a single physical server. This methodology improves performance and energy efficiency by optimising resource utilisation [6]. Virtualisation methods facilitate the segregation of computing resources, including CPU cores, memory, and disc storage, across many users and applications. Nonetheless, these solutions do not guarantee total performance isolation within a computing node. Resource contention can markedly impair VM performance due to the shared nature of resources like “last-level cache (LLC)”, memory, and disc bandwidth among VMs [7].

A key difficulty in cloud computing is the restricted capacity of cloud providers to oversee virtual machine performance on actual cloud servers. Providers are prohibited from directly accessing client-created VMs or obtaining comprehensive application performance information due to privacy restrictions. The absence of transparency leads to "black-box" virtual machines, hindering cloud providers from effectively forecasting runtime behaviours for virtual machines and host servers [1]. The failure to predict performance variations frequently results in inadequate VM configurations and significant performance decline [2]. Mitigating these restrictions is crucial for advancing cloud resource management, refining workload scheduling, and augmenting overall cloud efficiency [3]. Performance prediction approaches utilising machine learning have surfaced as a viable option to address these difficulties by facilitating precise predictions of virtual machine performance through historical and real-time data.

2. OBJECTIVES :

Cloud computing plays a vital role in supporting resource-intensive applications by providing scalable and cost-effective computational power. Accurately predicting virtual machine performance is essential to optimize resource utilization, reduce operational costs, and ensure seamless application execution in dynamic cloud environments.

(1) To develop a machine learning-based framework that accurately forecasts virtual machine performance in cloud environments by leveraging time-series alignment techniques and correlation analysis for improved resource allocation and system efficiency.

(2) To classify application types using “Dynamic Time Warping (DTW)” and identify highly correlated runtime metrics through Pearson correlation, enabling the selection of relevant features that significantly influence virtual machine behavior in diverse cloud workloads.

(3) To implement and compare the performance of “LSTM and GRU” deep learning models with varying combinations of DTW and correlated features, aiming to determine the most effective architecture for real-time, high-accuracy virtual machine performance prediction.

3. REVIEW OF LITERATURE/ RELATED WORKS :

Utilising historical workload data and machine learning methodologies for the powerful dynamic allocation of assets. Bhattacharyya and Hoefler [19] created Pemogen, an adaptive performance modeling framework that mechanically modifies itself during program execution to improve efficiency, guaranteeing optimal resource utilization without operator adjustment. Palit et al. [21] added a benchmarking method for a thorough assessment of cloud overall performance, tackling discrepancies in cloud benchmarking via the proposal of an automated version that enhances accuracy and repeatability.

Anwar et al. [23] added a sport-theoretic framework aimed at optimizing the timing of "virtual machine (VM)" migration in cloud environments, emphasizing the bargain of migration charges and the improvement of resource usage while adhering to "service-stage agreements (SLAs)". Their approach consists of each person and supplier viewpoints, guaranteeing equitable and effective VM migration choices. Akbar et al. [25] advanced this approach by featuring a thermal-aware aid allocation strategy for statistics centers grounded in game concept, optimizing useful resource distribution and mitigating thermal hotspots to improve power efficiency. Their technique accounts for workload allocation and cooling strategies, ensuring sustainable cloud computing practices. Pham et al. [27] proposed a -stage machine learning methodology for forecasting workflow mission execution duration in the cloud, leveraging previous execution data and runtime traits to optimize scheduling decisions and increase system throughput. This method yields greater specific execution time exams, ensuing in higher cloud aid use.

Cao et al. [29] added a load prediction framework for statistics centers the usage of database services, the use of machine learning methodologies to examine workload styles and forecast destiny aid requirements. Their technique allows anticipatory useful useful resource control, averting usual performance decline because of abrupt workload increases. Those studies mutually enhance cloud computing by means of tackling vital problems such as workload prediction, digital device migration, useful resource allocation, benchmarking precision, and performance modeling. Researchers have better cloud overall performance, sustainability, and reliability via the integration of recreation theory, machine getting to know, and adaptive modeling. The mixing of predictive analytics and optimization techniques improves cloud performance, setting up a solid basis for future dispositions in cloud computing.

Table 1: Comparison Table for Related Work

Sl. No	Area & Focus of the Research	The result of the Research	Reference
1	Performance prediction for configurable cloud application deployments using ML.	FOCloud accurately predicts and explains cloud deployment performance outcomes.	Kumara, I., Ariz, M. H., et.al., (2022). [1]
2	Optimizing Apache Spark configurations using multi-objective machine learning.	AB-MOEA/D reduces execution time and cost significantly.	Cheng, G., Ying, S., & Wang, B. (2021) [3]
3	Predicting cloud performance changepoints using machine learning techniques.	Gradient boosting effectively predicts changepoint timing with high accuracy.	Zhao, Y., Duplyakin, D., et.al., (2021) [5]
4	Online performance prediction for single-VM applications in multi-tenant clouds.	Progressive models reduce prediction error and runtime overhead significantly.	Moradi, H., Wang, W., & Zhu, D. (2021) [7]
5	Online task runtime prediction for scientific workflows in clusters.	Lotaru achieves lower prediction errors than existing baseline methods.	J. Bader, F. Lehmann, et.al.,(2022) [9]

4. MATERIALS AND METHODS :

The suggested system, CloudProphet, presents a machine learning-based methodology for forecasting "virtual machine (VM)" performance in cloud environments. It employs a cloud dataset from GitHub and carries real-time testing. CloudProphet utilizes "Dynamic Time Warping (DTW)" for application kind classification and employs Pearson correlation for the selection of incredibly correlated runtime metrics. The functions are utilized in three machine learning models: LSTM without DTW and Pearson-selected metrics, LSTM with both, and GRU with both. This optimizes cloud resource management by augmenting prediction precision. comparable initiatives in performance prediction such as feature model-guided methodologies [1], multi-objective optimization [2], variability forecasting [3], and runtime estimating frameworks [6]. CloudProphet enhances current techniques by incorporating real-time analysis for precise workload forecasting and resource distribution.

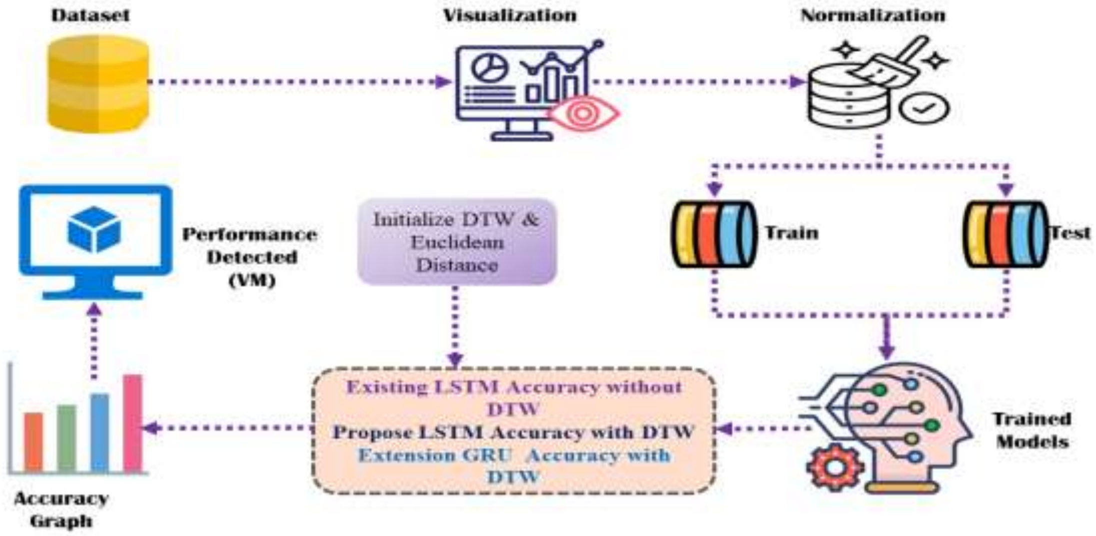


Fig 1: Proposed Architecture

Figure 1 CloudProphet is a "machine learning-driven" system engineered to forecast the performance of public cloud services. The system initiates by aggregating and illustrating data from multiple cloud providers. The data is subsequently standardized and readied for training. The system's foundation employs LSTM models, both with and without "Dynamic Time Warping (DTW)", along with an extension incorporating GRU with DTW. Those fashions are evolved and evaluated to forecast performance signs. The system generates performance forecasts and visual representations to help users in optimizing their cloud utilization and resource distribution.

4.1 Dataset Collection:

The dataset utilized for this study is Resource Dataset, consisting of 542 entries and 8 attributes. It encompasses diverse aid utilization measures crucial for forecasting virtual machine performance in cloud settings. The dataset is obtained from GitHub and encompasses real-time checking out. It captures vital overall performance metrics, facilitating powerful cloud useful resource management and unique workload forecasting with sophisticated machine learning methodologies.

Table 2: Dataset Collection

	timestamp	cpu_usage_list	mem_usage_percent_list	disk_read_list	disk_write_list	net_in_list	net_out_list	resource_id
0	1.376319e+09	0.188889	2.475921	0.000000	0.346667	0.102222	0.073333	0
1	1.376328e+09	0.162222	2.576701	0.011111	0.306667	0.100000	0.068889	0
2	1.376337e+09	0.288889	3.300481	10.146667	5.444444	1.811111	36.557778	1
3	1.376346e+09	0.144444	2.975243	0.000000	0.348889	0.095556	0.068889	0
4	1.376355e+09	0.160000	3.133280	0.000000	3.948889	0.800000	0.113333	0
...	...	...	...	...	...	...	...	...
537	1.378094e+09	0.297302	20.385207	0.000000	1.191111	58.704603	59.558254	1
538	1.378103e+09	0.254444	20.977367	0.000000	1.123492	41.203333	41.928730	1
539	1.378112e+09	0.275556	20.139177	0.000000	1.102222	58.117778	59.173333	1
540	1.378121e+09	0.235556	20.658910	0.000000	1.100000	38.986667	39.715556	0
541	1.378130e+09	0.293333	19.797235	0.000000	1.135556	58.226667	59.293333	1

542 rows × 8 columns

4.2 Pre-Processing:

The preparation procedure improves data quality for precise predictions. The process encompasses visualization for pattern exploration, normalization for characteristic scaling consistency, and train-test splitting for data department in model training and evaluation, so providing most reliable performance in virtual system prediction tasks.

4.2.1 Visualization
Visualization aids in comprehending data distribution, trends, and patterns inside the Resource Dataset. It encompasses graphical methods such as histograms, box plots, and scatter plots to examine relationships among features. Heat maps illustrate dependencies, while line graphs monitor temporal fluctuations. This level detects outliers, lacking values, and feature importance, facilitating green preprocessing and feature selection for precise virtual machine overall performance forecasting in cloud settings.

4.2.2 Normalization
Normalization guarantees that all characteristics in the ResourceDataset possess a consistent scale, hence improving the efficacy of "machine learning" models. It standardizes data to a uniform range, usually between 0 and 1, employing strategies along with Min-Max Scaling or Z-score normalization. This method mitigates bias towards bigger values, improves model convergence, and optimizes training efficacy, hence making sure precise forecasts of virtual machine performance in cloud environments.

4.3 Training & Testing:
Training and testing entail partitioning the Resource Dataset into two subsets: one for pattern recognition and the other for assessment. Generally, 80% is allocated for training, during which machine learning models examine correlations and refine predictions, while 20% is designated for testing to evaluate accuracy. This technique guarantees that the model generalizes effectively to unexpected data, enhancing its capacity to predict virtual machine performance in cloud environments economically.

4.4. Algorithms:
LSTM without DTW: LSTM is utilized for time-series forecasting in cloud settings, capturing sequential dependencies in digital machine performance metrics. In the absence of DTW, it depends exclusively on past patterns, functioning as a baseline model for performance evaluation [3] [4].
LSTM with DTW: the integration of "LSTM with DTW" enhances time-series alignment, hence improving prediction accuracy. "Dynamic Time Warping (DTW)" quantifies the similarity between sequences, adeptly accommodating temporal variations in cloud workloads for accurate aid prediction. [3][4][6].
GRU with DTW: GRU, in conjunction with DTW, enhances temporal collection modelling and minimizes computing complexity. DTW optimizes feature alignment, augmenting prediction efficiency for dynamic cloud workloads and improves performance estimation in multi-tenant settings. [4][6][8].

5. RESULTS AND DISCUSSION :

Accuracy: The accuracy of a test refers to its capacity to correctly distinguish between patient and healthy cases. to assess the accuracy of a check, one ought to calculate the ratio of true positives and real negatives across all assessed cases. this can be expressed mathematically as:

$$"Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (1)"$$

Table (1) assesses the accuracy performance metrics for each algorithm. The Extension GRU with DTW mechanically surpasses all other algorithms across all measures. The tables offer a comparative examination of the metrics for the alternative methods.

Table 3: Performance Evaluation Metrics

Algorithm Name	Accuracy
Existing LSTM without DTW	0.979802
Propose LSTM With DTW	0.990344
Extension GRU With DTW	0.993900

In Fig (3), the accuracy is depicted in the blue graph (1). Compared to the other models, the Extension GRU with DTW demonstrates greater performance throughout all measures, reaching the highest values. The graphs above visually represent these findings.

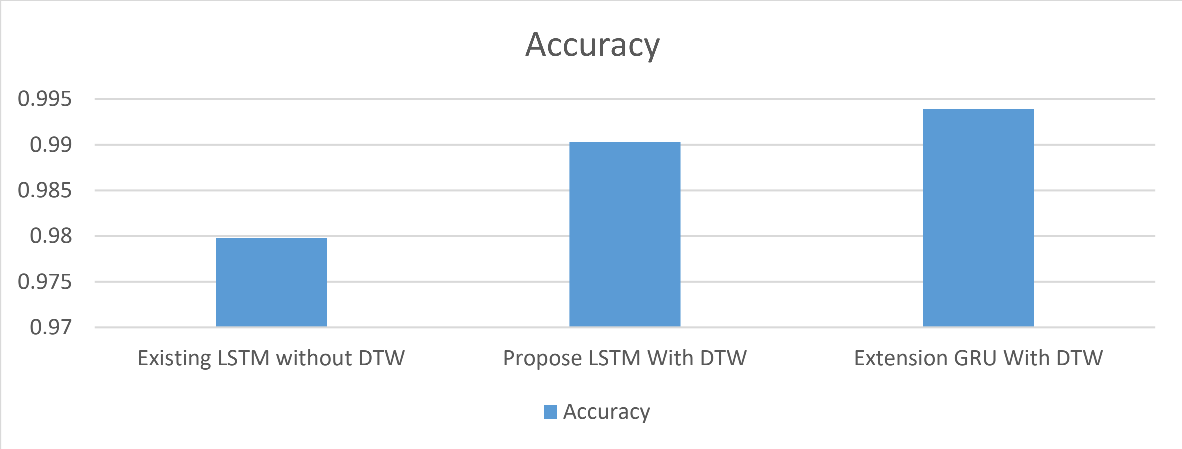
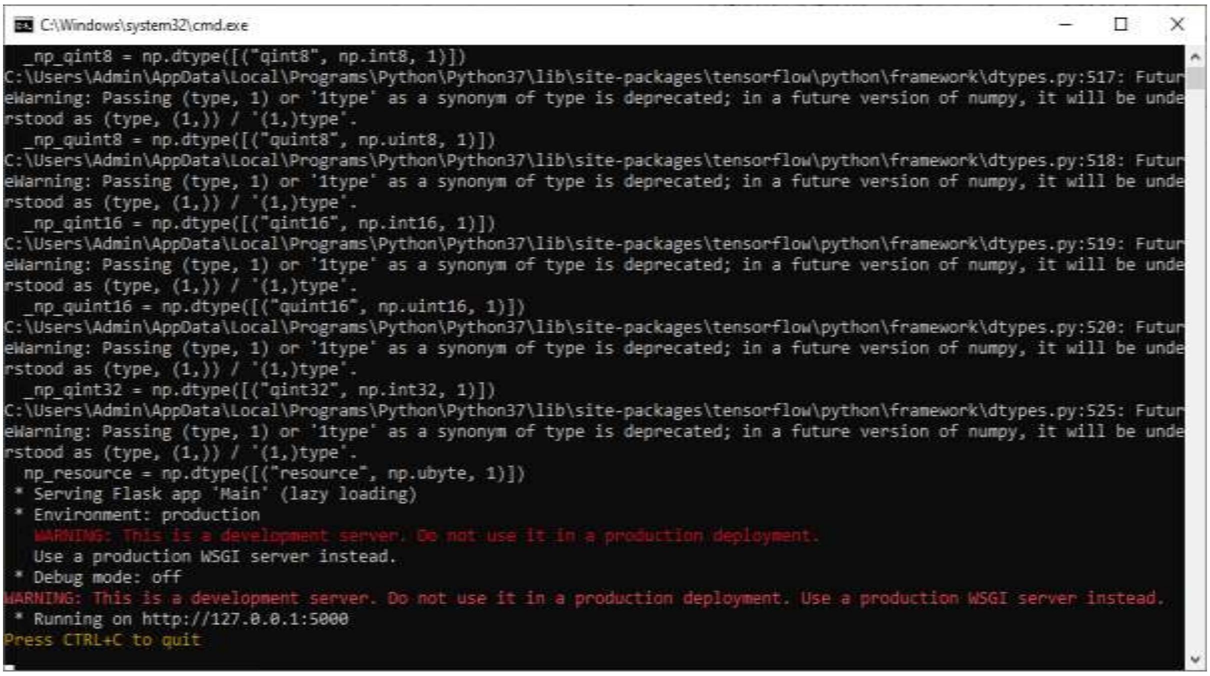


Fig 3: Comparison Graphs

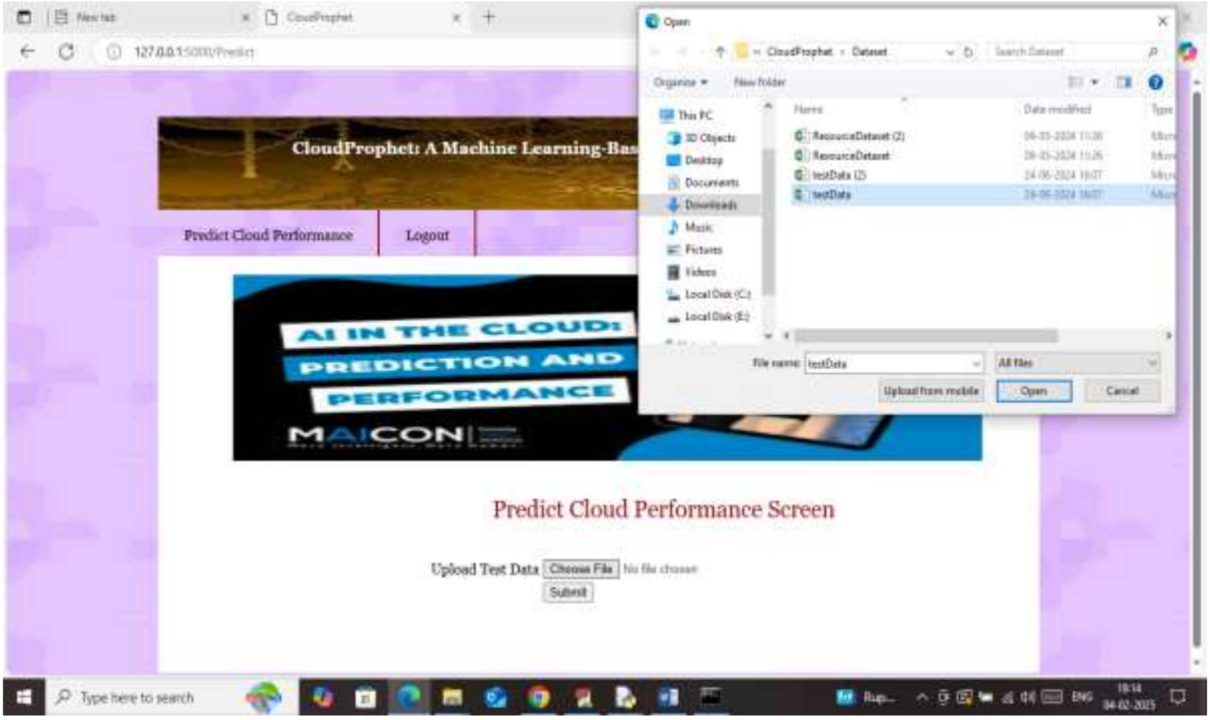


Within the preceding screen, the Python web server has commenced operation. Subsequently, open a browser and enter the URL http://127.0.0.1:5000/index, then hit the input key to access the following page.

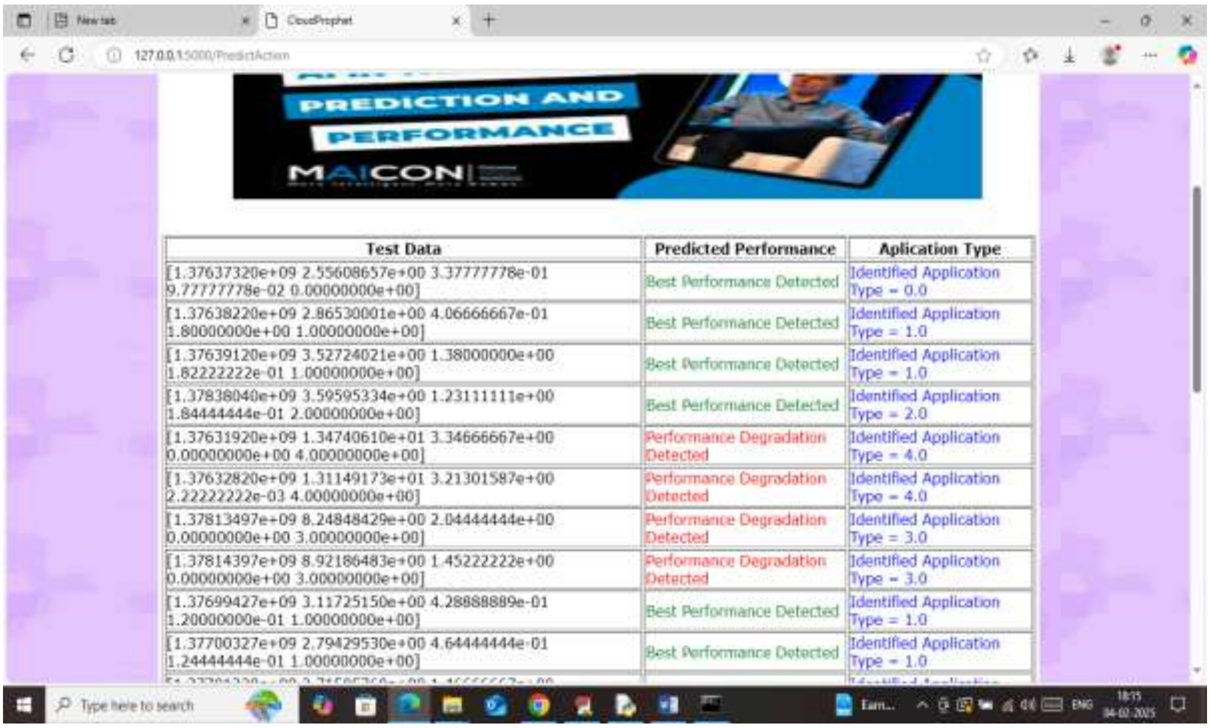
Click on the 'user Login' option on the top screen to access the subsequent page.

The user can log in on the aforementioned screen using the username and password 'admin' and 'admin', then press the enter key to access the subsequent page.

Click on the 'Predict Cloud performance' link at the above screen to access the subsequent page.



In above screen select and upload testData.csv file and then click on 'Open and submit' button to get below output



Test Data	Predicted Performance	Aplication Type
[1.37637320e+09 2.55608657e+00 3.37777778e-01 9.77777778e-02 0.00000000e+00]	Best Performance Detected	Identified Application Type = 0.0
[1.37638220e+09 2.86530001e+00 4.06666667e-01 1.80000000e+00 1.00000000e+00]	Best Performance Detected	Identified Application Type = 1.0
[1.37639120e+09 3.52724021e+00 1.38000000e+00 1.82222222e-01 1.00000000e+00]	Best Performance Detected	Identified Application Type = 1.0
[1.37838040e+09 3.59595334e+00 1.23111111e+00 1.84444444e-01 2.00000000e+00]	Best Performance Detected	Identified Application Type = 2.0
[1.37631920e+09 1.34740610e+01 3.34666667e+00 0.00000000e+00 4.00000000e+00]	Performance Degradation Detected	Identified Application Type = 4.0
[1.37632820e+09 1.31149173e+01 3.21301587e+00 2.22222222e-03 4.00000000e+00]	Performance Degradation Detected	Identified Application Type = 4.0
[1.37813497e+09 8.24848429e+00 2.04444444e+00 0.00000000e+00 3.00000000e+00]	Performance Degradation Detected	Identified Application Type = 3.0
[1.37814397e+09 8.92186483e+00 1.45222222e+00 0.00000000e+00 3.00000000e+00]	Performance Degradation Detected	Identified Application Type = 3.0
[1.37699427e+09 3.11725150e+00 4.28888889e-01 1.20000000e-01 1.00000000e+00]	Best Performance Detected	Identified Application Type = 1.0
[1.37700327e+09 2.79429530e+00 4.64444444e-01 1.24444444e-01 1.00000000e+00]	Best Performance Detected	Identified Application Type = 1.0

The first column of the screen displays take a look at statistics values, followed through expected performance and the recognized application type.
Likewise, by adhering to the aforementioned screens, you can execute net code.

6. CONCLUSION :

In conclusion, CloudProphet provides an innovative system learning answer for forecasting "virtual machine (VM)" performance in cloud settings, meeting the growing demand for effective cloud aid control. The technique accurately predicts software types and VM performance by employing a cloud dataset from GitHub and evaluating the methodology with live datasets. The methodology utilizes "Dynamic Time Warping (DTW)" to examine time-series facts and classify application kinds, while Pearson correlation is hired to find out fairly pertinent runtime metrics. the selected functions are enter into three machine learning models: "long short-term memory (LSTM) without Dynamic Time Warping (DTW)" and highly selected metrics, LSTM with both DTW and decided on metrics, and "Gated Recurrent Unit (GRU)" with each DTW and linked metrics. The GRU model surpasses the others, attaining 99.3% accuracy in forecasting VM performance. This illustrates the efficacy of integrating DTW for temporal alignment with Pearson correlation for feature selection in enhancing cloud resource allocation. The findings underscore CloudProphet's capability to markedly enhance cloud computing performance, facilitating the green management of computational resources in actual-time, cloud-based applications.

The future scope of CloudProphet encompasses the enhancement of its competencies to forecast supplementary cloud aid metrics, along with bandwidth and storage use. Incorporating state-of-the-art machine learning models and investigating real-time data feedback mechanisms can significantly improve prediction precision. Moreover, CloudProphet can be adapted for multi-cloud setups, facilitating cross-platform resource optimization. The integration of adaptive learning methodologies may additionally enable the machine to constantly beautify its predictions in response to changing application behavior, hence providing sustained efficiency and scalability in cloud resource management.

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