

Applying Machine Learning Technologies to Predictions for Lithium-ion Batteries

Abstract

- Battery cells/pack are widely used in Electric Vehicles and Hybrid Electric Vehicles (HEVs), portable power tools and x-ray machines [1].
- Predicting or estimating battery attributes such as remaining useful life (RUL) and cell temperatures are vital concepts in a battery management system.
- RUL is the number of battery cycles from its rated capacity to the end of its life (EOL). $RUL = N_{eol} - N$
- On the other hand, without accurate cell temperature prediction and effective thermal management, batteries can become overheat, cause lethal problems. The overall cycle life of the battery will be shortened.

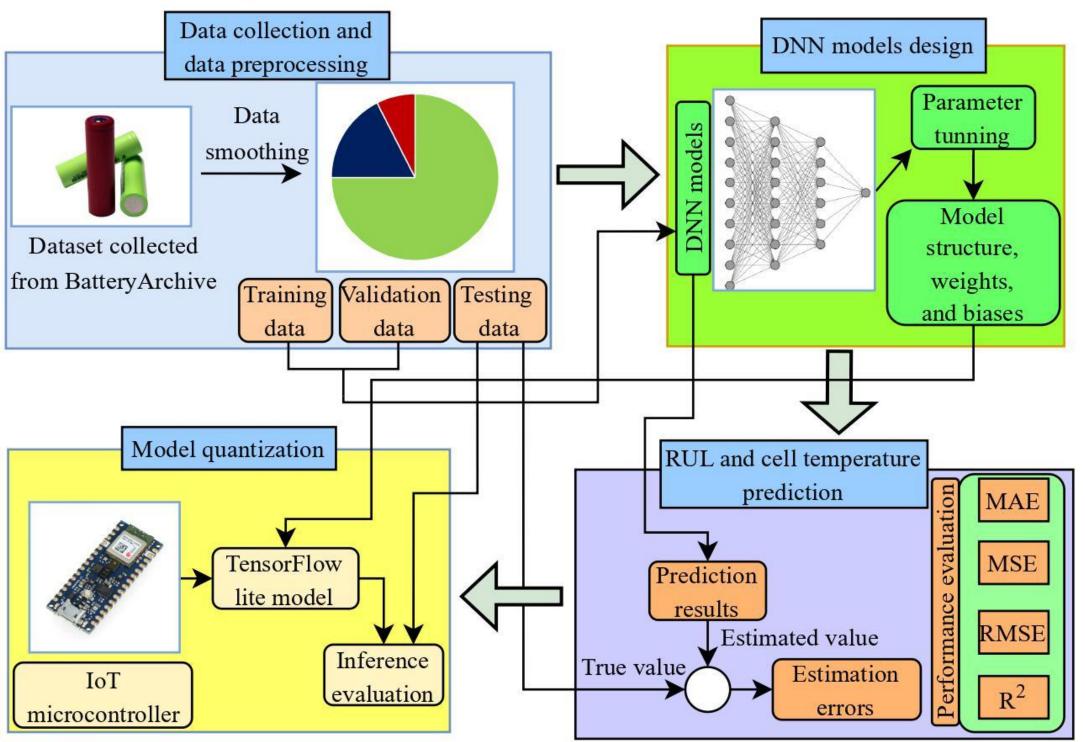
Related Work

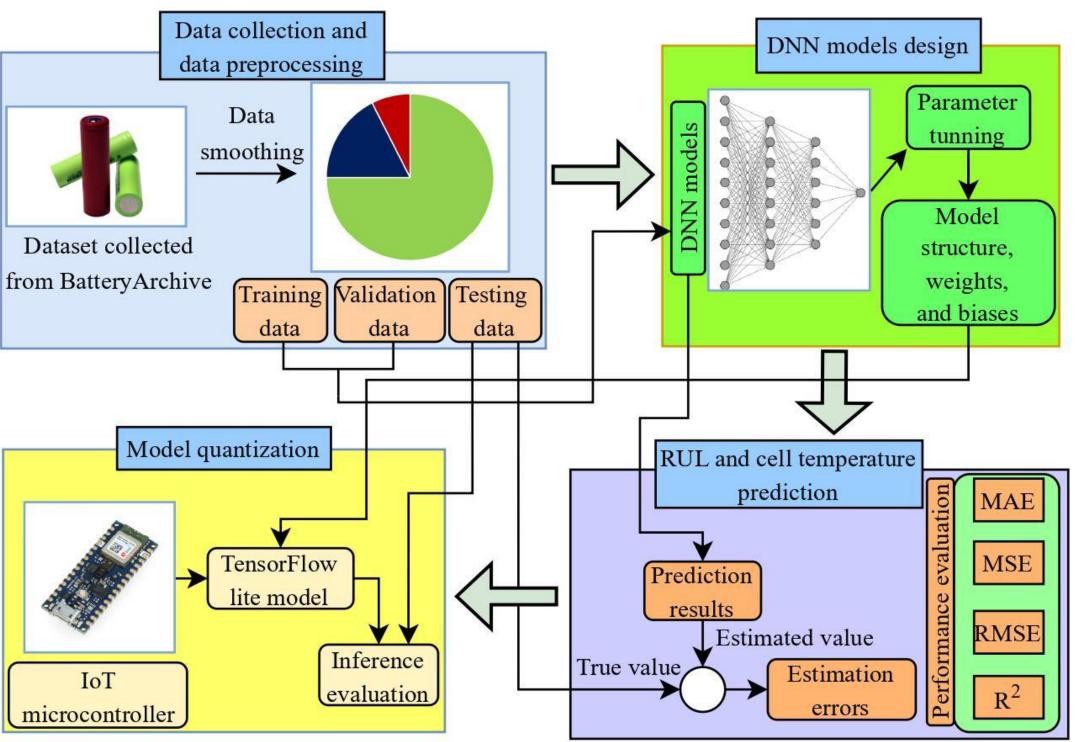
Model-based	Data-driven	Hybrid approaches
By using an algorithm of unscented Kalman filter (AUKF)	Dense Neural Network (DNN), and other machine learning models such as SVM and random forest	Combination of a signal processing and deep learning algorithm

TinyML techniques on Microcontroller Unit

Battery State of Health
(SoH)

Battery State of Charge (SoC)





- degradation.



Real Time Communications Conference and Expo at Illinois Tech IEEE International Conference

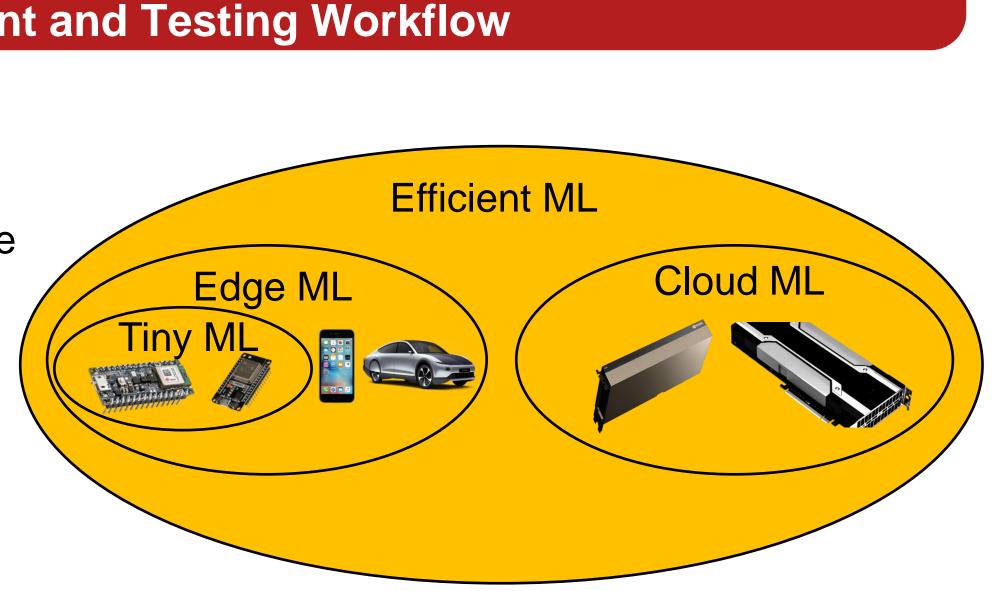
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Model Development and Testing Workflow

• Efficiency is critical for machine learning. • CloudML targets accelerators like GPUs, while EdgeML focuses on portable devices like mobile phones. TinyML further pushes the efficiency boundary, enabling powerful ML models to run on ultra-low-power devices. • TinyML has several key advantages. It enables machine learning using only a few hundred kilobytes of memory.

• There is a growing need for low-power, always-on, on-device AI [2].



Google's TensorFlow Lite (TFL) can convert the developed model into an optimized format that can be easily integrated into C/C++ applications run on the Arduino board and ESP32 board.

• The optimization technique is quantization, which is to convert the model from floating point 32-bit to 8-bit integer precision. And this will help reduce significantly the size of the model.

• The advantage of quantization is the model will be smaller in storage size and memory usage. However, the trade-off is performance

- discharging current.
- and TCN) development.
- different error matrices.
- the connection between the IoT device and the computer.

Convert the

model

1

TensorFlow

Train a

model



We select two types of battery cells: Nickel Manganese Cobalt (NMC) and Nickel Cobalt Aluminum (NCA), and the cycling experiments used different values for temperature range and

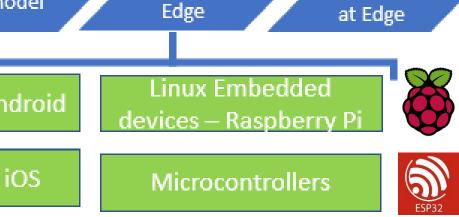
The train and validation portions are used for deep learning models (CNN

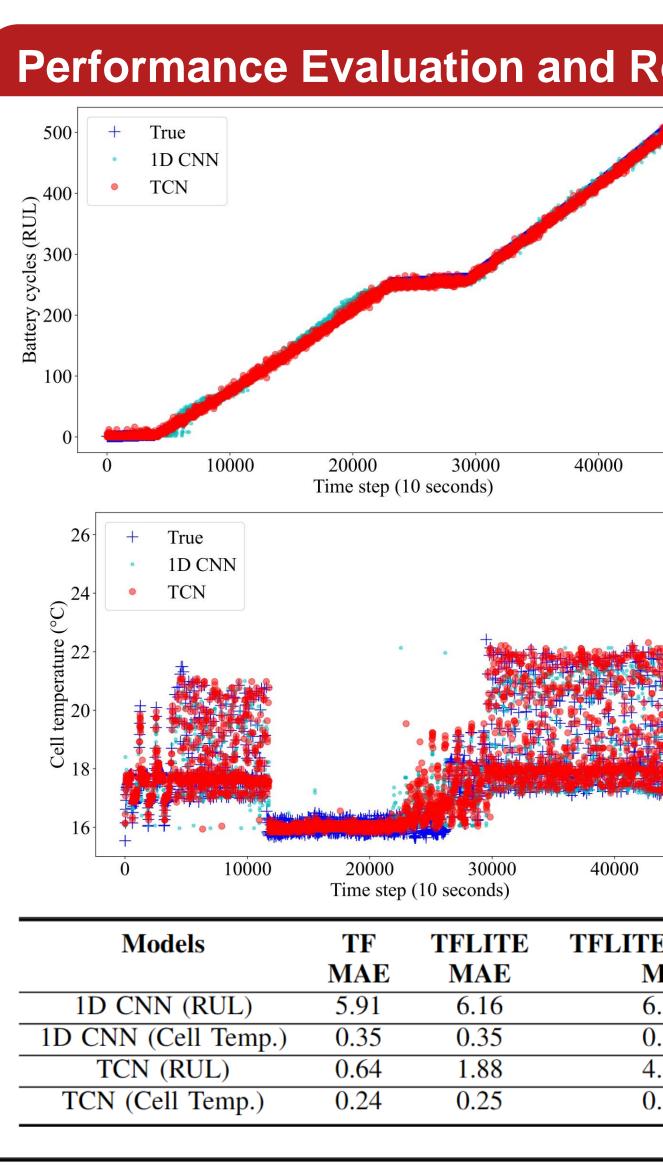
The prediction results are evaluated in

This step is done by simulations in Python and TensorFlow conducted on computers since the models have not been optimized/quantized for deployment to microcontrollers.

• The best-found deep learning model is then deployed on an IoT MCU by using TensorFlow lite and the inferencing results are obtained by URAT serial communication through

FensorFlowLite Deploy the Make Optimize model at inferences the model





MARQUETTE

Models	TF model size (KB)	TFLITE model size (KB)
1D CNN (RUL)	656	26.91
1D CNN (Cell Temp.)	508	13.07
TCN (RUL)	1208	40.59
TCN (Cell Temp.)	1239	57.84

Conclusion and Future Wo

- Deep learning models are investigated predicting battery cell RUL and temper
- The proposed TCN models are deploy device microcontrollers using tinyML a the best performance.
- We plan to develop similar deep mach models to predict multiple variables of further reduce the memory capacity restore and use for inference such mode

Reference

- [1] Y. Weng, W. Guan, and C. Ababei, "Prediction Remaining Useful Life and Cell Temperature for Li-ion Batteries using TinyML," IEEE Inter. MWSCAS, 2024.
- [2] J. Lin, L. Zhu, W. -M. Chen, W. C. Wang, and S. Han, "Tiny Machine Learning: Progress and Futures [Feature]," in IEEE Circuits and Systems Magazine, 2023.

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valua	ation a	and F	Results		
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).64	1.88		4.213 0.256		
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