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A Global Brain fuelled by Local intelligence: Optimizing Mobile Services and Networks with AI

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Abstract—Artificial intelligence (AI) is among the most influential technologies to improve daily lives and to promote further economic activities. Recently, a distributed intelligence, referred to as a global brain, has been developed to optimize mobile services and their respective delivery networks. Inspired by interconnected neuron clusters in the human nervous system, it is an architecture interconnecting various AI entities. This paper models the global brain architecture and communication among its components based on multi-agent system technology and graph theory. We target two possible scenarios for communication and propose an optimized communication algorithm. Extensive experimental evaluations using the Java Agent Development Framework (JADE), reveal the performance of the global brain based on optimized communication in terms of network complexity, network load, and the number of exchanged messages. We adapt activity recognition as a real-world problem and show the efficiency of the proposed architecture and communication mechanism based on system accuracy and energy consumption as compared to centralized learning, using a real testbed comprised of NVIDIA Jetson Nanos. Finally, we discuss emerging technologies to foster future global brain machine-learning tasks, such as voice recognition, image processing, natural language processing, and big data processing.

Index Terms—Distributed Artificial Intelligence, Multi-Agent Systems, Machine Learning, Fog Networks, and Global Brain.

I. INTRODUCTION

The Internet can be considered identical to the human brain due to the massive amounts of data processed and the number of connected users. Almost 38% and 62% of all enterprises were using AI in 2016 and 2018, respectively [1]. The International Data Corporation (IDC) estimates that the investments in the AI market will grow to \$47 billion in 2020 [1]. The various interactions between users form a single super-organism [2], as first explored by Spencer [3] and modernized by Stock [4], with a developing global brain driven by data and knowledge on the web. It can be represented by a complex, adaptive network of interconnected agents [5]. The global brain constitutes a distributed intelligence from variant data sources and an evolved stage of intelligence. Intelligence resides in the interactions of various entities that share and exchange knowledge and data, which resembles the human nervous system. The primary role of the global brain is the coordination of the various activities while exploiting the collective data source of millions of people and computers. The global brain is an adaptive, self-organizing network formed by everyone on the planet via communication technologies as

Fig. 1. General overview of the global brain. Local brains contribute towards the global brain intelligence

illustrated in Fig. 1. Complex problems can often be effectively solved by division into sub-problems, forming a collective solution [5] by distributed AI techniques. We consider the following steps essential to construct the global brain:

- Intelligent agents collect and store data in real time
- Processing of the collected data
- Construct profiles based on the processed data
- Action evaluation (feedback).

Distributed AI includes distributed problem-solving by dividing complex problems into sub-problems. In particular, distributed agents collaborate to boost collective intelligence. This paradigm is fostered by immense amounts of data and devices available: Global mobile networks (e.g., sixth-generation (6G), Internet-of-things (IoT)), will reach up to 49 Exabytes per month by 2021. In 2025, more than 25 billion devices are expected to be connected [6], and 80 billion are expected by 2030 [7]. To ensure sustainability (energy consumption and communication load), efficient and scalable communication and privacy-conscious information-sharing is needed. Hence, we propose a global framework for an optimized communication mechanism and novel knowledge-sharing.

Fig. 2. Local artificial brain architecture

II. RELATED WORK

Several works have introduced the concept of global-brain intelligence or artificial general intelligence, such as Cajal Blue Brain [8], which studies human mental activity by understanding biological mechanisms. This project has approached to simulate neural activity in silicon by means of a supercomputer.

Another example is the Blue Brain Project [9] utilizes the model of the mammalian brain on the molecular level by reverse-engineering the brain. A model with about 10,000 neurons has been built using supercomputers.

The authors in [10] studied the consequences of externalization, computation, hearing, vision, brainstorming, emotion, and actions, and they acknowledged the externalization and distribution of cognition as an evolution that would lead to the next level of intelligence. Recently, an end-to-end data analytic framework for 5G was proposed in [11]. They discussed the importance of data analytics in improving 5G performance, investigating the integration of vertical customer operations for radio access network(RAN)-centric data, network-centric data, and application-level analytics.

Recently, Federated Learning (FL) is presented as an emerging technology to solve problems caused by conventional centralized machine learning (ML), and to learn in a global manner from multiple clients. The client updates the model locally then sends the model parameter to the server for model aggregation with no data exposure. Despite the promising advantages of FL, the fact that the server sends the model to all the clients at each iteration, is a communication overhead. Attempts to enhance communication for FL have been done for instance by [12] using an *Upstream and Downstream Compression* mechanism, and [14] based on sparse ternary

compression (STC) solution. However, in the existing FL techniques, the communication aspect as well implementation details are still not properly addressed [12] and require further research.

In this context and unlike FD, the proposed framework is generic and can learn from multiple datasets with an efficient communication mechanism that ensures scalability in terms of the number of user equipment (UE), while optimizing energy consumption and maximizing system performance in terms of learning accuracy or other defined KPIs .

We propose a novel architecture for a local brain, collaborating to form a global brain. Secondly, we propose an architecture based on novel knowledge-sharing and efficient communication. The architecture is evaluated in simulation and experiments with respect to network complexity, density, and the number of exchanged messages. To evaluate the performance of the global brain in a real-world scenario, we conduct experiments based on user activity recognition utilizing a real testbed. The results revealed the ability of our framework to improve accuracy using our optimized communication mechanism.

III. LOCAL BRAIN ARCHITECTURE

In this section, we introduce the local brain architecture and its functionalities. Based on this architecture, we build the global brain that constitutes several local brains in the following section. The local brain is the entity responsible for managing user's data and is an important step toward the development of a distributed intelligence. The local brain is supposed to share and exchange knowledge or data with other local brains according to the proposed global-brain communication mechanism. This implies that a local brain

Fig. 4. The global brain concept. Multi-agent systems are connected by an AI network that shares knowledge

Well-characterized data is then processed by the learning agent to develop a knowledge base using the modules in the brain component (prediction, classification, natural language processing, etc.). Once profiles and knowledge are available, they are exchanged with the mobile agent. Fig. 3 summarizes the interactions and tasks in the local brain architecture.

IV. GLOBAL BRAIN ARCHITECTURE

For the global brain architecture, we consider the *local brain* as the main component in which each user is situated as depicted in Fig. 2. This is expected to provide local user profiles based on the collected data. The processed data and the user profiles at the level of each local brain are stored in the learning profiles layer for better use of the data. Each user is represented by a local brain agent. The agent exchanges messages with other agents, forming a multi-agent system.

Behavior is learned and predicted via connections between agents and by analyzing the data storage of each local brain. Fig. 4 represents the global brain architecture. It comprises several local brains and communication links. In the following section, we present modeling based on a multi-agent system while considering the local and global brain architecture.

A. Multi-Agent System Modeling

The proposed model reduces the complexity of the global brain and ensures efficient communication between the artificial local brains. We can represent the global brain MAS_{Brain} as:

$$MAS_{Brain} = \langle E, U, I \rangle \quad (1)$$

where

- E represents the environment of the multi-agent system
- U is the set of user agents that compose the MAS, such that $U = \{u_1, u_2, \dots, u_k\}$.
- I represents the agent interactions occurring in the global brain, such that $I = \{i_1, i_2, \dots, i_s\}$.

The MAS environment E is composed of multiple local brains. An agent (local brain) can exchange messages with other agents according to its local rules and the set of interactions. The Environment E is represented as

$$E = \{ Lb_i \cup Mb_i \mid i \in [1, n], \forall Lb_i \in \mathcal{L}_b, Mb_i \in \mathcal{M}_b \} \quad (2)$$

where $\mathcal{L}_b$ and $\mathcal{M}_b$ represent the set of local brains and the set of mobile agents respectively. The local brain is modeled as a tuple

$$Lb_i = \langle L_i, M_i, E_i \rangle \quad (3)$$

where Lb_i represents the i -th local brain that comprises monitoring (M_i), learning (L_i), and evaluation (E_i) agents.

A user agent U is represented by its attributes A , behaviors B , and rules R as in Eq. 4 and can change its local brain ($Lb_i \in \mathcal{L}$) according to its rules and behaviors. Possible interactions for the agent are modeled as $\mathbb{I} \subseteq \mathbb{U} \times \mathbb{U}$. The local brain will recognize its agent by the attribute A .

$$U = \langle A, B, R \rangle \quad (4)$$

Fig. 5. Global brain architecture. Illustration of knowledge sharing between two nodes based on transfer learning

B. Utility and Knowledge-Transfer Models

We first identify the utility of the local and global brain before formulating the energy-efficient knowledge transfer as a utility-maximization problem.

Let $k_i^l \in \{0, 1\}, \forall i, l \in \mathcal{L}$ indicate whether local knowledge of the i -th local brain is shared with the l -th local brain. We define the knowledge transfer matrix $\mathbf{K}_{|\mathcal{L}| \times |\mathcal{L}|}$, where $\vec{k}_i \in \mathbb{R}^{|\mathcal{L}|}$ indicate the knowledge transfer of the i -th local brain.

We define the utility of the i -th local brain ϕ_i as

$$\phi_i = \sum_{l \in \mathcal{L}} k_i^l \quad (5)$$

or

$$\phi_i = \|\vec{k}_i\|_1 \quad (6)$$

Let Φ denote the overall global utility as

$$\Phi = \sum_{i=0}^N \sum_{l=0}^N k_i^l \quad (7)$$

or

$$\Phi = \sum_{i=0}^N \phi_i = \sum_{i=0}^N \|\vec{k}_i\|_1 \quad (8)$$

Hence, the problem can be formulated as

$$\max_{x_{il}} \Phi \cdot \vec{x} \quad (9a)$$

$$\text{subject to} \quad (9b)$$

$$C1 : x_{il} \in \{0, 1\}, \forall i \in \mathcal{L}, \forall l \in \mathcal{L} \quad (9c)$$

$$C2 : e_{il} \leq \tau_{il}, \forall i \in \mathcal{L}, \forall l \in \mathcal{L} \quad (9d)$$

$$C3 : \phi_i \leq |\mathcal{L}|, \forall i \in \mathcal{L} \quad (9e)$$

We maximize the global knowledge through the constraints C1 (Lb_i - Lb_l association), C2 (Energy threshold), and C3 (Lb_i utility smaller than count of local brains). With transfer

learning we preserve privacy and maximize global utility (knowledge).

C. Network Model

Let $\mathcal{F}$ and $\mathcal{I}$ be a set of fog nodes and IoT devices. Users are denoted by $u \in \mathcal{U}$. For the environment E of the MAS_{Brain} , each local brain $\langle L_i, M_i, E_i \rangle \in \mathcal{L}$ is represented by a tuple of devices $\langle F_l, I, F_e \rangle$, where $\{F_e \cup F_l\} \in \mathcal{F}$ and $I \in \mathcal{I}$. F_e and F_l represent the fog nodes for learning and evaluation, whereas I denotes the IoT devices to monitor, sense, and receive data from user u devices. The monitoring agent $Mb_i \in \mathcal{M}_b$ is represented by a set of mobile access points $\mathcal{A}$ for communication. The overall global brain network can be represented as a graph $\mathcal{G} = (\mathcal{A} \cup \mathcal{F} \cup \mathcal{I}, \mathcal{C})$, where $\mathcal{C}$ represents the communication links between fog nodes, IoT devices, and access points. Inter-local brain communication takes place through the wireless access points.

The bandwidth allocated in physical resource blocks (PRBs) for each Lb_i transmission is B^i . According to 5G specification, each PRB occupies 60 KHz and 0.25 ms. We consider a log-distance path-loss model with log-normal shadowing as $PL_{[dB]} = 140.7 + 36.7 \log_{10} d_{[km]} + \mathcal{N}(8)$ [15]. The transmission rate of the access points $a_i \in \mathcal{A}$ is

$$r_i = \eta_i B^i \log_2 \left(1 + \frac{p_i^{tx} - PL_i}{\sigma^2} \right) \quad (10)$$

where $\eta_i \in [0, 1]$ denotes the fraction of the bandwidth allocated to the access point at Lb_i for sending data, p_i^{tx} represents the transmission signal power of access point associated with Lb_i , and σ^2 represents the noise power. d is the distance between the antenna [16].

The communication between users and access points is similar to inter access node communication and follows Eq. 10. The energy consumption of a user/fog device is given by the

energy consumed for transmitting the data d . Therefore, the energy ($\mathcal{E}$) required to offload d is

$$\mathcal{E} = p_i^{tx} \delta_i^d \quad (11)$$

V. TRANSFER LEARNING ALGORITHM

We present a novel knowledge transfer technique between local brains that optimizes the overall knowledge gained by the global brain (Fig. 5). Instead of linking all agents, we utilize a hash table with utilities of each fog node. Fog nodes learn from their neighbor with highest utility until all fog nodes share the maximum local knowledge (Algorithm 1)

Algorithm 1: Local brain transfer learning algorithm

Input : A set of local brains $l \in \mathcal{L}$
Output : Global brain MAS_{Brain} with local knowledge

```

1  $\tau \leftarrow |\mathcal{L}|$  // The maximum cardinality for  $l$ 
2  $AgentHash \leftarrow \emptyset$ 
3 foreach  $l \in \mathcal{L}$  do  $AgentHash[l] \leftarrow 0$ 
4 while user is active
5   foreach  $l \in \mathcal{L}$  do
6      $t \leftarrow \arg \max(AgentHash)$ 
7     if  $t = \emptyset$ 
8        $t \leftarrow \text{SelectRandom}(\mathcal{L})$ 
9     if constraint (9c) - (9e) is satisfied
10       $\text{TransferLearning}(l, t)$ 
11       $k_l^t \leftarrow 1$ 
12      for  $i$  in 1 to  $\tau$ 
13         $k_i^t \leftarrow k_i^l$ 
14        if  $l == \tau$ 
15           $\text{BackPropagate}(t, i)$ 
16      if  $AgentHash[t] = \tau$ 
17         $AgentHash[l] \leftarrow AgentHash[t]$ 
18        goto line 5
19       $AgentHash[t] \leftarrow \phi_t$ 
20       $AgentHash[l] \leftarrow \phi_l$ 

```

In round i of the algorithm, the i -th node would learn from the fog node that has maximum utility or else select a node in random (line 6 – 8). The node then transfers its knowledge using Transfer Learning (line 10) and the utilities of the current fog node and all the preceding fog nodes from the which the knowledge was gained is updated (line 11). Hence, at the end of round i , each fog node contains the knowledge of $0 \dots i - 1$ fog nodes before it, but not of any succeeding fog nodes $i + 1 \dots n$ after it. When the last fog node is encountered, the final fog node will back-propagate the final knowledge to all the remaining $n - 1$ nodes, so that each node i would have the knowledge of all the fog nodes $0 \dots n$ (line 15).

Theorem 1. *The maximum rounds required for achieving stability and maximum knowledge is $\mathcal{O}(n)$, where n is the number of fog nodes (agents) in the network.*

Proof. The maximum utility for n agents is $\sum_{j=0}^n \sum_{l=0}^n k_j^l$. In round i , the i -th fog node learns from the $i - 1$ -th and comprises all knowledge encountered until then. The utility at the i -th node after round i is $\sum_{l=0, l \in \mathcal{L}}^i k_i^l$ with global utility

$\sum_{j=0}^{i-1} \sum_{l=0}^{i-1} k_j^l$. After transfer learning in the n -th round, global utility becomes $\sum_{j=0}^n \sum_{l=0}^{i-1} k_j^l$. To maximize it, node i learns from nodes $i + 1$ to n . The final back-propagation step transfers the knowledge from nodes $i + 1 \dots n$ to node i , which hence attains maximum utility $\sum_{l=0, l \in \mathcal{L}}^n k_i^l$ with maximum global utility $\sum_{j=0}^n \sum_{l=0}^n k_j^l$. After $\mathcal{O}(n)$ rounds stability and maximum global knowledge is achieved. $\square$

VI. GLOBAL BRAIN PERFORMANCE EVALUATION

Since additional or redundant communication burdens the network and consumes more energy, we propose an efficient communication mechanism to ensure scalability. Based on F radio, complexity and density indices [17]–[22], we perform the communication via the JADE platform¹

Complexity Index (β). measures the degree of connectivity of a graph. It represents the relation between the number of links and the number of agents (complexity of the communication network).

$$\beta = \frac{M}{N} \quad (12)$$

where M represents the number of interactions among the agent and N represents the total number of agents.

$$Complexity(MAS) = \begin{cases} Simple & \text{if } \beta < 1 \\ Connected & \text{if } \beta = 1 \\ Complex & \text{if } \beta > 1 \end{cases} \quad (13)$$

Density Index (γ). the number of observed and possible links in the MAS. The density varies within $[0, 1]$ ($1 \rightarrow$ fully connected).

$$\gamma = \frac{E}{N^2} \quad (14)$$

where A_{ij} represents a communication between the agent i and the agent j . N is the total number of agents:

$$E = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N} A_{ij} \quad (15)$$

θ ratio. average traffic as the weight of the exchanged message within a MAS.

$$\theta = \frac{\sum_{i=1}^{i=N} \sum_{j=1}^N P_{ij}}{M} \quad (16)$$

P_{ij} is the weight of message sent by Agent i to Agent j , N is the agent count and M the total message count.

Total Connectivity (σ). We define complete connectivity, to denote that all agents share identical knowledge.

$$\sigma = \frac{\sum_{i=0}^{i=N} Trust(Ag_i)}{M^2} \quad (17)$$

M is the number of possible communication messages of an agent. All exchanged messages have the same weight of 1. The

¹Jade platform, <https://jade.tilab.com/>

Fig. 6. Global brain communication evaluation comparison

Trust function is the sum of the interactions weight with agent i . Values of interaction σ range between 0 and 1. Parameter σ indicates the communication performance.

$$Connectivity(MAS) = \begin{cases} \text{Excellent} & \text{if } \sigma = 1 \\ \text{Medium} & \text{if } \sigma = 0,5 \\ \text{Bad} & \text{if } \sigma < 0,5 \end{cases} \quad (18)$$

When the total connectivity value is 0, the system is disconnected; with 1 it is fully connected and shares the latest available knowledge base.

A. Simulation of the Global Brain Communication

We evaluate our architecture in two scenarios as discussed below.

Scenario1 (Complete Graph). All agents communicate with each other and form a complete graph. Fig. 6 presents the results when the system comprises 10–100 agents.

- **Complexity Index β :**

$$\beta = \frac{M}{N} = \frac{N(N-1)}{2 * N} = \frac{N-1}{2} \quad (19)$$

- **Density Index γ :**

$$\gamma = \frac{E}{N^2} = \frac{N(N-1)}{2 * N^2} = \frac{N-1}{2 * N} \quad (20)$$

- **θ ratio :**

$$\theta = \frac{\sum_{i=1}^{i=N} \sum_{j=1}^N P_{ij}}{M} = \frac{2(N-1)}{2(N-1)} = 1 \quad (21)$$

Scenario2 (Optimized Communication Mechanism). Agent i communicates only with Agent j with the highest weight value in the network, and no additional communication takes place once all agents share the same information and have the same highest weight value. The weight of each agent increases when it communicates with another agent. The trust value is the sum of the links with other agents. Fig. 6 presents the

results. In the following, we present the number of exchanged messages between agents as a mathematical sequence:

$$M = u_n = \begin{cases} 1 & n = 2 \\ 4 & n = 3 \\ u_3 + 2 * (n - 3) & \forall n \in \mathbb{N} \end{cases} \quad (22)$$

- **Complexity Index β :** We model the communication

$$\beta = \frac{M}{N} = \frac{2N-2}{N} = \frac{2(N-1)}{N} \quad (23)$$

- **Density Index γ :**

$$\gamma = \frac{E}{N^2} = \frac{2(N-1)}{N^2} \quad (24)$$

- **θ ratio :**

$$\theta = \frac{\sum_{i=1}^{i=N} \sum_{j=1}^N P_{ij}}{M} = \frac{2(N-1)}{2(N-1)} = 1 \quad (25)$$

B. Communication Mechanism Evaluation

The evaluation results demonstrates that Scenario 2 is better in terms of complexity, density, and the number of exchanged messages. The complexity and number of exchanged messages lead to an exponential explosion in scenario 1. For scenario 2 the architecture complexity and network load decreased. As a result, we conclude that the communication mechanism and the global brain architecture are able to support a large number of agents (Table. I).

VII. CASE STUDY EVALUATION

In this section, we evaluate the proposed system using a real-world dataset. To measure the performance of our approach, we measure the classification accuracy of the obtained models and report the energy consumed during learning. For this purpose, we prepare ten Jetson Nano, a small device with 128 NVIDIA CUDA cores, a Quad-core ARM Cortex-A57 MPCore processor, 4 GB 64-bit LPDDR4 of RAM, and 16 GB of storage (the testbed is shown in Fig. 7). Jetson Nano is compatible with the most common, popular AI frameworks, such as Tensorflow, Keras, OpenCV, and Caffe. In addition, it can be used for various AI applications, such as audio recognition, video processing, object detection.

TABLE I
COMPARISON BETWEEN THE TWO SCENARIOS WHEN THE NUMBER OF AGENTS $= +\infty$

Number of Agents : $n=+\infty$	Exchanged messages	Complexity	Network density
Complete graph scenario	$\lim_{N \rightarrow +\infty} \frac{N(N-1)}{2} = +\infty$	$\lim_{N \rightarrow +\infty} \frac{N-1}{2} = +\infty$	$\lim_{N \rightarrow +\infty} \frac{N-1}{2N} = \frac{1}{2} = 0,5$
Optimized communication scenario	$\lim_{N \rightarrow +\infty} (a+2(N-3)) = +\infty$	$\lim_{N \rightarrow +\infty} \frac{2(N-1)}{N} = 2$	$\lim_{N \rightarrow +\infty} \frac{2(N-1)}{N^2} = 0$

Fig. 7. Global brain testbed (Nvidia Jetson Nano local brain nodes)

TABLE II
TECHNOLOGIES AND LIBRARIES FOR THE GLOBAL BRAIN

Library	Description	Task(s)
Tensorflow	An open-source framework for machine learning	Deep Learning
Keras	A neural module for deep learning	Deep Learning
scikit-learn	A machine-learning library used for data processing and learning based tasks	Classification, Clustering, Pre-Processing, Regression
Natural Language Toolkit (NLTK)	A collection of libraries used for statistical natural language processing	Natural Language Processing
LightFM	A library used for recommendation systems	Recommendation Systems
Xapian	An open-source search engine library for indexing and weighting models	Information Retrieval

A. Libraries and Frameworks

The global brain can provide various AI techniques and data-analytics services (Fig. 2). We select the most promising technologies to be installed on Jetson Nano nodes for ready-use operations (Table. II). In our case study, we use the needed frameworks (Tensorflow, Keras, and scikit-learn).

B. Dataset Description

We use the heterogeneity human activity recognition (HHAR) dataset in [23]. It consists of 43 million sensor readings for nine users to recognize: “Biking,” “Sitting,” “Standing,” “Walking,” “Stair up,” and “Stair down.” It uses four smartwatches (two LG watches and two Samsung Galaxy

Fig. 8. Initial local and global prediction accuracy for all nodes on the HHAR Dataset

Fig. 9. Global brain energy consumption for knowledge and data transfer

Gears) and eight smartphones (two Samsung Galaxy S3 minis, two Samsung Galaxy S3s, two LG Nexus 4s, and two Samsung Galaxy S+s). All devices were equipped with accelerometer and gyroscope sensors. The participants kept their smartphones in tight pouches around their waists and performed 5-minute measurements of each activity.

C. Experimental Setup

We assign the data of one user to each Jetson Nano node. Each node has entirely and only the data of one user. For testing, we construct a global set that contains a set of all users. This allows us to measure if a node is generalizable to the data of different users. We use a neural network with two layers of 200 and 20 neurons, respectively.

Fig. 10. Global prediction accuracy of nodes for each Iteration on the HHAR dataset

Fig. 11. Performance of global brain based on knowledge transfer and data transfer on the HAAR dataset

Fig. 12. Performance of global brain based on proposed communication approach and random-based communication on the HAAR dataset

Adam optimizer is chosen with a learning rate of 0.001 and a batch size of 32. The accuracy metric is the performance evaluation metric.

D. Global Brain Accuracy Performance

First, we measure the accuracy of local models on both local and global data. Fig. 8 shows that the models of all nodes perform well locally but fail to work on a global testing set with accuracies of less than 30%. We evaluate the performance of the global brain in terms of accuracy in two scenarios: (1) knowledge transfer and (2) data transfer.

We define the local accuracy as the accuracy on the local test set of each node and the global accuracy as the accuracy of a node based on the unseen global test set.

1) *Knowledge transfer*: We transfer the weights from one node to another (Fig. 5). The receiver retrain with the new weights and then evaluates with the local and global data.

2) *Data transfer*: We send the original data from one node to another, and the next receiver node trains with all data and evaluates both locally and globally.

In Fig. 10, the global accuracy of each node rises based on knowledge transfer (all nodes have reached an average accuracy of 75%). We also compare the performance of the global brain based on data transfer in terms of accuracy where the average accuracy reaches 63% for all nodes. The global brain improves from one iteration to another based on both data and knowledge transfer; however, the knowledge transfer produced the best results (Fig. 11). Along with the better

accuracy of the proposed knowledge-transfer, this method does not expose any user's data.

E. Random Node Selection Communication Mechanism

We compare our communication mechanism with a random strategy in which a node randomly selects another node for learning in each iteration. We set the same number of iterations needed by our proposed system to achieve optimal knowledge sharing. Fig. 12 shows the classification accuracy obtained for each strategy. The results show that a random selection mechanism is not optimal and requires more iterations to reach the defined optimal accuracy, while our proposed communication mechanism achieves optimal accuracy with the same number of iterations. Moreover, with the random selection mechanism, some nodes remain unexplored during the learning process.

F. Energy Consumption Measurement

We monitor the energy consumption of the Jetson Nano node during all the training iterations using the module's onboard INA monitors. We report energy every 2 seconds based on the recommendation of the Jetson Nano thermal design guide². We measure the energy consumption of the two scenarios (data transfer and knowledge transfer), as shown in Fig. 9. Knowledge transfer consumes an average energy of 3.6 Watts (6.48 kWh), while data transfer consumes an average of 3.2 Watts (5.76 kWh). Thus, knowledge transfer consumed slightly more than data transfer due to the knowledge vector shared with other nodes being bigger than the data vector.

VIII. CONCLUDING REMARKS

In this paper, we discussed and proposed an architecture for a global brain: an emerging, collectively intelligent network comprising the people of the planet connected through computer and knowledge bases. It is a complex [2], self-organizing system that can collect and process data and take actions.

Initially, we proposed an architecture for a local brain as a main component of the global brain. We also proposed a system model based on multi-agent system technology and an optimized communication mechanism between the local brains. We evaluated its communication based on network complexity, density, and the number of exchanged messages using JADE and our optimized communication mechanism.

We further prepared ten Nvidia Jetson Nano nodes as local brains, and the results showed the ability of the nodes to form a collective intelligence with high accuracy and consume a reasonable amount of energy along with data privacy-preserving ensured by the proposed knowledge-sharing approach.

In future research, we plan to consider other real-world problems. In particular, one future direction is the integration of data analytics (NWDAF) and management data analytics (MDAF) proposed in the latest 3GPP specification [13].

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