


Chapter 7

AIoT and Deep Neural Network–Based Accelerators for Healthcare and Biomedical Applications

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ABSTRACT

Convolutional neural network (CNN) systems have an increasing number of applications in healthcare and biomedical edge applications due to the advent of deep learning accelerators and neuromorphic workstations. AIoT and sense of care (SOC) medical technology development may benefit from this. In this chapter, the authors show how to develop deep learning accelerators to address healthcare analytics, pattern classification, and signal processing problems using emerging restrictive gadgets, field programmable gate arrays (FPGAs), and metal oxide semiconductors (CMOS). Neuromorphic processors are compared with DL counterparts when it comes to processing biological signals. In this study, the authors focus on a range of hardware systems that incorporate data from electromyography (EMG) and computer vision. Inferences are compared using neuromorphic processors as well as integrated AI accelerators. In the discussion, the authors examined the issues and benefits, downsides, difficulties, and possibilities that various acceleration and neuromorphic processors bring to medicine and biomedicine.

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INTRODUCTION

Artificial intelligence can best manage the expanding needs of the universal healthcare system (Goyal, 2019). By 2022, it is anticipated that the healthcare sector will generate over \$10 trillion in revenue, and the related burden for medical professionals would increase at a similar rate (Ditterich Thomas G, 2000). To monitor the patient for abnormalities and/or to anticipate illnesses, a smart DL system may be used to process data obtained from the persistent, which may be a mix of biomodels, medical imaging, disease, progress, etc. Deep Learning (DL), whose accuracy is rising, has infiltrated many facets of healthcare, including monitoring, prediction, diagnosis, therapy, and prognosis (Frenkel, 2019). In a closed-loop scenario, DL systems may be utilized to provide prognosis and treatment options, which influence monitoring and prediction.

AIoT is a helpful tool for infrastructure development, traffic monitoring, and other areas of transportation. AIoT connects with the signal in the contemporary healthcare system because of this benefit (Y. Geng, 2018).

The healthcare system offers the initial link (T. Hirtzlin, 2019) and a higher standard of living (Frenkel, 2019). Machine learning for prediction is the primary goal of this effort. Connecting sensors with AIoT enables the collection of uninterrupted time series information and cloud-based data processing. Heart illness is challenging to diagnose (O. Krestinskaya, 2018), and many times individuals are not even conscious that they are ill until they have cardio problems like arrhythmia or even stroke. A trained physician must examine the individual to identify the usual symptoms of a cardiac illness to make the diagnosis of heart disease. Currently, there are insufficient doctors, and most countries do not believe computers can accurately detect cardiac problems with clarity and precision (X. Zhang, 2017). To ensure that customers obtain the results before the deadline, existing healthcare systems connect before devices for patient information processing. These systems are constructed using cloud or fog computing platforms that are AIoT driven. Many earlier studies tried to predict heart-related health conditions using AIoT, but they were able to do so with the degree of accuracy necessary by the strict standards of medical standardizing bodies. Given the prominence of deep learning in recent years, more modern technology can even identify cardiac problems with more precision than doctors can (A. R. Aslam, 2019).

To address the doctor shortage issue, this effort attempts to combine deep learning with AIoT in the healthcare sector. It is hoped that this would encourage medical standards organizations to embrace a model that offers low latency and high accuracy. Few researchers, such as (C. Lammie, 2020), have attempted to combine these two paradigms, but none have taken use of edge computing's dispersed nature to boost accuracy using ensemble deep learning models. Data from AIoT systems

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