Machine Learning Enabled Estimation of Remaining Useful Life for Turbofan Engine using NASA CMAPSS Dataset

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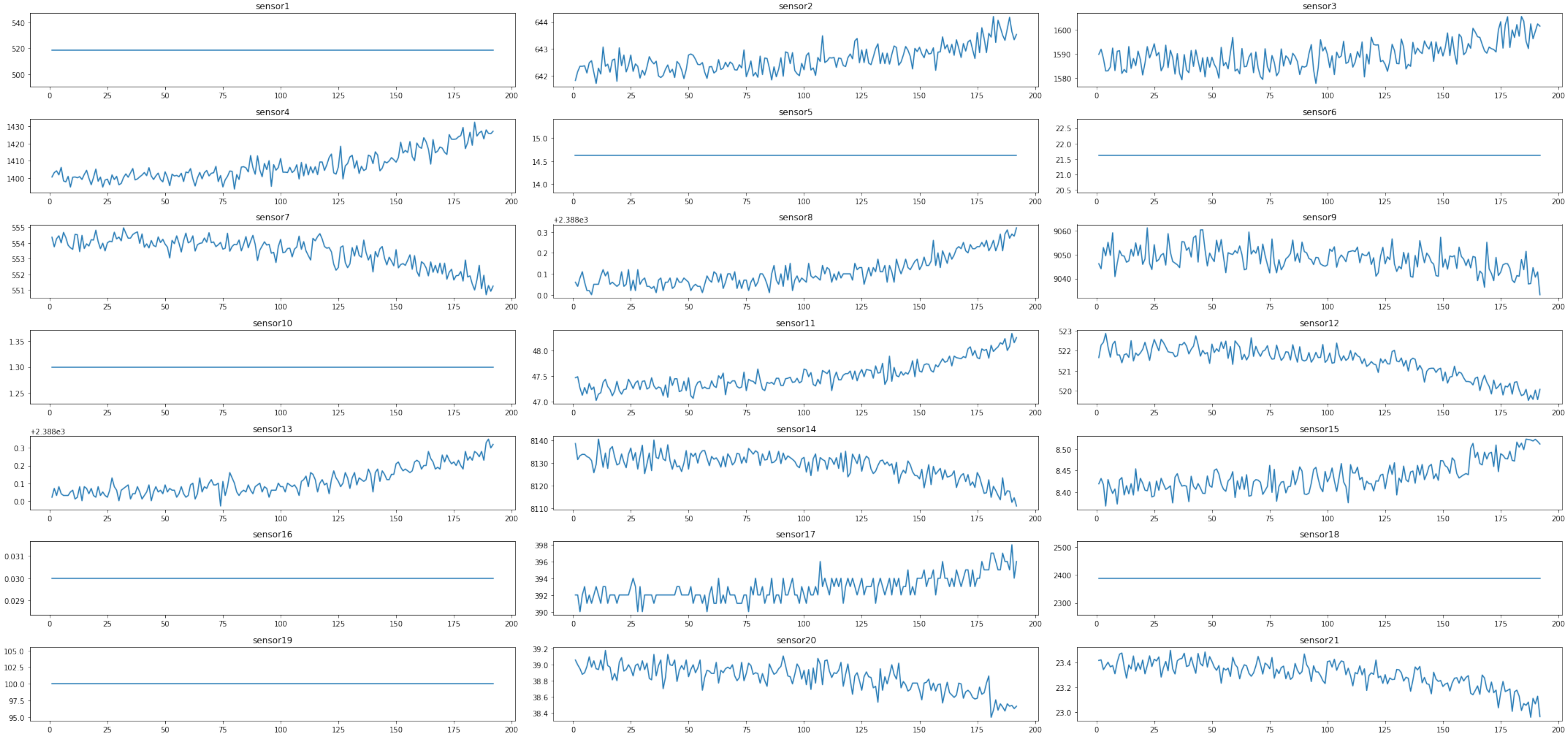
Date: 05/08/2024

Data description

- Engine ID – 1 column
- Time stamp – 1 column
- Operating conditions – 3 columns
- Sensor measurements – 21 columns
- 4 sets of data: FD001-4

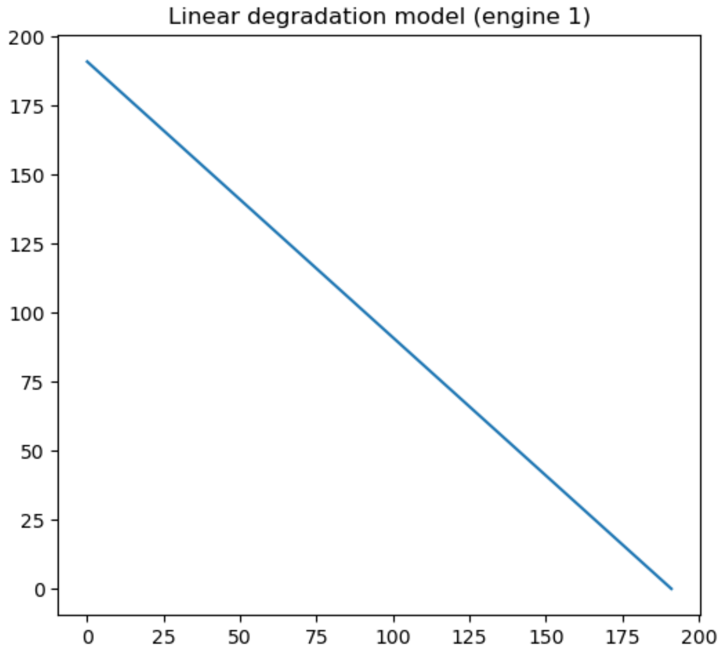
Dataset	Training Data	Testing Data	Operating Conditions	Fault Modes
FD001	100	100	1	1
FD002	260	259	6	1
FD003	100	100	1	2
FD004	248	249	6	2

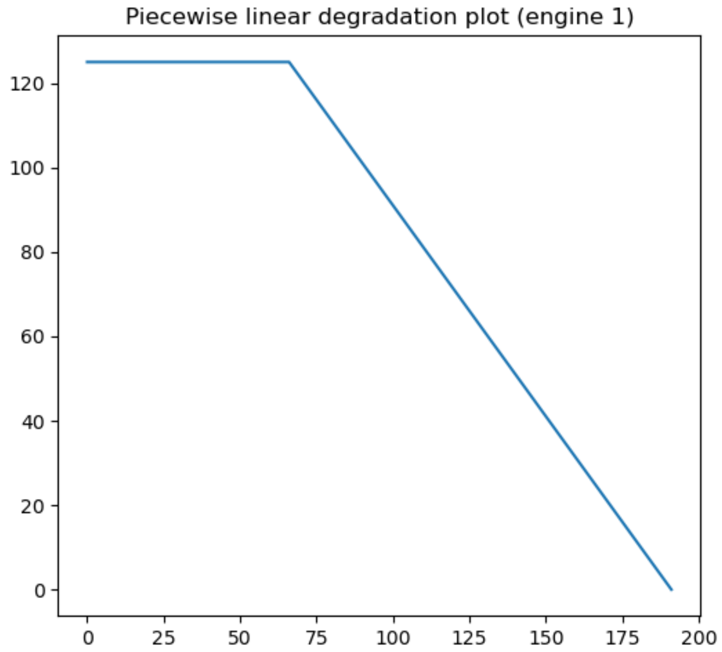
Data description



Data preprocessing

- Only take sensor measurements
- Scale using Min-Max between [-1,1]
- Obtain RUL from number of cycles of each engine
- Apply piecewise linear degradation model to RUL (R_{early} = 130)
- Take windows of the scaled data (30/20/30/15 respectively)





Evaluation metrics

- RMSE

$$RMSE = \sqrt{(\Sigma(y - \hat{y})^2 / n)}$$

- Scoring parameter

$$s = \sum_{\mathrm{i}=1}^{n} \mathrm{s_i}$$

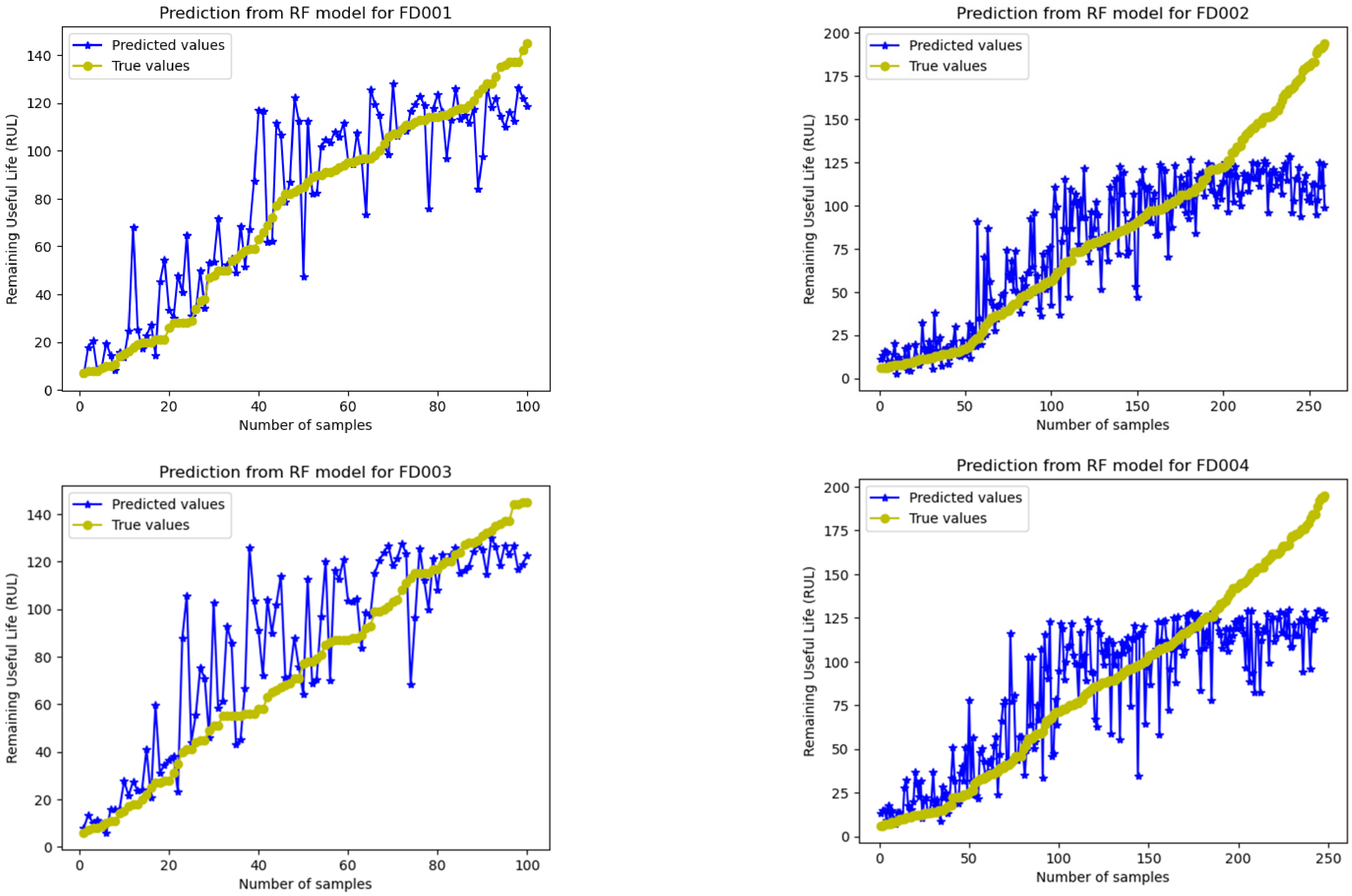
where $s_i = e^{-\frac{d_i}{13}} - 1, if\ d_i < 0$

$$s_i = e^{\frac{d_i}{10}} - 1, if\ d_i \geq 0$$

Random Forest Regression

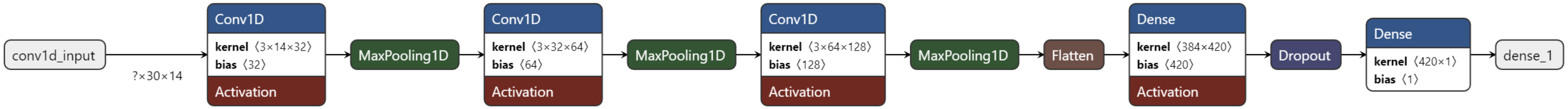
- Baseline model for the project
- Hyperparameter tuning implemented
  - n_estimators: 100, 200, 300, 400, 500, 1000
  - max_features: log2, sqrt
- Scoring: neg_rmse

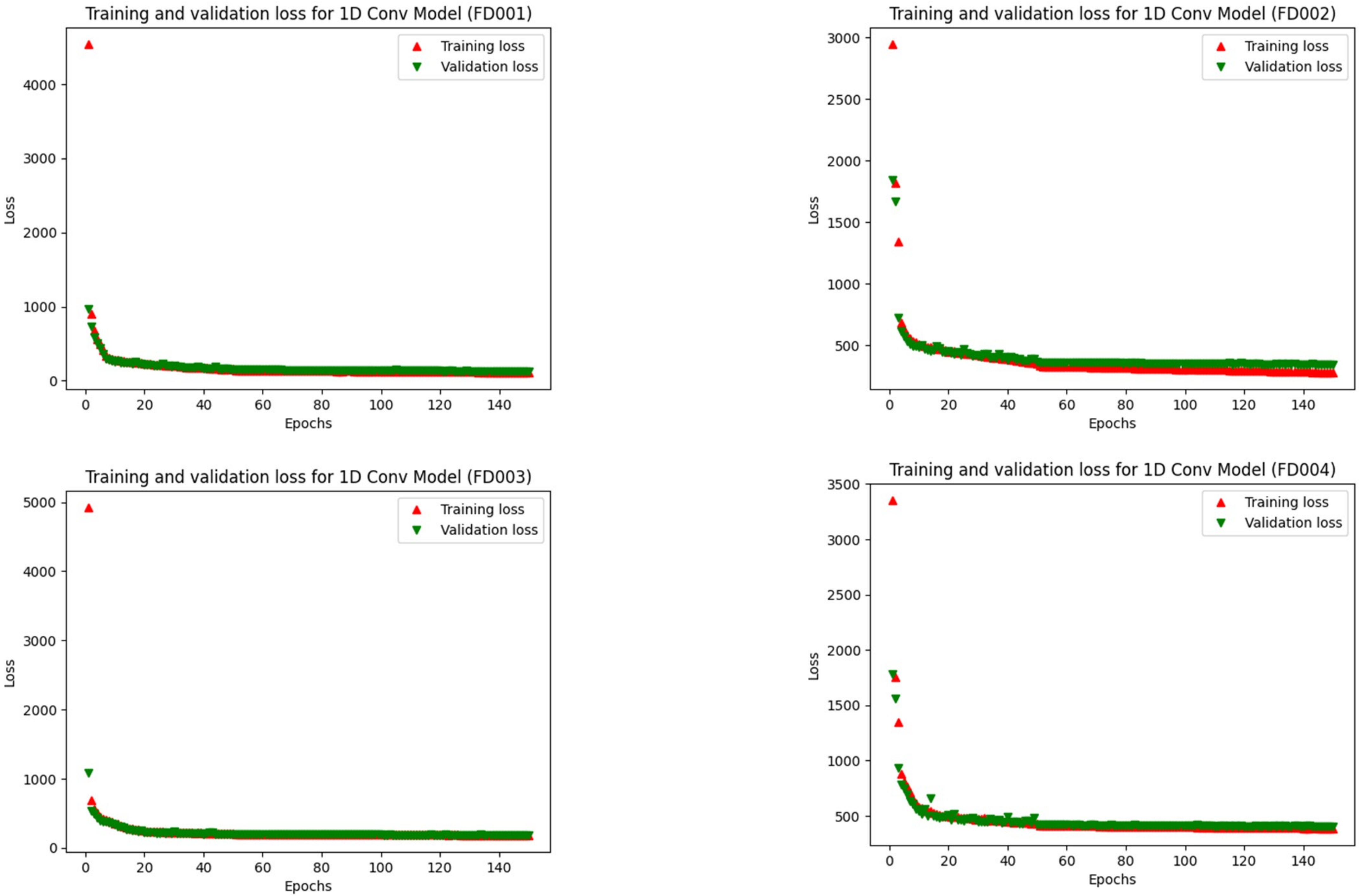
Dataset	RMSE	Score
FD001	18.15	958.09
FD002	28.59	10690.96
FD003	21.63	2833.31
FD004	30.09	8619.93


Prediction from RF model for FD001
Predicted values
True values
Remaining Useful Life (RUL)
Number of samples
Prediction from RF model for FD002
Predicted values
True values
Remaining Useful Life (RUL)
Number of samples
Prediction from RF model for FD003
Predicted values
True values
Remaining Useful Life (RUL)
Number of samples
Prediction from RF model for FD004
Predicted values
True values
Remaining Useful Life (RUL)
Number of samples

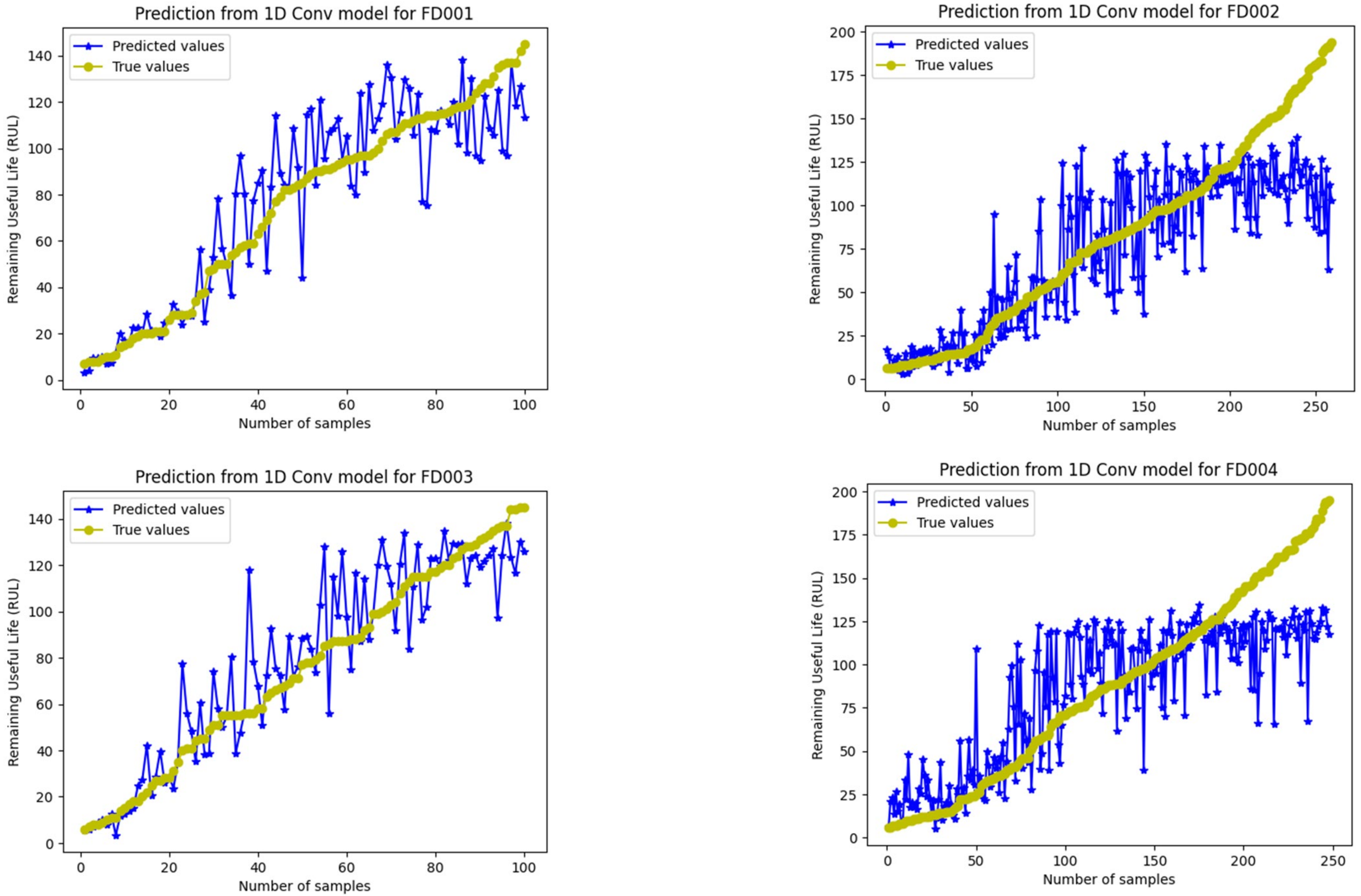
1D Convolutional Neural Network

- 3 convolutional layers with increasing no. of filters (32, 64, 128)
- Adam optimizer and mse loss
- Batch size 512
- Trained for 150 epochs (first 50 at LR 0.001, then at LR 0.0001)





Training and validation loss for 1D Conv Model (FD001)
Training and validation loss for 1D Conv Model (FD002)
Training and validation loss for 1D Conv Model (FD003)
Training and validation loss for 1D Conv Model (FD004)
Training loss
Validation loss
Loss
Epochs



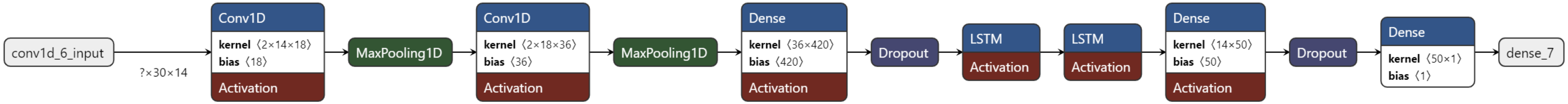
Prediction from 1D Conv model for FD001
Prediction from 1D Conv model for FD002
Prediction from 1D Conv model for FD003
Prediction from 1D Conv model for FD004
Predicted values
True values
Remaining Useful Life (RUL)
Number of samples

1D Convolutional Neural Network

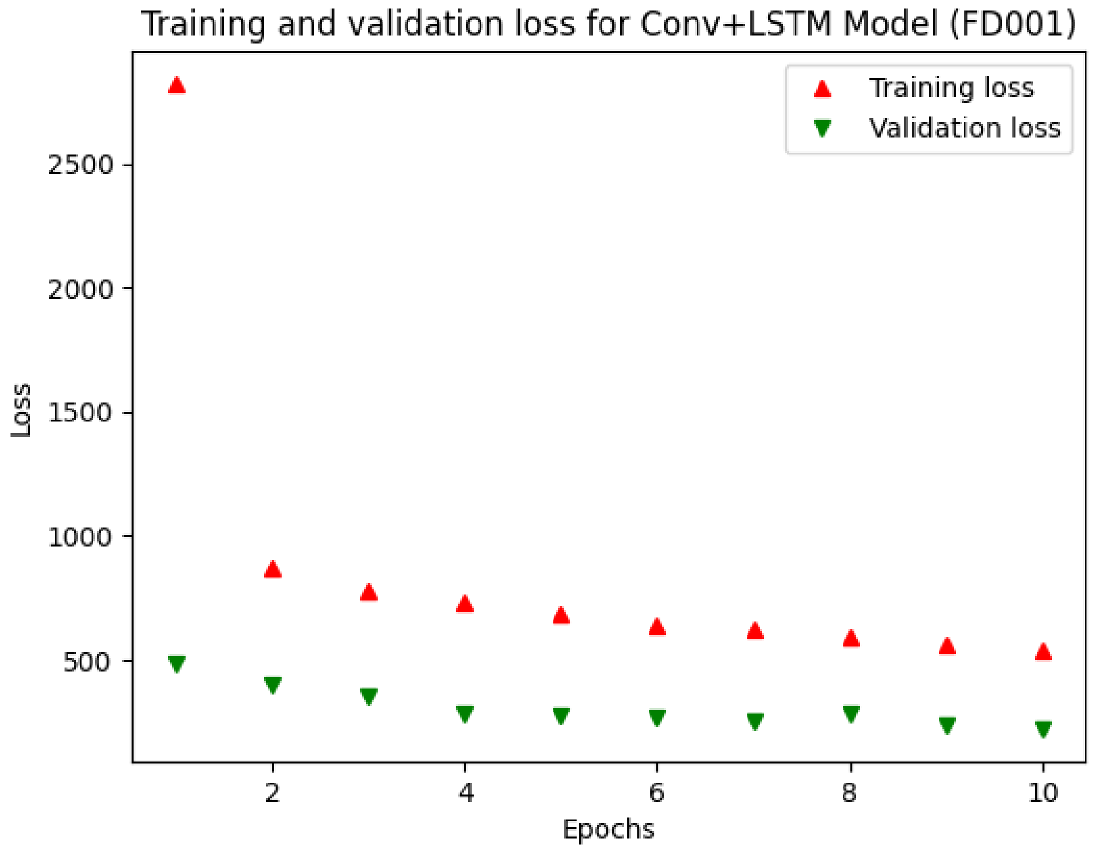
Dataset	RMSE	Score
FD001	17.24	507.05
FD002	29.68	33331.88
FD003	16.26	920.78
FD004	32.72	19835.46

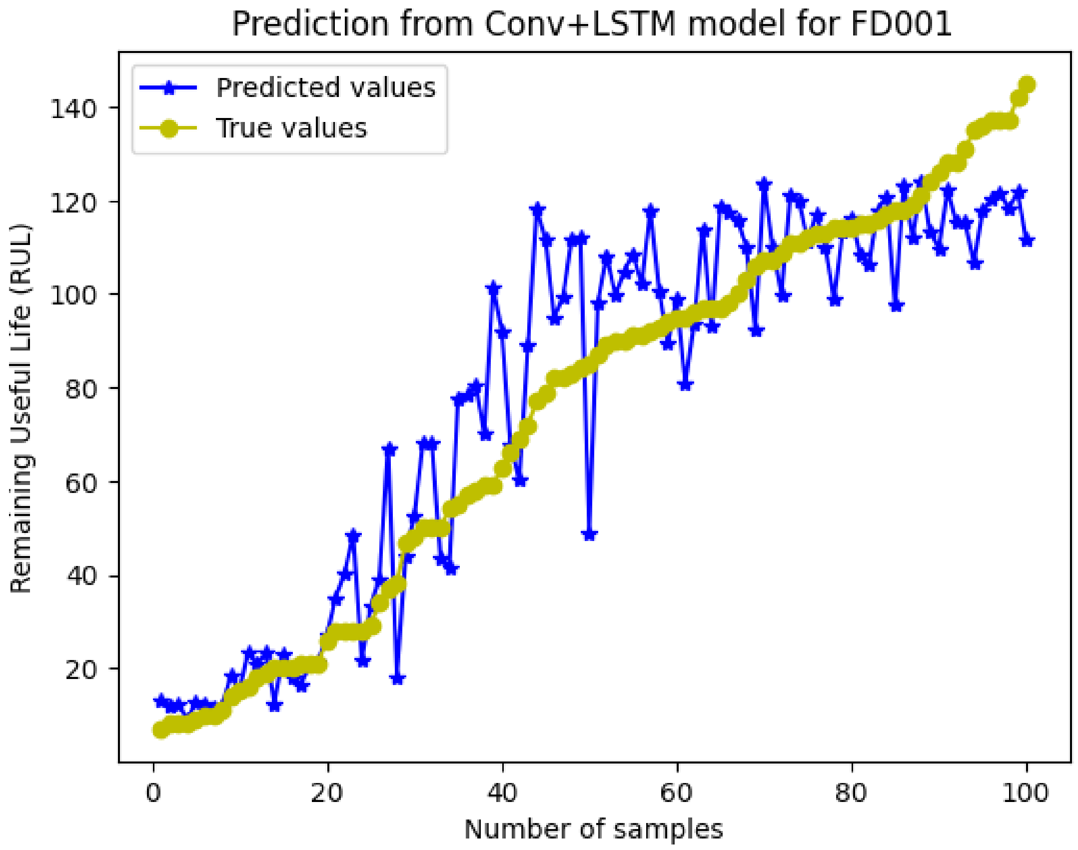
Conv+LSTM Model for FD001 Dataset

- Two 1D-CNN layers (18, 36) followed by two LSTM layers
- Dropout layers implemented to prevent overfitting
- Adam optimizer and mse loss
- Batch size 32
- Trained for 10 epochs



Conv+LSTM Model for FD001 Dataset





Conv+LSTM Model for FD001 Dataset

ML Model	RMSE	Score	No. of parameters
Random Forest	18.15	958.09	-
1D-CNN	17.25	507.05	194409
Conv+LSTM	16.19	440.40	111659

Comparison with reference paper

Dataset	Random Forest	1D-CNN	Conv+LSTM	Literature*
FD001	18.15	17.25	16.19	12.61
FD002	28.59	29.68	-	22.36
FD003	21.63	16.26	-	12.64
FD004	30.09	32.72	-	23.31

*A. Saxena, K. Goebel, D. Simon and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," 2008 International Conference on Prognostics and Health Management, Denver, CO, USA, 2008, pp. 1-9, doi: 10.1109/PHM.2008.4711414.

Conclusion

- Random Forest served as a good baseline model.
  - Temporal features are not captured efficiently.
- 1D-CNN improved on the RF model
  - With fewer parameters compared to existing literature, performance is comparable.
- Conv-LSTM model provided best performance for FD001 model.
  - Fewer parameters and epochs needed compared to 1D-CNN.
- Models provide good predictions where RUL values are low.
- Models can be further improved with hyperparameter tuning.
- Approach can be implemented where resources are limited.

Thank you!