Optimized Lightweight LSTM model for SoC Estimation on the Edge

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***Abstract*—To ensure that batteries that power electric vehicles are used to their full capacity, it is critical that the state of charge (SoC) is monitored in real-time. However, due to the computation-intensive nature of long short-term memory (LSTM) models, it is difficult to achieve real-time state of charge (SoC) estimation at the edge. This paper addresses this issue by developing a lightweight LSTM model using Tensorflow Lite. The model is further evaluated on the publicly available UNIBO Powertools dataset.**

***Index Terms*—SoC estimation, LSTM, Edge computing, Electric vehicles**

I. Introduction

The utilization of electric vehicles (EVs) as a preferred means of transportation is gaining momentum, owing to their ability to conserve energy and provide greener energy solutions. Due to their properties of high voltage, longer lifetime, and reliable power supply, lithium-ion batteries are preferred for powering EVs. To ensure that these batteries perform optimally, battery management systems (BMS) are used to monitor their operating conditions. [1]. Some critical concerns about BMS include ensuring that the lives of these batteries are maximized and monitoring their state of health (SoH) and state of charge (SoC).

SoC is a core parameter in BMSs and can be defined as the ratio of the remaining battery capacity to the battery's full capacity [2]. The SoC's accuracy is critical to preventing overcharging or overdischarging the battery. Deep learning (DL) algorithms have shown better robustness in providing accurate estimates when compared to classical model-based methods. One widely used DL algorithm is the LSTM model, which is known to be adept at modeling temporal data such as battery data [3].

One challenge with the LSTM model is that, just like other DL algorithms, it is composed of a deep architecture that often requires high computing resources and would eventually fail in a real-time scenario. To combat this issue, cloud computing has been proposed [4]. However, it is preferable to have the computation conducted closer to the source of the data by using edge computing. However, a compute-intensive model like the LSTM model will fail to deliver real-time results at the edge. To overcome these challenges, this paper proposes a lightweight LSTM model for real-time SoC estimation at the edge.

II. System Model of the SoC Estimation on the Edge

A. SOC Estimation

The longevity of a battery is determined by the quantitative measurement of electrical energy stored in battery cells. It is calculated by estimating the ratio of the current charge of battery cells to the nominal capacity when it is fully charged [2]. The SoC of a Lithium-ion battery can be represented as follows:

$$SoC_t = \frac{\int_{t_0}^{t} I_b(\tau)d\tau}{Q_0} \times 100\%, \tag{1}$$

where $I_b(\tau)$, represents the charging current, and $\int_{t_0}^{t} I_b(\tau)d\tau$ depicts the proportional charge yielded into the battery, while Q_0 represents the capacity of the battery at time t measured in hours.

B. Lightweight LSTM

The LSTM [5] is a form of recurrent neural network (RNN) that can be used to solve a variety of sequential data learning challenges. During state transitions, RNN has a problem preserving information from the distant past in current memory. LSTM, on the other hand, has no long-term temporal dependency issues. However, in comparison to other types of neural networks, LSTM is arguably the best network handling sequential sensor data. We propose an optimized lightweight LSTM-based model that is converted from a fully functioning SoC Estimator using Tensorflow Lite.

C. Dataset

The dataset used to conduct the experiment is the UNIBO Powertools Dataset [6]. This is a massive dataset made up of 27 batteries. It was collected in a laboratory by an Italian Equipment Producer.

D. Architecture

Fig. 1 illustrates the overall structure of the proposed system. The acquired datasets are combined and preprocessed before starting the model training. The model is trained using the LSTM Architecture which consists of 3 LSTM Layers and 2 Dense Layers. After the model is done training, it will be converted into Tensorflow Lite to be able to run on Edge Devices such as Raspberry PI 4. The reason the converted model used an optimized battery dataset is that the edge device struggles to run a huge amount of data.

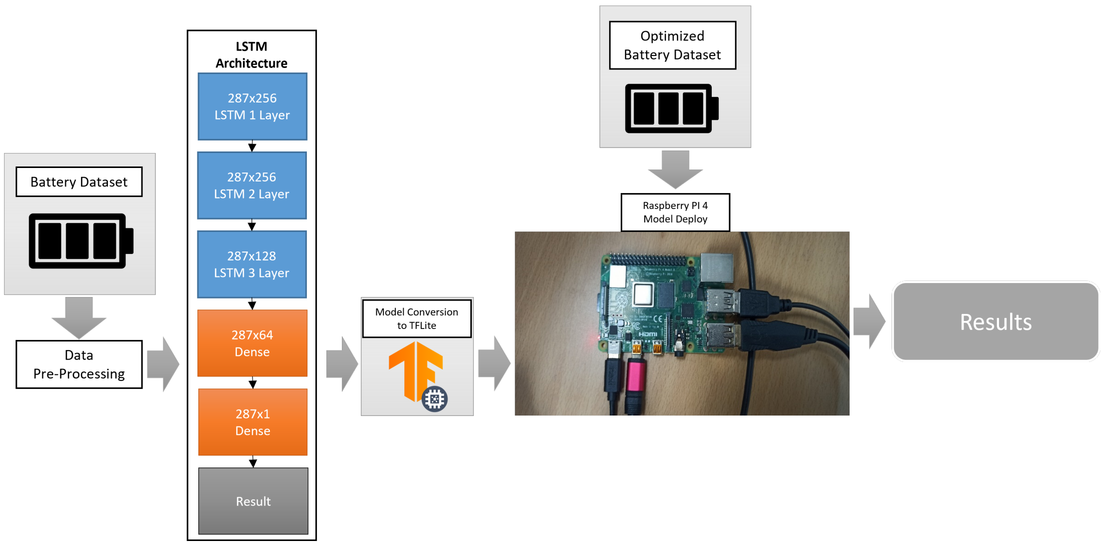

Fig. 1. Flowchart of the Proposed Edge-based Lightweight LSTM Model

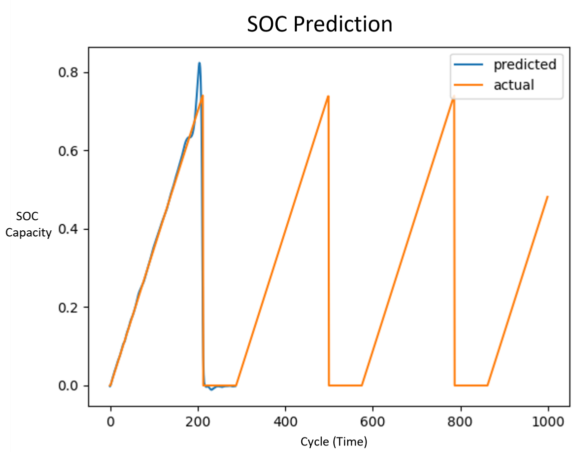

Fig. 2. Edge Device Model Result

III. Result and Performance Evaluation

A. Result

The model is first trained using different types of optimizers. The Root Mean Square Error (RMSE) of the different optimizers is depicted in Table I. The goal of this experiment is to develop a lightweight and optimized architecture for SoC estimation.

TABLE I
RMSE Results of Optimizers

Optimizer	**Adam**	**Nadam**	**RMSProp**	**Adamax**	**Adagrad**	**SGD**	**Adadelta**	**FTRL**
RMSE	**0.1687**	0.1794	0.1880	0.2111	0.4696	0.4811	0.5239	1.2458

The table sorted by least RMSE to the greatest shows that the ADAM optimizer is a preferable choice. The model is then converted to Tensorflow Lite to be deployed on the edge device, which is the Raspberry PI 4. The result of running an optimized dataset on the edge is shown on Fig. 2.

IV. Conclusions

This paper highlights the deployment of lightweight models on edge devices, to offer unique advantages while choosing a model with efficient computation requirements for SoC modeling of Li-ion batteries. Additionally, the experimental analysis investigates different LSTM optimizers for optimal performance of which the ADAMs RMSE result is selected.

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