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Applying Cloud Computing in Medical Interventions

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Abstract

The main aim of this study was to establish a mechanism for probabilistic data collection, which would transform into the performance of the collected data's correction analysis. Also, the study sought to develop a stochastic prediction framework towards predicting future health conditions among patients. The prediction model would be implemented in a way that focused on the current health status of the selected subjects. With cloud environments' extension simulations, there was the evaluation of the proposed system. In the findings, it maintained bandwidth utilization and 90% CPU. It also achieved a prediction accuracy of 98%, superior outcomes that led to a significant reduction in the time of analysis.

1 Introduction

For outdoor and in-hospital patient experiences, applications such as mobile networks and wireless sensor networks (WSNs) have paved the way for the use of the Internet of Things (IoT) to monitor their experiences [1]. In this arrangement, individuals are equipped with various smart gadgets, including motion sensors, electroencephalography (EEG), electrocardiogram (ECG), and in-plant pacemakers [2, 3]. Indeed, the role of such wearable gadgets lies in the collection of health information, including variables such as heart rate, blood pressure, and body temperature [4]. The variables aid in activities such as medical treatment and the tracking of one's physical activity. Imperatively, bid data reflects one of the emerging analytical settings through which voluminous patient data has been handled, whether structured or unstructured [5-7].

2 Methodology

In a quest to enhance patient monitoring quality, the proposed model relied on a window-based temporal data monitoring and collection framework. For the data collection system, it was designed in such a way that there was the collection of the data that had been recorded via a data acquisition scheme, which would then transmit the information to cloud data centers. The centers played the role of information analysis and storage. It is also notable that beyond the inter-class correlation analysis, there was the identification and grouping of highly influenced health parameters relative to the correlation values that they exhibited. Similarly, there was the establishment of a threshold that would reflect high risk level, eventually compared with the resultant correlation values that were obtained.

3 Results and Discussion

In the findings, this study established that followed the implementation of the proposed system, there was an increase in prediction accuracy with increase number of attributes. In situations where the implementation focused on one attribute only, a value of about 51% was the accuracy status.

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However, upon considering two attributes, there was a notable increase, with 58% being the value of accuracy. With 8 attributes considered, there was a more significant increase in which 80% remained the value of accuracy. For the maximum accuracy, which stood at 98%, it was achieved when the simulation process focused on 14 attributes.

Apart from the aspect of prediction accuracy, this study also analyzed the concept of processing time in relation to the proposed model's implementation process. From the literature, this factor (of processing time) plays an important role when it comes to the evaluation of an algorithm's overall performance [7-9]. In this study, processing time reflected the total amount of task scheduling time when there was a transfer of data from various datacenters, a process that aimed to realized execution time and data locality. In this case, when different data centers employed multiple virtual machines, there was a reduction in the processing time. When the algorithm had three data centers, there was less processing time, compared to situations where algorithms exhibited two data centers, especially because of the map tasks' parallel processing procedure. Therefore, a merit that accrued due to the use of the cloud platform or system entailed reductions in the processing time. The latter findings led to the study's inference that there is direct proportionality between the time of execution and the time of data transfer.

When the system encountered large patient data, the parameter of CPU utilization or usage was also evaluated, a step that aided in gaining critical insights relative to the proposed model's performance. From the simulation outcomes, gigabytes were values set for the sizes of the input data. These sizes ranged between 5 and 50GB. In the findings, the study found that when there was an increase in data size amount, there tended to be a notable increase in the system's CPU utilization, having implemented the proposed prediction framework. As such even as data centers received more and more data size amounts, CPU utilization increased. This trend would be observed up to a moment where the processing threshold was achieved. In circumstances where hard deadlines were associated with the given data centers, the system would operate in such a way that there would be an addition of new data centers. This addition's role lay in the criticality of ensuring that within the execution system, there was the balancing of the over and under utilization. Also, the central aim of the latter stage would be to ensure that resource utilization is maximized while also ensuring that the processing deadline is not compromised. Cost minimization was also associated with the latter performance arrangement and outcome.

For the cloud service linked to the proposed model, a final attribute that was investigated constituted bandwidth utilization. In this case, there was the creation of 5 VMs before fixing for the respective data centers. From the results, the study established that the factor of data size determined bandwidth utilization percentage in the system. Also, cloud services exhibited a close correlation with geographically distributed data centers. A specific illustration is that in which DC5 bandwidth utilization stood at 59%, having considered the data for 10GB. When the data of 50GB was considered, there was an increase in bandwidth utilization, standing at 96%. Despite these outcomes, however, it is important to note that aspects of time variance and network traffic affected the bandwidth behavior directly. The trickle-down effect was an impact on the cost estimation for the bandwidth.

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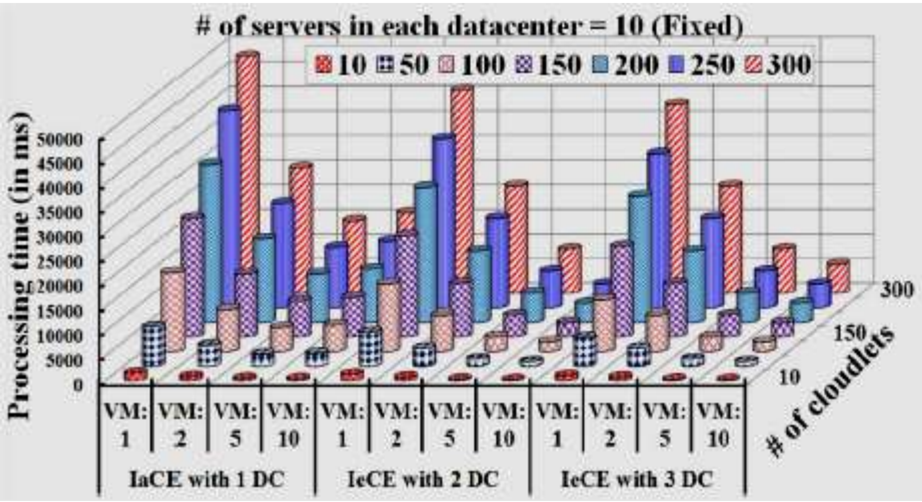
From the financial perspective, it becomes important to analyze the cost factor in relation to the adoption and implementation of a prediction model for health conditions in the healthcare sector. From the simulation results, four major parameters were evaluated. They included the data migration cost, computation cost, storage cost, and bandwidth cost. The pricing model that was used to calculate the costs was the Amazon Web Service, achieved via a simulation process. From the results, about 0.5 USD was found to be the cost that would be incurred relative to the cost through which data in GB would be processed for each moment. However, with different data centers having different data transfers, the simulation also pointed to a possibility of variations in costs, posing a direct impact on the total cost that would be incurred. However, a similar path would not be followed in regard to each GB's cost growth rate, especially when the arrival data's growth rate is considered. A specific illustration of this observation is that in which there is a linear increase in the total cost when data amounting to 90GB is processed, but a steady path or trend is observed when the processing proceeds in the range of 90GB to 100GB.



4 Conclusion

In summary, the main aim of this study lay in the design or development of a model of probabilistic data acquisition. The research environment or target setting for system application and implementation was the case of a cloud-based healthcare platform. The design of algorithms targeted inter and intra cluster correlation analyses. The study was motivated by growing interest in big data evolution, as well as its implications for the healthcare sector. Thus, the design of the framework strived to provide room for the prediction of possible emergences of health conditions in the future. This prediction would be achieved by allowing the proposed and designed model to focus on and analyze the current or given health status of an individual. Indeed, the model achieved an accuracy of 98%. It is also important to highlight that in the study, the processing framework or model that was employed involved the case of the cloud-based MapReduce system, aiding in the analysis of big data in healthcare and, in turn, allowing for the performance evaluation of the proposed prediction model.

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