Training a Neural Network on Virtual Reality Devices: Challenges and Limitations

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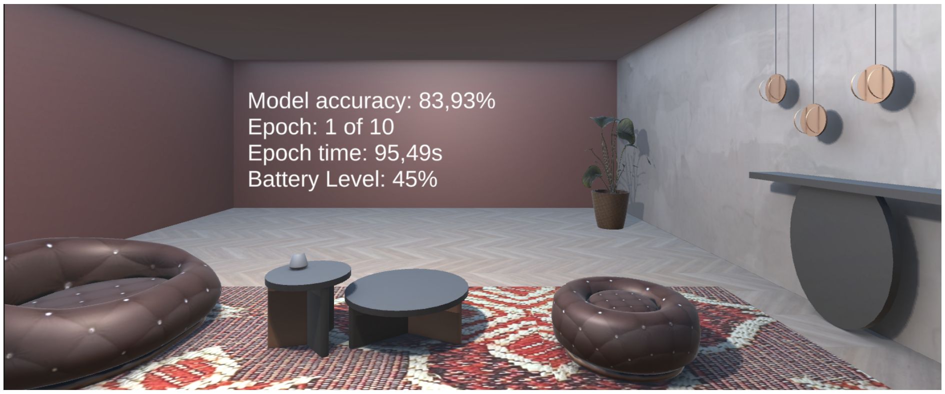

Figure 1: VR scene where NN model is trained with the MNIST database of handwritten numbers. Different parameters such as model accuracy, epoch number, time of the epoch and the battery of the device are displayed.

Abstract

The processing power of Virtual Reality (VR) devices is constantly growing. However, few applications still take advantage of these capabilities. Machine learning algorithms have shown promise in enabling an immersive and personalized experience for VR device users. Therefore, it is interesting that these algorithms are processed directly on the devices themselves, without needing other external resources. In this work, a Neural Network (NN) is trained for real-time image classification using different VR devices. The results show the feasibility of incorporating VR devices for NN training without compromising the quality of the interaction, simply and saving external resources.

Index Terms: Computing methodologies—Computer graphics—Graphics systems and interfaces—Virtual reality; Computing methodologies—Machine learning—Machine learning approaches—Neural networks

1 Introduction

VR devices have been increasingly used in recent years due to an evolution of technology to create immersive scenes [5]. Regarding the different types of technology standalone, devices with their CPU and GPU are becoming increasingly popular [1]. In this way, new possibilities are opened up for computational techniques that were previously limited, since a computer was even needed to render virtual scenarios. Assuming that the future of VR development will see an exponential increase in the number of devices on the market and the number of users, this could solve computational problems by providing information that cannot be obtained from other types of devices, such as eye tracking data or information on human behavior in different simulated situations to predict events. Previous work has used pre-trained NN to predict situations in VR scenes [4]. However, we have use the potential of standalone devices to create an NN model in considerably cheaper and low power devices. Moreover, this kind of device could work as a node in a federated learning environment to solve any problem requiring NN [6]. In this approach, we have analyzed different VR devices (Meta Quest, Meta Quest 2, and Meta Quest 3) to measure their performance in battery usage and runtime by training an NN feed-forward on the handwritten digits MNIST database.

2 Neural Network architecture

In this work, we developed a feed-forward network in C# language under the Unity graphics engine. Due to the inexistence of libraries that support real-time training in VR, we developed our network on a virtual scene development platform, avoiding to use of pre-trained neural networks just for result inference. The network consists of a multi-layer structure with two hidden layers, each containing 150 neurons, an initial layer with 784 neurons, and an output layer with 10 outputs corresponding to digits from 0 to 9, as illustrated in Fig. 3. For optimal performance, we selected parameters such as 10 epochs for training, a learning rate of 0.1, and a batch size of 8.

3 Virtual reality devices used

In this section, we analyze the technical specifications of the VR devices used for this work. In this analysis, we specify the processor (chip), the RAM, the integrated graphics, and the firmware version. This information is available in Table 1.

4 Results

Figure 2 shows the execution time evolution across various Meta VR devices. Notably, there's a significant improvement from Meta Quest to Meta Quest 2 (around 45%). However, the latest Meta Quest 3, which promised to be as 2.5 times more powerful than Quest 2, exhibits suboptimal execution times [2]. Meta attributes this

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[1]https://towardsdatascience.com/designing-your-neural-networks-a5e4617027ed

[2]https://blog.learnxr.io/extended-reality/quest-3-review-and-developer-setup

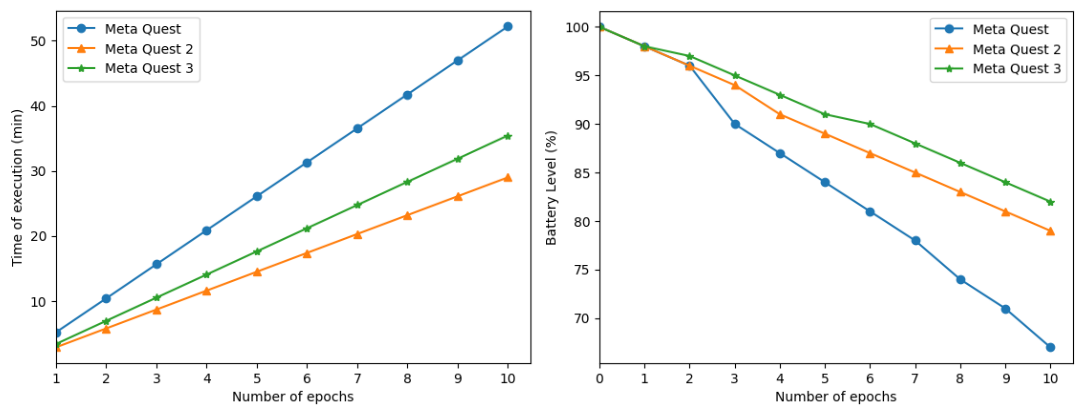

Figure 2: On the left, the execution time after each epoch for all VR devices. On the right, is the battery percentage after each epoch.

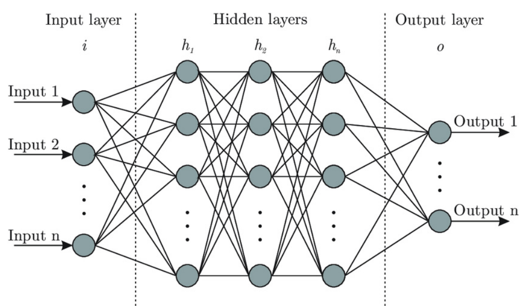

Figure 3: Multilayer feed-forward NN with input, hidden, and output layers defined and interconnected with each other [1].

to a firmware update unlocking its full potential, similar to their previous devices. Additionally, Figure 2 also depicts the battery drain evolution over epochs, showcasing a more than 15% reduction in consumption for Quest 3 compared to Quest and 4% compared to Quest 2.

5 Federated Learning on VR: A challenge

In the imminent future, a proliferation of standalone VR devices worldwide is anticipated, reaching millions in number. Meta and other collaborative entities are working together to create a virtual realm referred to as the metaverse. This innovative landscape holds the potential to unveil unprecedented applications and functionalities [7]. A notable prospect within the metaverse is leveraging the data captured by VR headsets for real-time model training, enabling the application of artificial intelligence [3]. Regardless of the amount of time the consumer uses the device, the collaborative model using the cloud will be able to enhance the model that is being trained and obtain completely different and customized data depending on the observer [2].

6 Conclusions

In conclusion, it is possible to run real-time training algorithms on standalone VR devices. This produces a battery drain on the devices although we see that over the years and hardware optimization, it has decreased drastically and the execution time has been reduced as well.

Table 1: Technical specifications of the different VR devices used.

			
	Meta Quest	**Meta Quest 2**	**Meta Quest 3**
Released Date	May, 2019	October, 2020	October, 2023
System on a chip	Snapdragon 835	Snapdragon XR2	Snapdragon XR2 2ºGen
RAM Memory	4GB	6GB	8GB
Graphics (TFLOPS)	Adreno 540 (545-567)	Adreno 650 (up to 1.32)	Adreno 740 (up to 1.74)
Firmware version	v49	v54	v59

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