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ME599 U Final Report

**Hybrid CNN-LSTM for Battery Remaining Useful Life Prediction**

**Abstract (Paragraph or less)**

Portability of energy in the form of electricity is important to modern life, and predicting battery degradation is a critical metric in improving battery life. Previous works have used advanced machine learning techniques,such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to help predict battery degradation. These methods were shown to predict battery degradation moderately.This paper seeks to better prediction accuracy by optimizing and tuning the Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models parameters.

Optimization was done by adjusting the LSTM units and……

Improving battery degradation prediction will reduce trial and error testing of batteries and help sizing of batteries for use cases. It was found that the models could be further accurate changing the LSTM units from 32 to 400 and …..

**Introduction & Background (Two paragraphs or less)**

The ability to accurately predict the remaining useful life (RUL) of lithium-ion batteries (LIBs) is critical to the reliability and efficiency of modern electronic devices and electric vehicles. Li-ion batteries are widely used due to their high energy density, long cycle lif, and relatively low self-discharge rate. However, accurately predicting their RUL remains a major challenge due to the complex and non-linear degradation processes involved. This project focuses on the development of a data-driven Auto-CNN-LSTM prediction model for LIB RUL that integrates advanced machine learning techniques to improve prediction accuracy. Recent advances in machine learning, especially deep learning architectures, have shown promise in dealing with the complexity of LIB degradation predictions. Convolutional neural networks (CNNs) excel at extracting spatial features from data, while long short-term memory (LSTM) networks specialize in capturing temporal dependencies. By combining these two architectures, the Auto-CNN-LSTM model aims to leverage their strengths to provide more accurate and reliable LIB RUL predictions. This approach addresses the limitations of traditional methods by enhancing data representation and capturing complex patterns during degradation.

The motivation for this project stems from the need for reliable and efficient battery management systems, which are critical to the performance and safety of electronic devices and electric vehicles. Accurate RUL predictions allow for better maintenance scheduling, lower operating costs, and prevention of unexpected failures. Our goals include developing an innovative Auto-CNN-LSTM framework, verifying its performance using real battery datasets, and evaluating its effectiveness against existing methods such as ADNN and SVM.

**(Optional) Background (1 Page combined with intro)**

**Methods (1-2 Pages)**

***Table 1 - LSTM Units Range Graphs***

| **[32, 64, 128, 256, 512, 1024]** |  |
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**Results or Demonstration of X Method (1-2 Pages)**

**(Optional) Conclusions (1 page or less)**

**Summary (1 Paragraph)**

**Links to code**

**(Optional) Acknowledgments**

**Bibliography**