Democratization of Artificial Intelligence (AI) to Small Scale Farmers: A Framework to Deploy AI Models to Tiny IoT Edges That Operate in Constrained Environments

Chandrasekar Vuppalapati[1][a], Anitha Ilapakurti[1], Sharat Kedari[1], Jaya Vuppalapati[2], Santosh Kedari[2] and Raja Vuppalapati[1]

[1]*Hanumayamma Innovations and Technologies, Inc., 628 Crescent, Fremont, U.S.A.*

[2]*Hanumayamma Innovations and Technologies Private Limited, HIG-II, Hyderabad, India*

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Abstract: Big Data surrounds us. Every minute, our smartphone collects huge amount of data from geolocations to next clickable item on the ecommerce site. Data has become one of the most important commodities for the individuals and companies. Nevertheless, this data revolution has not touched every economic sector, especially rural economies, e.g., small farmers have been largely passed over the data revolution, in the developing countries due to infrastructure and compute constrained environments. Not only this is a huge missed opportunity for the big data companies, it is one of the significant obstacle in the path towards sustainable food and a huge inhibitor closing economic disparities. The purpose of the paper is to develop a framework to deploy artificial intelligence models in constrained compute environments that enable remote rural areas and small farmers to join the data revolution and start contribution to the digital economy and empowers the world through the data to create a sustainable food for our collective future.

1 INTRODUCTION

Artificial intelligence (AI) stands out as a transformational technology of our digital age - and its practical application throughout the economy is growing apace (Chael et al., 2018). One of the chief reasons why AI applications are getting prominence and industry acceptance is in its software ability to learn, albeit continuously, from real-world use and experience, and its capability to improve its performance(Chael et al., 2018). It is no wonder that the applications of AI span from complex high-technology equipment manufacturing to personalized exclusive recommendations.

Nevertheless, this data has not touched every economic sector, especially rural economies, e.g., small farmers have been largely passed over the revolution, in the developing countries due to infrastructure and compute constrained environments even when AI is critical for food sustainability (Luiz, 2019).

In noting the promise and challenge of AI, the McKinsey Global consulting Firm noted numerous use cases across many domains where AI could be applied and for these AI-enabled interventions to be effectively applied, several barriers must be overcome (James & Jacques, 2018). These include the challenges of data, computing, and talent availability, as well as more basic challenges of access, infrastructure, and financial resources that are particularly acute in remote or economically challenged places and communities.

One chief reason, importantly, for AI not touched every economic sector is the current AI algorithms are only made to run on very powerful research workstations without considering how they can be used on real-world hardware, embedded constrained hardware. Machine learning in embedded systems

specifically target embedded system to gather data, process data, and apply mathematical rules to produce insights (Van, 2019). The embedded systems typically consists of low memory, low Ram, limited power compared to regular computers. Increase in

[a] https://orcid.org/0000-0003-2261-759X

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factors such as processing power (Devin, 2016) leads to higher accuracies – the cost to bear is battery life.

To successfully disseminate AI to masses and enable successful democratization, we need to bring rural communities to digital revolution (people, technology and data together) and the purpose of the paper is to achieve such digital revolution. The paper proposes AI deployment to Small Foot Print (Tiny) IoT Edge device that operate in constrained device and presents the data collected in real production environment. Our goal is the achieve AI for all, a true Fourth Industrial Revolution (ANDREW, 2019).

2 DEMOCRATIZATION OF AI

The democratization of AI is need of the day. The current AI is more applicable for businesses and end-consumers who are mostly city dwellers. Lack of data that could potentially help local businesses and societies are one of the most significant challenges in AI adoption. One limiting challenge is the availability of Data for social good use cases, especially in rural communities. Lack of technologies, importantly, in the hands of the users exacerbating the issue. For instance, global penetration of Internet in rural areas are very low compared to suburban and urban area and this is persisting wider digital gap between rural and urban area (ANDREW, 2019). Lack of internet connectivity is causing inhibition of digital data services dissemination, resulting into sparse vital datasets capture for better governance purposes and preventing rural population to participate in the digital economy.

2.1 Waves of Compute

AI applications can be categorized into four waves of Compute / AI (please see Fig 1. and Table 1) (Neil and Michael, 2019) and with the 5G, the invent of fifth wave is on horizon (Kai-Fu, 2018).

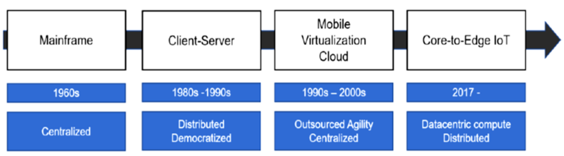

Figure 1: Waves of Computing.

Table 1: Waves of Compute & AI.

First Wave of compute - Mainframe	Characterized by processing of Large Scale Social Media Analytics. Use Cases include: click streaming, personalization, exclusive recommendations and notifications to end-user.
Second Wave of compute – client-server	Business AI developed during the Second Wave. The algorithms were trained on proprietary business datasets and enabled business analytics.
Third Wave of compute – Mobile	"Perception A.I."— gets an upgrade with eyes, ears, and myriad other senses, collecting new data that was never before captured, and using it to create new applications
Fourth Wave compute – Core IoT Edge	Autonomous AI – start of autonomous cars. IoT fuelled the fourth wave.
Fifth Wave (Simon, 2019)	5G Infused AI – the 5G network provides speeds that AI requires.

2.2 Data

Small Farmers make big contribution to agriculture and dairy production in developing countries (Devii, 2017). Unlike the dairy farms of the west, milk originates in highly decentralized villages with the help of small farmers who own three to five cattle and they bring milk twice a day to milk collection centers to get paid (Prahalad and Stuart, 1999). Simply put, the livelihood of roughly 2 billion people (26.7% of the world population) of small farmers in developing world depend on agriculture and the climate change adversely impacting their survival (see fig 2) (Robert, 2009).

Figure 2: Farmer Protest

Additionally, lack of data for serving these farmers putting food sustainability and food security in a huge risk mode.

2.3 The Last Mile – Constrained Compute Environments & "Ai Chasm"

Fourth wave of compute has spurred the development of Edge devices. Edge devices come in various forms and shapes with varying compute capacities (Class 0, Class 1 and Class2) (Bormann, Ersue and Keranen, 2014). Class 0 and Class 1 devices collect vast amount of environmental & geolocation data on a periodic basis. Due to constrained environments, the class 0 devices require external devices such as gateways & mobile phones to relay to the Internet. However, these devices deployments for small farmer is sporadic.

2.3.1 Class 0 Devices

Class 0 devices are ***very constrained*** sensor-like motes. These devices are so severely constrained in memory and processing capabilities that most likely they will not have the resources required to communicate directly with the Internet in a secure manner.

In order to connect Class 0 devices to the Internet, larger compute devices such as desktop workstations or central nodes acting as proxies, gateways, or servers are required at the site of Class 0 devices deployment. For device management purposes, class 0 device could answer keep alive signals and send on/ off or basic health indications.

2.3.2 Class 1 Devices

Class 1 devices are ***quite constrained*** in code execution space (Stack & Register Level) and processing capabilities, such that they cannot easily talk to other Internet nodes employing a full protocol stack such as using Hyper Text Transport Protocol (HTTP), Transport Layer Security (TLS), and related security protocols and Extensible Markup Language (XML)-based data representations(Bormann, Ersue and Keranen, 2014). However, Class 1 devices are capable enough to use a (Internet Protocol (IP) stack specifically designed for constrained nodes (such as the Constrained Application Protocol (CoAP) over UDP [COAP]) and participate in meaningful conversations without the help of a gateway node. Therefore, they can be integrated as fully developed peers into an IP network, but they need to be parsimonious with state memory, code space, and often power expenditure for protocol and application usage (Ilapakurti et.al, 2017).

2.3.3 Class 2 Devices

Class 2 devices are ***less constrained*** and fundamentally capable of supporting most of the same protocol stacks as used on notebooks or servers. However, even these devices can benefit from lightweight and energy-efficient protocols and from consuming less bandwidth. Examples of the devices include Smartphones.

2.3.4 Constrained Device (Tiny IoT Edge) Architecture

As shown in Fig.3, constrained devices are limited by the compute power, memory, storage space, stack space and work in limited infrastructure. In general, the devices have a central microcontroller as a processing unit with sensors tied to the device unit. The Sensors collect data on time frequency – frequencies of collection would affect the battery useful time.

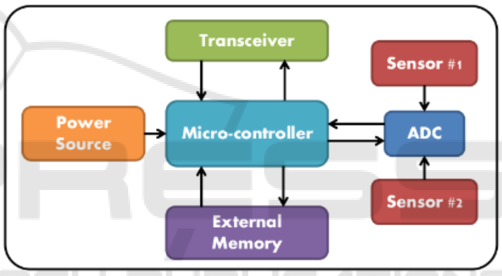

Figure 3: Constrained Device Architecture.

2.4 Hardware in Constrained Environment

Small Tiny Edge devices or Class By addressing following challenges by private sector (see Fig 4), purpose built hardware manufacturers, AI developers, Cloud providers and local & national governments, we can achieve AI for all, a true Fourth Industrial Revolution (Sanjeev, 2018):

- Infrastructure Conditions
- Operating Environment
- Device Characteristics

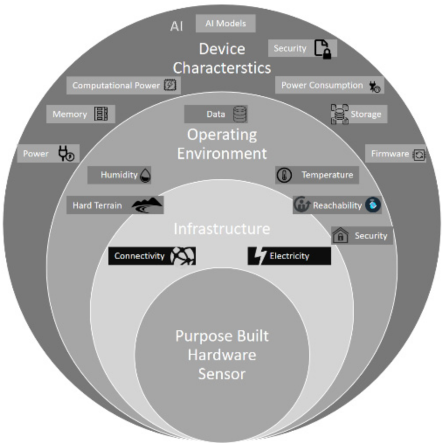

Figure 4: Purpose Built Hardware vs. Constrained Environment.

3 ML MODEL FRAMEWORK

We have deployed model as part of Cow Necklace. The following hardware consists of Accelerometers, Gyroscope, Temperature, Humidity and on-board Bluetooth connectivity.
The Sensor module is built (see Fig 5) on working in constrained environments (Kedari et al, 2017).

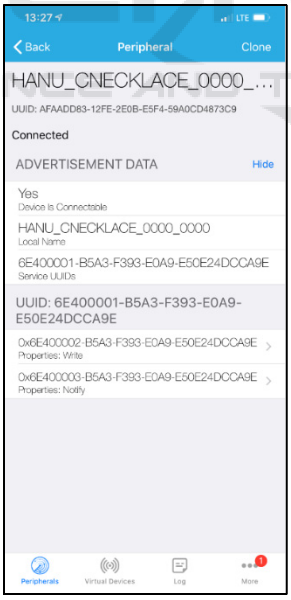

Figure 5: Mobile App.

The Cow Necklace sensor connects to mobile (See Fig. 6) using Bluetooth Low Energy (BLE) and uploads data to the Dairy Analytics Cloud.

The Machine Learning Model in constrained environment is subjected to various constraints and trade-offs (Jiawei et al, 2011).

- Hardware to Model Accuracy
- Model Accuracy to Connectivity
- Connectivity to Hardware

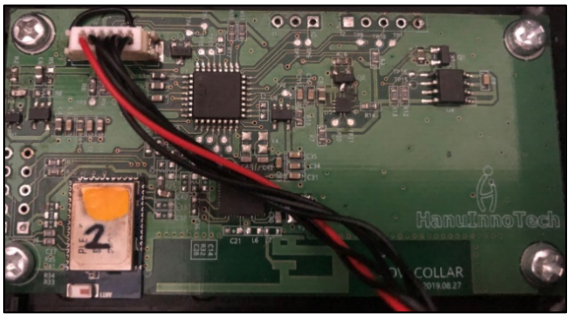

Figure 6: Cow Necklace (Tiny IoT Edge) - PCB Board.

The Sensor collected data (see Figure 7):

0	Date	Time	X	Y	Z	SensorBo	Ambient_	SensorBo	Ambient_	Heat_inde	Heat_inde	Warnings_	Warnings_	Kalman_e	setFlag_ar	Kalman_e	setFlag_humidity
[103]	11/30/2019	15:00:01	-931	-188	-16185	11.4	11.7	69.5	66.7	51.2	50.74	Normal	Normal	19.9	FALSE	NaN	FALSE
[103]	11/30/2019	15:00:01	931	188	16185	11.4	11.7	69.5	66.7	51.2	50.74	Normal	Normal	17.17	FALSE	NaN	FALSE
[103]	11/30/2019	15:00:01	-931	-188	-16185	11.4	11.7	69.5	66.7	51.2	50.74	Normal	Normal	15.34	FALSE	NaN	FALSE
[104]	11/30/2019	16:00:01	-893	-229	-16153	11.4	11.7	68.6	67	51.22	50.7	Normal	Normal	14.13	FALSE	NaN	FALSE
[105]	11/30/2019	17:00:01	-914	-198	-16153	11.4	11.7	68.4	67	51.22	50.69	Normal	Normal	13.32	FALSE	NaN	FALSE
[106]	11/30/2019	18:00:01	-961	-210	-16184	11.3	11.6	68.4	67	51.02	50.49	Normal	Normal	12.75	FALSE	NaN	FALSE
[107]	11/30/2019	19:00:01	-884	-199	-16194	11.3	11.6	68.6	67	51.02	50.5	Normal	Normal	12.36	FALSE	NaN	FALSE
[108]	11/30/2019	20:00:01	-908	-216	-16149	11.2	11.5	69	67.2	50.83	50.32	Normal	Normal	12.08	FALSE	NaN	FALSE
[109]	11/30/2019	21:00:01	-933	-210	-16169	11.3	11.5	69	67.3	50.83	50.52	Normal	Normal	11.88	FALSE	NaN	FALSE
[110]	11/30/2019	22:00:01	-935	-238	-16155	11.3	11.6	72.7	67.4	51.04	50.69	Normal	Normal	11.79	FALSE	NaN	FALSE
[110]	11/30/2019	22:00:01	935	238	16155	11.3	11.6	72.7	67.4	51.04	50.69	Normal	Normal	11.73	FALSE	NaN	FALSE
[110]	11/30/2019	22:00:01	-935	-238	-16155	11.3	11.6	72.7	67.4	51.04	50.69	Normal	Normal	11.68	FALSE	NaN	FALSE
[110]	11/30/2019	22:00:01	935	238	16155	11.3	11.6	72.7	67.4	51.04	50.69	Normal	Normal	11.66	FALSE	NaN	FALSE
[110]	11/30/2019	22:00:01	-935	-238	-16155	11.3	11.6	72.7	67.4	51.04	50.69	Normal	Normal	11.64	FALSE	NaN	FALSE
[110]	11/30/2019	22:00:01	-935	-238	-16155	11.3	11.6	72.7	67.4	51.04	50.69	Normal	Normal	11.62	FALSE	NaN	FALSE
[112]	12/1/2019	0:00:01	-921	-240	-16195	11.8	12	70.3	68.1	51.86	51.57	Normal	Normal	11.75	FALSE	NaN	FALSE
[112]	12/1/2019	0:00:01	-921	-240	-16195	11.8	12	70.3	68.1	51.86	51.57	Normal	Normal	11.83	FALSE	NaN	FALSE
[112]	12/1/2019	0:00:01	921	240	16195	11.8	12	70.3	68.1	51.86	51.57	Normal	Normal	11.89	FALSE	NaN	FALSE

Figure 7: Sensor Data.

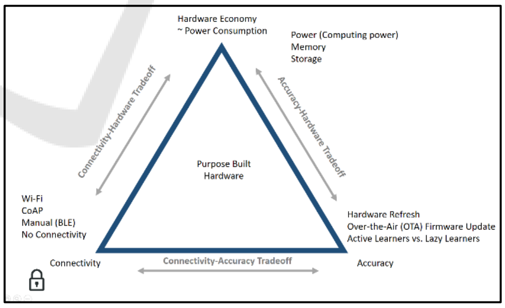

Figure 8: Hardware-ML Model-Connectivity Framework.

The balance has to be drawn with respect to applicability vs. model accuracy (see Fig 8). For instance, if ML deployed model is active learner (e.g., K-means Cluster), the power consumption is taxed very high as the algorithm dynamically allocates K values. On the other hand, if deployed model is Lazy learners, the model evaluation is based on the memory resident stack space algorithm evaluation. Here, the rules are in high-drive mode to execute the model.

3.1 Hardware-model Accuracy Table (Constraint – Connectivity)

For evaluating various conditions that are subjected to Hardware to Model Accuracy, holding Connectivity, an infrastructure aspect, as a constraint the following to be considered:

Model: Hardware vs. Model Accuracy
Constraint: Connectivity

The connectivity, which is infrastructure service, could vary based on the geographical location:

Connectivity Options:

- Wi-Fi
- Manual (Bluetooth Low Energy)
- No Connectivity

3.1.1 Constraint – Wi-Fi Connectivity

With Wi-Fi availability, the model could be updated during the hardware refresh or via over the air (OTA) (See Fig 9). With OTA, would provide more flexibility as the latest model could be deployed.

Let us run through the different options:

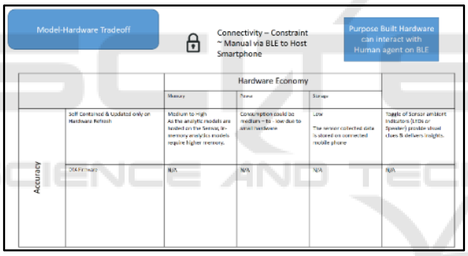

Figure 9: Connectivity: Manual.

Over the Air Model Update

This option provides more flexibility as it has influence on the model in-memory and storage options (see Fig 10):

Hardware – Memory: Low

- The most optimized & updated models could be deployed on the Sensor

Hardware – Power: High

- Since on-board Wi-Fi consumes considerable power

Hardware – Storage: Low

- Sensor collected data is posted to backend server on a periodic basis

3.1.2 Constraint – Manual Connectivity

With manual connectivity, either Bluetooth Low Energy, the Model execution and Hardware have huge performance or tax penalties. Let us look following cases:

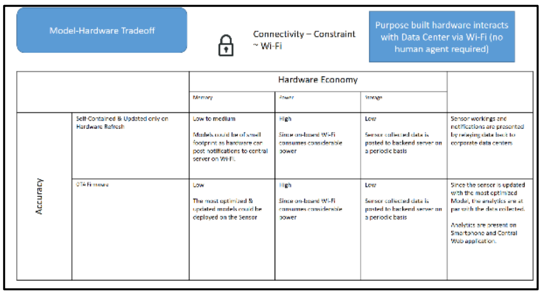

Figure 10: Connectivity: Wi-Fi.

In this case, no OTA applicable as sensor is not connected directly to the Internet. For Model update during Hardware refresh, following are considered:

Hardware – Memory: High

High due to self-contained model with high memory - host models (for historical & Outlier detection)

Hardware – Battery: High

- High – to support in-memory & compute operations

Hardware – Battery: Storage

- Since no connectivity, the data collected to be saved on

Hardware design consideration: Toggle of Sensor ambient indicators (LEDs or Speaker) provide visual clues & delivers insights.

3.1.3 Kalman Model Code

The following code predicts Kalman Temperature (Rajaraman and Ullman, 2011):

```
# Formulas
def TempPrediction(PreviousEstimate,currentMeasurement,PreviousErrorInEstimate):
  ErrorInEstimate = 2
  ErrorInMeasurement= 4
  KalmanGain = ErrorInEstimate /(ErrorInEstimate + ErrorInMeasurement)
  CurrentEstimate = PreviousEstimate + KalmanGain*(currentMeasurement - PreviousEstimate)
  # step2
  ErrorInEstimate = (1-KalmanGain)*(PreviousErrorInEstimate)
  return CurrentEstimate,ErrorInEstimate
```

4 CONCLUSIONS

Democratization of artificial intelligence is the need of the day. It is our responsibility to develop models and hardware equipment that enable the collection of the data from the constrained environments so as to model the AI for food sustainability and threats that we face as humans – climate change. Finally, it is our ardent believe that the ***data is our best defense and the savior*** against the negative effects of climate change. The ***sooner we embark*** on democratization of AI to small farmers, the better we leave our progeny a wonderful life on the earth, i.e., better than what we have inherited.

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