IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

REVIEW ON EDGE-CLOUD COMPUTING COLLABORATION

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Abstract: The traditional cloud-based paradigm is under tremendous pressure on network bandwidth and communication latency, which is why a newly emerging paradigm of computing paradigm is involved. As a result, AIoT applications can be implemented in a cloud-based environment, where model building and model abuse are embedded in the cloud and edges, respectively. However, engineers still face the challenge of building AIoT systems in practice due to the natural diversity of IoT devices, diminishing accuracy of trained models, security and privacy issues, etc. In this paper, I want to introduce the development of an industrial edge-cloud based collaboration platform aimed at facilitating the implementation of AIoT applications. In addition, a land use case was filed in this paper, which proved the effectiveness of the AIoT application building on the platform.

Index Terms – **edge computing, cloud computing, edge-cloud collaborative computing; efficiency**

I. INTRODUCTION

More recently, the world has seen the advent of the big data era, with two regulatory technologies, namely Internet of Things (IoT) and Artificial Intelligence (AI). IoT defines a network of multiple physical connections (aka. Devices), where they collect and share their data with their environments to allow full monitoring, analysis, efficiency and system control [1], and AI is an exciting data technology technology. imitating human ingenuity with machines. While IoT provides communication infrastructure between devices and data collection, AI provides file \ brain "throughout the system, which enhances the processing power of available data. In this sense, these two technologies have the ability to interact, leading to other promising technologies, namely, Artificial Intelligence of Things (AIoT Generally, AIoT's vision to achieve effective IoT functionality, improve human integration and improve data management and analytics capabilities, eg smart sensors, actuators and low-power chips [2]) and software (eg embedded systems, virtualization technology, in-depth learning algorithms) over the years Among the many functional areas, Smart Home [3], Smart Factory [4], and Smart City [5] are leading the way in the adoption of AIoT. Cloud computing [8] seems to be the right solution as both categories for \ Model Building "and \ Model Inferencing" are uploaded to a remote cloud, wh ile devices only need to download burn their data and wait for the cloud to make decisions, as shown in Figure 1 (a). In addition, the demand and alarming state of the cloud computing can also benefit many AIoT systems, given the features of the problems facing AIoT applications. However, with the growing amount of data generated by large IoT devices, this cloud-based paradigm suffers from the huge pressure exerted on existing work, especially the cost of data transfer [9]. In other words, network bandwidth and communication delays between devices and remote cloud servers can be critical barriers for highly responsive applications [7]. To achieve high bandwidth and ultra-low latency, many AIoT systems embrace the newly developed computer paradigm, where calculation and storage resources are remotely controlled from cloud servers to the edge of the network, allowing real-time insights and local operations.

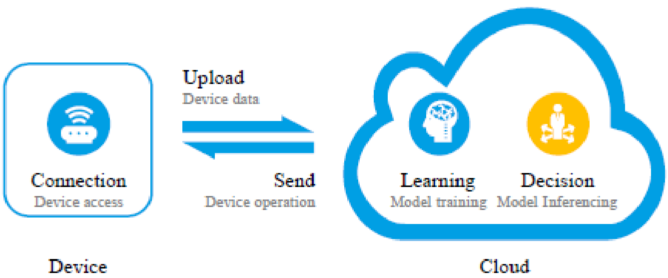

Fig-1.a Cloud Computing

As a result, the AIoT cloud-by-edge interaction emerges, as shown in Figure 1 (b). Devices are now connected to servers that are closer to remote servers. The \ Model Inferencing "stage is loaded at the edges to support decision-making in real time, while the" Model Building "section is made in the cloud, taking into account the fact that the edge has less computer power and storage capacity. only important data (e.g. statistical data) on the cloud server, thereby reducing data transfer costs.

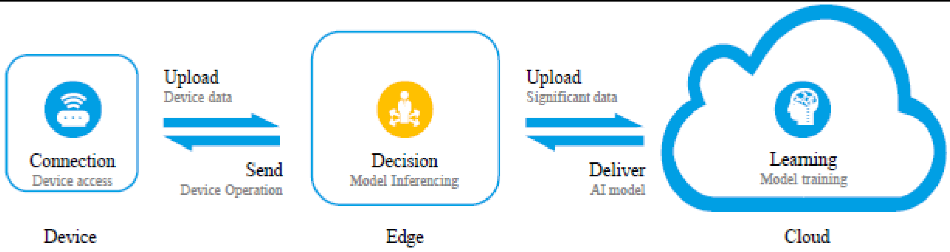

Fig-1.b Edge-Cloud Computing

Edge-cloud integration allows for efficient AI model training \ and a highly responsive user experience in AIoT applications. However, engineers still face some challenges when designing AIoT applications.

• Heterogeneity. The natural separation of devices in a large IoT system makes the process of connecting and connecting very difficult. In addition, the data generated has a variety of types, sizes, and time stamps, which is a challenge for processing, transmission, and storage Performing standard calculations on servers with a different application or operating time also requires consideration.

• Accuracy. The algorithms used by AI need to be optimized to understand and interpret data so that more accurate decisions can be made. In addition, due to the extremely powerful nature of the physical world, a once-trained AI model may not always function properly. Models need to be refined using the newly produced IoT data to achieve better accuracy.

• Security and privacy. Security and privacy are important issues. As AIoT collects sensitive information from its users, it is important to ensure that the data is safe and in safe hands. Users may not want to place data in the hands of cloud providers when they do not have full control and cannot ensure proper data usage.

II. ARCHITECTURE

Figure 2 (a) shows an overview of the high level of platform construction. As can be seen, the platform has two main components, namely Edge Node and Edge Hubs. Edge Nodes are computer servers sent to the edge of a network. Edge Node is primarily concerned with managing the communication and performance of devices, performing edge computing, and transferring important data to the cloud

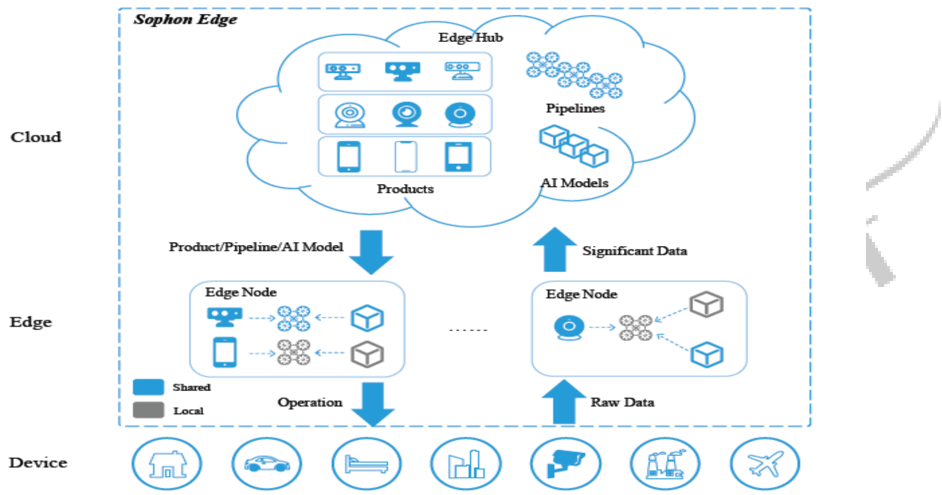

Fig-2.a. High level overview

The internal structure of the Edge Node is shown in Figure 2 (b). To facilitate device access, the platform supports various communication processes, including Modbus, MQTT, COAP, AMQP, ONVIF, RTSP, RTMP, UVC, OPCUA, HLS, GB28281, etc. Many drivers, brokers, and clients of these systems are used. Raw device data is collected and converted into a data stream that facilitates subsequent data processing with the use of a multimedia gateway and message bus. Multimedia gateway collects real-time streaming media data (e.g. photos, videos) from multimedia devices, while the message bus collects structured data from standard devices. Depending on the computer, Edge Node manages a certain number of available pipelines from the cloud or made locally. Pipe conditions are created by the processing engine. Edge Node also controls many of the AI models found from the cloud, and these models can be called to make consideration in the case of used pipelines. Edge infrastructure mainly supports local data storage and cloud navigation. Edge Hubs are truly cloud servers, managing Edge Nodes and performing highly computer-based tasks such as model training.

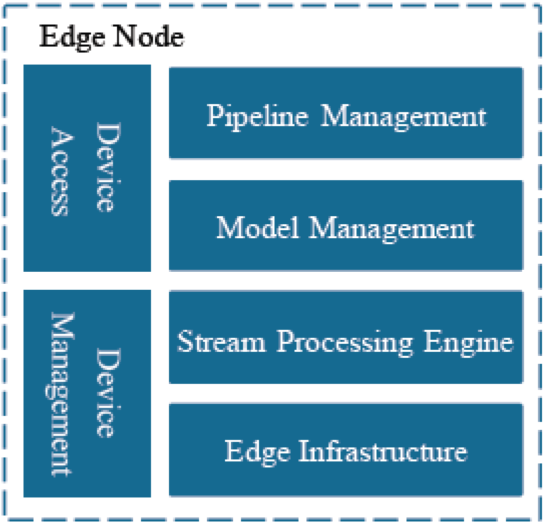

Fig-2.b Edge-Node

Similarly, Figure 2 (c) shows the internal structure of the Edge Hub. Pipes are handled not only in the Edge Node, but also in the Edge Hub, called shared pipelines. As the scale of the AIoT application increases, the number of Edge Nodes can increase, making it easier for the same calculation function to work across multiple Edge Nodes. It would be expensive if we had to make a pipeline for each Edge Node. To address this issue, these shared pipes are managed in the Edge Hub and later sent to the Edge Node. The warehouse stores all trained models such as container images that can be sent immediately to Edge Node. The above-mentioned products are also hosted on the Edge Hub as product descriptions are usually shared by all Edge Nodes in a single AIoT system. Cloud infrastructure takes on the burden of computing, as it includes large data retrieval (e.g. Spark) data processing and AI backend (e.g. Tensorow) model training. In addition counselling is also used.

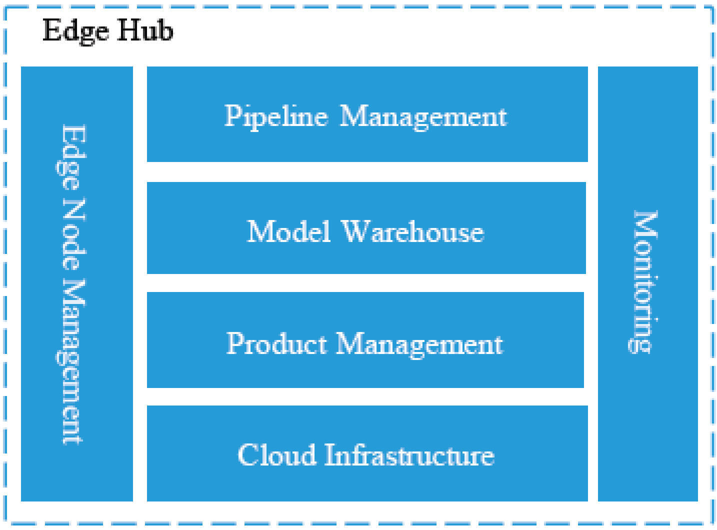

Fig-2.b Edge-Hub

Figure 3 introduces the entire model iteration process in Sophon Edge. Let's say some of the training details are stored in the Edge Hub. First, the training data will be sent back to the AI of Edge Hub for model training. Once the training has been completed, a model model will be created with the technology of the vessel. The model will then be stored in the Edge Hub warehouse. Developers can bring specific models to specific Edge Nodes on demand, and distributed models can be upgraded with the latest version of Edge Hub. After obtaining model input by processing raw device data, Edge Node can call a specific local model for reference. Important details during model violations in Edge Node, including inputs and outputs, will be sent to Edge Hub for data details, which may update the original training data. For now, one duplicate is complete. As can be seen, the whole process creates a closed loop, which allows the AIoT system to rotate in a repetitive manner.

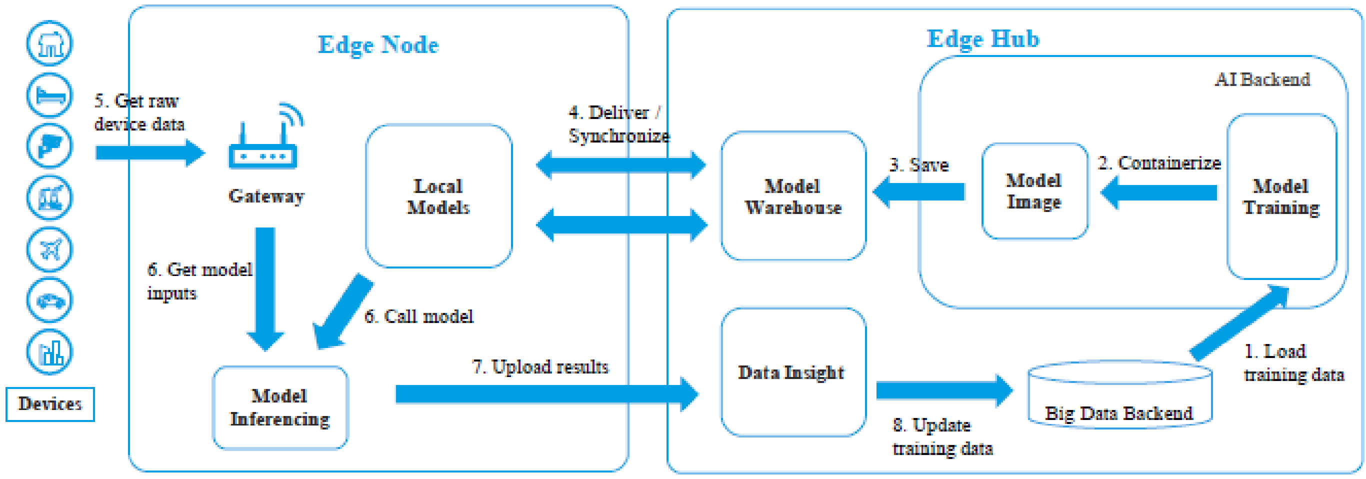

Fig-3 the process of model iteration

III. CONCLUSION:

Sophon Edge is proposed as a promising solution to these challenges. The pipeline computer-based computer model facilitates the compilation of computational tasks, and allows the computer to measure consumption on multiple edge servers and on various IoT devices. Edge-cloud interaction continues to allow AI models to adapt to continuous output device data and respond quickly to application logic changes. The Smart City real-world system built on Sophon Edge demonstrates the functionality and usability of the platform. Significant encryption efforts have been saved to build the app with the help of many previous platform operators. For future work, an effective computer deceleration program can be used to measure computer load and storage across all edge servers to maximize the resources available. Distributed machine learning, especially federate learning about data confidentiality, is another promising guide to achieving greater efficiency, as the AI model is currently one-way trained in the Sophon Edge platform

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