Internet of Things Information Analysis using Fusion based Learning with Deep Neural Network

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Abstract. The development of the Internet of Things (IoT) is driven by recent technical advances and a growing melding of fields including sensing and actuating technology, integrated networks, radio and data processing. The vast number of IoT sensors produce high volume data for a wide variety of applications, such as intelligent house, intelligent health, intelligent engineering, smart transport, intelligent grid and intelligent agriculture. In order to promote improved decision-making, efficiency and precision, reviewing these data is a vital mechanism that renders IoT a successful market concept and paradigm-enhancing quality of living. While it is promising to improve the quality of our lives to obtain covered knowledge and inferences from IoT data, this is a complex task which traditional paradigms cannot carry out. Deep learning can play a key role in developing smarter IoT, as it has demonstrated promising effects in a number of areas such as image recognition, knowledge gathering, voice recognition, natural language processing, indoor location, physiological and psychological condition identification, etc. In this context it becomes imperative to explore the capacity of Deep Learning for IoT data processing.

Keywords: IoT, Machine Learning, Deep Learning, Neural Network

1. Introduction

Machine Learning (ML) technologies have become commonly used in different fields, in particular deep learning (DL) technology and achieve state-of-the-art performance. In the meantime, the Internet of Things (IoT) is still booming and evolving mobile computing. As a consequence, ML and cloud computing mergers generate considerable change in the areas of autonomous behaviour, healthcare and ID technology. A further move is also being taken to render deep learning a fact, especially at the edge of the IoT. If IoT devices are used only as sensors or video-stream captors, a variety of processing functions, including analysis of the film, data fusion, face or entity, will need to be performed by central cloud servers. As a consequence, a successful solution is to shift these low-level processing systems into edge computers, thereby freeing central servers from these activities and allowing them to undertake high-level processing including concept extraction, content review, etc. However, many of the profound learning models have tremendous parameters, which include very large total computational costs. It is
also difficult to move a profound research model such as the Deep Neural Network (DNN) to IoT. As they are built for low power with minimal processing capacity, for instance, few to a handful of ARM cores in the majority of IoT devices such as security cameras, communications systems and sensors. We first carried out a brief review of descriptive methods for deep learning on mobile / IoT devices in this study. We are primarily concerned with analyzing three approaches across all current methods: 1. acceleration in the parallel; quantization; pruning of the model. In the experimental section, we tested the results of these approaches on the Nvidia Tegra X2 exemplary model, which has ARM cores and integrated GPUs.

Many IoT applications have cover in the last couple of years in many area, such as fitness, mobility, clever house, smart city, agriculture, school, etc. Deep Learning ( DL) has been used extensively in multiple IoT implementations in the last years among the various machine learning approaches. These two innovations, i.e., DL and IoT were revealed at the Gartner Symposium 2016 as one of the top three strategic technology developments in 2017 [4]. The explanation for DL’s aggressive ads is that classical machine learning methods do not meet the current theoretical criteria of IoT systems. Instead, IoT structures require numerous modern methods of data processing and of artificial intelligence ( AI), as seen in Figure 1, centered on a hierarchy of IoT data generation and management. Stakeholders need to be consistent about their concept, building blocks and opportunities and obstacles, about order to cultivate an increasing interest in the Internet of Things and its related Big Data. There's a two-way connection between IoT and big data. In order to enhance IoT processes and resources, the first is to be a primary source of large data and the second is to be an significant goal in the field of big data analysis [5].

Figure 1. IoT Data Generation at Different levels and deep learning models to address their Knowledge Abstraction

In comparison, IoT Big Data Analytics has proved that it brings benefit to community. For eg, the Department of Park Maintenance, based in Miami, allegedly saved around $1 million from their water bills by identifying and repairing broken pipes[6]. IoT data is separate from the Big Data standard. We need to analyze the properties and how they are not the same as those of general big data in order to properly grasp the criteria for IoT data analysis. The following attributes are seen in the IoT data [6].

- Large-Scale Streaming Data: A multitude of data collection devices for IoT applications is dispersed and deployed and data streams are created continuously. It contributes to an immense amount of ongoing info. Complexity: varied IoT data collection systems capture data variability in various forms. Time and space correlation: Sensor sensors are bound to a single position in most IoT implementations and are both place and time stamps for and data object.

- High noise data: All of those data may be exposed to error and noise in processing and delivery because of small data fragments in IoT applications. Although it aims to increase the standard of our lives to obtains secret information and data from big data, it is not a quick and clear job. New technology, algorithms and infrastructures are required in order to accomplish this dynamic and demanding challenge that goes beyond the capacities of conventional inference and learning approaches[7]. However, we need quick analytics in smaller systems (i.e., on the
machine edge) or even on the IoT devices themselves for the above described IoT applications, and others. Autonomous vehicles, for example, need to make swift driving choices, including shifts in lane or direction. Indeed, quick analyzes of likely multi-modal data, For review and return the data is subject to the delay that could contribute to traffic accidents or collisions, switch to a cloud server. In those situations. The identification of pedestrians by such cars will be a more important situation. In order to stop serious injuries correct identification can be achieved in absolute real time. These situations mean that fast IoT data processing must be near or at the data source to avoid unwanted and prohibitive contact delays.

To organize our paper in this format, second section we describe the related work, second section proposed methodology and approach, in the section 4 to describe the results analysis and last section conclusion.

2. Related work

In this section, we give a quick review of research on how to learn deeply on IoT devices. In this section, Next, we discuss some traditional ML model processing approaches. Moreover, as in this field we also examine approaches to model optimization for an IoT environment as another important factor in DL models.

Pradhan C et al. [1], In this paper, established a latency-restricted computational offload problem for an xL-MIMO C-RAN uplink. The designed problems with optimization, which minimize the overall transmitting power of the IoTDs while meeting the latency requirement, are not convex. The joint optimization for the baseband combiner is locally achieved by the HSF matrix at the xL-MIMO RRH. H Jafari, et al[2] In order to ensure the stability of our models with different wireless channel conditions in operation.

M Shobana et al. [3] Malicious system calls produced are processed in order to obtain the required functions using n-gram techniques. The system calls extracted have been classified by a recurring neural network in two classes (RNN) i.e. normal and malicious sequence). Different efficiency measures test the effectiveness of this deep learning. In real time, IoT malware samples from IOTPOT honeypot have been obtained that simulate a variety of IoT devices' Processor architecture. T Sirojan et al[4] This study describes the potential and obstacles of deep education on embedded hardware and discusses the strategies of optimization for deep learning.

P Das R., et al. [5] In this paper explored a modern approach to image the retinal fundus based on a definition of an HMD. Automated retinal photographs may be collected from patients via HMDs. These photos are used to diagnose chronic and long lasting illnesses and to serve as biomarkers. Profound learning strategies for automation of disease diagnosis and corrective advice are given to patients through their smartphones. In the age of intellectual health care, we transform science into clinical treatment.

X Qi and C. Liu et al. [6]first looked at some descriptive methods for deep learning on mobile devices. In this paper we discussed We then tested the efficiency and effect of these approaches with an integrated GPU and ARM processor on the IoT platform. Our findings demonstrate that if you execute these methods successfully, you can activate the deep learning capabilities at the edge of IoT.

X He et al. [7] A new privacy weakness is found in this paper because of the wireless transfer of the MEC-enabled IoT. A newly suggested deep post-decision state (PDS)-learning algorithm is built in order to resolve the weakness.

B K. Mishra et al. [8] Separation of filters is analyzed by focusing exclusively on the region of concern inside the picture as one of the approaches to improve the specificity of the classification. In existing framework before the testing, segmentation is implemented in the data pre processing step. To train and evaluate our model, S Yao et al., et al. [9] Deep Sense is designed for neural networks with drop-out
processing, one of the most commonly adopted methods of deep learning regularization. For uncertainty assessment purposes, no additional preparation is required. In Intel Edison systems we test ApDeepSense with four IoT applications.

A. Jettakul et al. [10] Finally, noise effects decrease the efficiency of all the algorithms in these simple tasks and the findings suggest that our OOV handling technologies may boost noisy data output.

A Sing Rajawat et al. [11] Our proposed smart model map reducer is based on the principle of machine learning. The findings of this research are important for the training and testing of broad data sets for a classification problem centered on the algorithm of Back Propagation Reduce Fusion Deep Learning.

3. Proposed Approach

Deep Neural Network architectures. The Deep Neural Network (DNN) consists of many computing layers that are responsible for the hierarchy of input data. The functionalities of the human brain imitate the working of DNN. The processing units called neurons compose each plate. The weighted total of the inputs is determined by a neuron and the resulting amount passed as input to a function to trigger (table 1) the required value. A collection of weights and a propensity to maximize the training process is correlated with each neuron. Figure 2 shows the role of artificial neuron. DNN consists of a broad range of design, which is controlled and non-supervised, including: the Boltzmann computer, the Deep Belief Network, the CNN, Deep learning is an underpinning of a wide machine learning area. The learning strategies are specific to a individual brain’s operating system. The most famous and frequently used approach to machine learning is neural networks that are generated from the combination of the key computing feature in a human brain named neuron. Each neuronal communication has a weight-defined scaling factor to quantify the input signal to a neuron. Neuron is capable of producing the input signal output through its related activation feature. The neurons normally form a neural network as layers. Many dynamic systems on the basis of the above-mentioned building blocks are now being designed. Which introduces a modern practice named fundamental study.

The fundamental operations of weighted numbers of input matrix are multiplication and addition. In order to generate an production, it is essential for a common deeper education framework such as AlexNet[6], GoogLeNet[7] and ResNet[8] respectively to generate 724 million, 1,43 billion and 3,9 billion arithmetic operations. It is not necessary to provide embedded systems with certain computing specifications. In the early stages fundamental learning systems are built in order not to take into account design difficulty but to optimize role precision. Recent studies emphasized that in order to improve efficiency of in-depth modeling methods for realistic implementations, deeper model modeling could be built to optimize precision while growing the energy cost and computational complexity. The output of the convoluition layers is the characteristic maps generated by the input product and the filter. Figure 3 shows the detailed process of fusion based learning with deep neural network.

![Figure 2. Types of connections in Deep Neural Networks](image)

3.1 Recurrent Neural Network
The Neural Network Feed-forward is not ideal for time series simulation activities. The Recurrent Neural Network (RNN) has been established for these tasks. Data for the RNN is fed both the latest data and the previous one.

The RNN output does not rely on the RNN output in step-\(t-1\) at the time. To this end, each neuron’s output is transmitted as input into the next stage. So, each neuron in an RNN has an internal memory that stores the previous input data. A Back Propagation Algorithm (BPTT) is used to build the Network. For testing, a version is used.

![Diagram of Fusion based Learning with Deep Neural Network](image)

**Figure 3.** Fusion based Learning with Deep Neural Network

### 3.2 Long Short Term Memory

RNN suffers from a disappearing gradient problem when modelling long-term dependency issues. A modern DNN model named Long Short Term Memory has been designed to overcome this constraint. LSTM unit has a storage cell, a writing gate, a missing gate and a reading gate. For indefinite times, the memory cell holds the values, and gateways monitor data motions in and out of the memory cell. As gate activation functions, silk or hyperbolic tangent functions are used. BPTT algorithm, like RNN, is used for network processing.

### 3.3 Data Pre-processing

IoT pre-processing data is complicated, because data from different sources are dealt with by the device, which can include noise and unwanted, and incomplete data[5]. • High speed: the pace of IoT data output poses a challenge for the accelerated evaluation and review of these data. The solution to this issue is online learning. However, more study is required to combine meaningful learning with online learning.

### 3.4 Heterogeneity

Even though Deep Learning Models are able to interpret data from heterogeneous sources it is another challenge to cope with inconsistencies between various types of data. Large IoT Data Sets requirements:

As deep learning models that are supervised need training data with multiple cases in which accurate results are obtained, the lack of large IoT data sets is a major impediment to Deep Learning models' incorporation into IoT applications[5]. Deep IoT apprenticeship programming: running deep learning models on resource-restricted IoT is a huge task for designers of IoT appliances.[5]

### 4. On Deep Learning Models for Sensor Data

The design of deeper neural networks architectures which effectively estimate the outputs of interest from noisy time series multisensor measuring systems is a key research challenge in order to implement the learning-enabler IoT-systems.1 Despite the wide range of embeddable and mobile computing tasks
within IoT context, they are typically categorized into two types: estimation and classes. Therefore, the issue becomes whether or not the design of the overall neural network can effectively understand the model structure needed to estimate and identify sensor data tasks. Such a general deep-training design of the neural network can, in theory, overcome the disadvantages of current approaches focused on simplifications of the analytical model or on the use of manufacturing functions. Sensor inputs are historically interpreted based on physical simulation of the phenomenon concerned for estimation-oriented problems such as monitoring and position. Physical measures like speed and angular velocity are created by the sensors. Other physical quantities (for example, movement by double integration of acceleration over time) are extracted from these measures. However, product sensor measurements are legendary. The weighing noise, it is nonlinear and may over time be associated, rendering simulation challenging. The isolation of signal from noise contributes to measurement errors and distortions. A standard solution is to measure suitable features extracted from raw sensor data for classification concerns, such as operation and background detection. The handmade characteristics are then fed into a training system. The creation of good engineered features will take time; comprehensive tests are required, for example, to generalize various sensor noise patterns and heterogeneous user behaviour.

A deep learning architecture is able to effectively address all these challenges by tuning the trained network automatically with complex clustered noise patterns, while simultaneously converging on extracting maximally robust signal characteristics to best fit the task involved. A new structure, known as DeepSense, reveals that such a general approach can be feasible. Convolutional neural networks (CNNs) and recurring neural networks (RNNs), as seen in Figure 1. For processing time-series details, sensory inputs are synchronized and separated into cycles. DeepSense applies a single CNN on each sensor for each time, encoding specific local characteristics within the data stream of the sensor. A (global) CNN is used to model interactions between many sensors on the respective outputs in order to efficiently fuse sensors. A RNN is then used in time pattern extraction. Finally, an affinity transformation or a softmax effect is used based on whether an approximation or classification activity is to be modeled.

| Block Name | Kernel Size | Num of Feature of Maps |
|------------|-------------|------------------------|
| Input      | 64*64       | 1                      |
| Inception  | 4 Paths 1x3 x3, 5 x5 convolution and max pooling |
| CONV 2     | 3x3         | 96                     |
| CONV 3     | 3x3         | 128                    |
| FC1        | -           | 128                    |
| FC2        | -           | 64                     |
| Output     | (Sigmoid)   | 1                      |

**Table 1. Size, Name Feature of Map**

5. Results Analysis

Experimental framework GPU and ARM cores are the Nvidia Jetson TX2 device used in this function. The GPU has 256 SPUs that provide the required processing capacity to deal with massive overhead computation and bandwidth tasks. The GPU is therefore perfect to operate tasks that require purely in real-time. Six ARM core systems are also enabled on the TX2 platform with ARM-V8 guidance. Two of these 6 core cores are Nvidia custom-designed high-performance "Denver" core cores suitable for operating systems (OS) activities and key programmes; the remaining four are power sensitive ARM A57 cores suitable for non-emergence or concurrent work tasks. B. DNN model for assessment Lightweight models such as CNN models with few convolution layers are intended for IoT edge applications. The disparity between precision, latency and comparatively limited computing resources offered by IoT edge devices is the factor behind this decision. Furthermore, people often run widescale DNNs such as VGG-16, with a rather broad structure on IoT computers, without a strict latency
constraint. Light-weight DL models are typically used in pre-processing voice / video series, with an appropriate computational overhead that satisfies real-time value. In this experiment, we use in video an illustration of a CNN model for the Face Consistency Assessment (FQA). The FQA model has the purpose of estimating image quality and choosing the appropriate structure for further analysis and growing the amount of data [9], [10]. Table 2 displays the CNN design of our FQA application. The lightweight CNN consists of five blocks of convolution, three of which are ordinary convolutionary operations. One block defined as the main node[14] includes four parallel paths and a cumulative set of both directions. The first block is the node. In order to obtain the estimation value between 0.0 and 1.0, the last sigmoid feature is used.

Large DNN model - VGG16: VGG16 is often used for testing optimization procedures for the IoT application. VGG 16 is a dl model of 16 convolutionary and entirely linked layers, without bundling layers. Table II displays VGG16 layout, combining different convolutionary layers into one block and manipulating them inside the block in the same space. The model extends in all the max-pooling layers 3 to 3 as the only convolutionary kernel and 2 to two kernels. From the table we can see that, in terms of its depth and map sizes, the VGG16 is far larger than the FQA motor defined in Table 1.

Table 2. Displays the CNN Design

| Conv Block 1 | Num of Layers | Feature Size | Map Kernels |
|--------------|---------------|--------------|-------------|
| Conv Block 2 | 2             | 224*224      | 64          |
| Conv Block 3 | 2             | 112*112      | 128         |
| Conv Block 4 | 3             | 56*56        | 256         |
| Conv Block 5 | 3             | 28*28        | 512         |
| Fc layers    | 3             | -            | -           |

We test both small-scale models, including our FQA CNN and large sized models such as VGG-16[11], that are used widely for different purposes, in the running of DL models at ARM cores. 1) CNN lights: First, on four ARM bases, we operate the CNN light weight. With additional cores, the experimental findings in Table 2. The processor occupancy is a crucial aspect to note here. If we can see, just one picture at a time cannot completely exploit the multiple nuclei and if we incorporate cores from 2 to 4, pace would not clearly increase. Therefore, the small-scale DL design would contribute to greater processor usage and efficiency with a wider batch scaling and more photos being sent to the device at the same time. Refer details in Table 3.

Table 3. Running light- weight DL model on ARM

| Batch Size | Num of Cores | Total Time | Throughput (Faces/ Sec) | Speedup |
|------------|--------------|------------|--------------------------|---------|
| 1          | 1            | 51.073     | 25.4                     | -       |
| 2          | 2            | 36.580     | 73.1                     | 1.396   |
| 3          | 4            | 33.326     | 80.2                     | 1.533   |
| 2          | 2            | 51.316     | 52.1                     | -       |
| 2          | 2            | 34.215     | 78.1                     | 1.500   |
| 3          | 4            | 23.432     | 114.1                    | 2.190   |
| 3          | 2            | 30.379     | 88.0                     | 1.710   |
| 3          | 4            | 20.957     | 127.5                    | 2.478   |

The development in both hardware and software technology makes automation learning feasible, especially in-depth learning of mobile devices and IoT edge devices with limited computer capabilities.
Three descriptive methods, namely simultaneous acceleration, quantization, and model sizing of IoT systems, have been investigated and assessed in this article. We may find ways to refine profound IoT computing skills through hardware levels to machine-level learning algorithms. And if we want to examine optimization results, many factors should be regarded together. In model quantization, for example, it is often important to understand the form of reduced precision calculation that is enabled by aim hardware, not merely by moving the concept with reduced precision parameters.

6. Conclusion
Deep Learning is a very successful for the analysis of the extremely complex IoT results. Deep learning frameworks are in the following respects stronger than traditional paradigms. Next, the need for controlled structure sets to be used for instruction is alleviated. Therefore, Deep Learning models will remove features that might not be familiar to a person. In comparison, deep learning models yield prediction outcomes more reliably. In addition, deep learning technology is ideal for the analysis of complex behaviours. This essay offers a comprehensive overview of many architectures in deep learning. A comprehensive review will also be provided of the theoretical work carried out by the Deep Learning models for data analytics in IoT situations. The problems and potential study recommendations for more studies in this area are now being addressed. It is worth mentioning that IoT data analytics also have to provide deep learning, further study is required to leverage the maximum potential of IoT data analysis deep learning models.

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