ABSTRACT

Internet of Things and fog computing play significant roles in the development and implementation of smart cities. Smart cities aim to improve the quality of life for citizens and visitors by leveraging technology and data to optimize resource utilization, enhance environmental protection, improve infrastructure operations, and ensure safety and security. IoT forms the foundation of smart cities by connecting various physical devices, sensors, and actuators through the internet. These connected devices collect and exchange data, enabling real-time monitoring, control, and automation of various systems and services in urban areas. IoT enables the integration of diverse data sources and allows for data-driven decision-making to improve efficiency and effectiveness. Fog computing complements IoT in the context of smart cities. It is a decentralized computing infrastructure that extends the cloud closer to the edge of the network, bringing computational resources and services closer to the IoT devices and data sources. Fog computing addresses the limitations of traditional cloud computing, such as high latency, bandwidth constraints, and dependency on the internet connection. By distributing computing capabilities at the edge, fog computing enables faster data processing, real-time analytics, and low-latency responses. The combination of IoT and fog computing in smart cities creates a powerful ecosystem. IoT devices generate massive amounts of data, and fog computing provides the necessary computing power and storage capacity to process and analyze this data locally. By utilizing fog computing, smart cities can perform real-time data analytics, implement intelligent decision-making algorithms, and enable timely responses and actions. This distributed architecture also improves reliability and resilience, as fog nodes can continue to operate even in the event of network disruptions or cloud service unavailability.

The objective of this research work is to propose a protocol-based technique called "SMART FOG" that facilitates resource sharing among Fog computational devices and addresses the latency issues associated with cloud computing. The key goals of the study include studying and analyzing existing IoT architectures and protocols to gain a comprehensive understanding of IoT device connectivity, evaluate the current IoT infrastructure and assess different communication protocol layers to develop the SMART FOG Protocol, which will serve as the foundation for the proposed technique, identify and

examine the challenges that may arise during the implementation of the SMART FOG protocol-based technique on computation-enabled devices, explore task scheduling and allocation techniques specific to Fog Computing nodes within the SMART FOG framework, develop a fault tolerance mechanism for the SMART FOG protocol-based technique by implementing task allocation to multiple recipients, ensuring robustness and reliability and assess the efficiency of Fog computational devices across various parameters such as processing speed, scheduling, and task allocation within the Fog layer. The primary focus of this research is to leverage the computational power of computation-enabled devices to collaboratively execute tasks and enhance processing efficiency. By addressing these objectives, the research aims to contribute to the advancement of Fog Computing and its application in improving the performance and capabilities of IoT systems.

Comparing the performance of task scheduling algorithms in Fog and cloud environments, it is observed that the First-Come-First-Serve algorithm performs better in the Fog setting in terms of optimizing latency, network utilization, and energy consumption. On the other hand, in Fog environments, the Integer Linear Programming algorithm demonstrates improvements in latency, quality of service, and cost compared to cloud environments. To minimize latency and power consumption, the Shortest Job First Heuristic approach proves to be effective in task scheduling. Similarly, the Resource Allocation for Soft and Hard Real-Time Tasks with Precedence and Temporal Constraints algorithm enhances both QoS and efficiency. Utilizing fuzzy logic, the Resource Fulfillment Network scheduling technique achieves optimization in latency and energy usage. Additionally, the Fuzzy Logic & Particle Swarm Optimization method can significantly optimize the quality of service in Fog environments. These findings highlight the importance of selecting appropriate task-scheduling algorithms based on the specific requirements and objectives of Fog or cloud environments. Each algorithm offers distinct advantages in terms of optimizing different performance metrics and can contribute to improving the overall efficiency and effectiveness of Fog-based systems.

Hypothesis testing results confirm that the hypothesis "Ha1: SMART FOG protocol-based technique to create Fog Computing environment will share computational power to IoT devices with low computational power and other aspects" is accepted, implying that the SMART FOG protocol-based technique reduces computational power consumption for

Fog devices and shares computational power with IoT devices by lowering total consumption.

The classification algorithms were applied to task offloading and resource allocation in the SMART FOG environment, and their performance was evaluated using various metrics. The MLP (Multiple Layer Perceptron) classifiers achieved the highest overall accuracy of 0.83, followed closely by Logistic Regression with a value of 0.80. The J48 classifier had an overall accuracy of approximately 0.75, while Bagging, IBK, and K-Star classifiers had lower accuracy values of 0.60, 0.61, and 0.48, respectively. Based on total accuracy, MLP and Logistic Regression were identified as the best classifiers.

When considering Kappa statistics, which are used to assess agreement between classifiers in task offloading and resource allocation, MLP and Logistic Regression outperformed other classifiers with higher Kappa statistics values of 0.67 and 0.6, respectively, indicating their superiority. In terms of precision, MLP achieved the highest value of 0.85, followed by Logistic Regression at 0.83. J48 had a precision of 0.79, while Bagging, IBK, and K-Star had lower precision values of 0.48, 0.76, and 0.49, respectively. MLP and Logistic Regression were the most precise classifiers. For recall, MLP obtained the highest overall value of 0.84, followed by Logistic Regression with 0.80. Bagging, IBK, and K-Star had recall values of 0.61, 0.62, and 0.49, respectively, while J48 achieved a recall of 0.75. MLP and Logistic Regression were the top classifiers in terms of recall.

In terms of mean absolute error, MLP achieved the lowest value of 0.17, indicating better prediction accuracy. Logistic Regression had a slightly higher mean absolute error of 0.23. J48, Bagging, IBK, and K-Star had mean absolute error values of 0.27, 0.58, 0.39, and 0.45, respectively. MLP and Logistic Regression exhibited better performance in minimizing mean absolute error.

In conclusion, considering the various accuracy metrics, it can be determined that MLP and Logistic Regression are the most suitable classification algorithms for resource allocation and task offloading in the SMART FOG environment.

Keywords: SMART FOG, IoT, MLP