HUMS2025 Data Challenge Result Summary

Team Name: NRC AERO SMPL

Team Members: Nikita Fenev, Catherine Cheung

Institutions: National Research Council of Canada

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1. Summary of Findings

The HUMS2025 Data Challenge focuses on detecting and tracking the progression of a critical crack in the gearbox casing using vibration data from a helicopter's main rotor gearbox test. The process began with the given Hunting Tooth Signal Synchronous Averaging (H-SSA) data [1] which was then standardized, allowing us to generate Pinion-SSA and Bevel-SSA datasets for assessing various condition indicators. These indicators, grounded in the time domain and order analysis, were essential for identifying fault characteristics within the gearbox. A long-short term memory (LSTM) model, specifically designed for anomaly detection, was trained using the initial 10% of the dataset, which is considered to represent the gearbox in its normal operational state. The model's increasing loss highlighted deviations from this baseline, effectively charting the crack's progression through three distinct phases: an initial crack growth phase (Day 5 to Day 10) with the initial detection of the crack on Day 5, a sustained crack growth phase (Day 11 to Day 19), and an accelerated crack growth phase (Day 20 to Day 22) [2]. This data- driven analytic approach, validated across multiple vibration channels, provides early fault detection and tracking, which is vital for improving gearbox reliability and safety.

2. Description of Analysis Methods

Our analysis, whose steps are shown in Figure 1, started with the utilization of the provided Hunting Tooth Signal Synchronous Averaging (H-SSA) data. This data was first standardized using z-scores and then re-sampled to produce the Pinion-SSA and Bevel-SSA datasets [1], with the objective of minimizing noise and amplifying signals associated with potential faults. These refined datasets formed the basis for calculating key condition indicators (CIs) through both time domain and order analysis techniques. These CIs have historically been effective at detecting mechanical faults [3,4], as they spotlight deviations from standard operational behavior. We focused on 9 primary CIs [3,4]:

- Peak Value: Identifies the maximum amplitude in the time domain, useful for detecting extreme deviations.
- Root Mean Square (RMS): Measures the average signal strength, indicating overall vibration energy.
- Crest Factor: The ratio of the peak value to RMS, highlighting impulsive vibrations indicative of faults.
- Kurtosis: Analyzes the sharpness of the signal distribution, sensitive to outliers and peaks.
- Skewness: Assesses the asymmetry of the signal distribution, which can indicate shifts in the signal pattern.

- Figures of Merit (FM0, FM4): FM0 is used for detecting major faults within gear meshes, while FM4 targets faults affecting a limited number of gear teeth.
- M6A and M8A: Indicators that provide sensitivity to surface damage by analyzing higher-order moments of the signal.

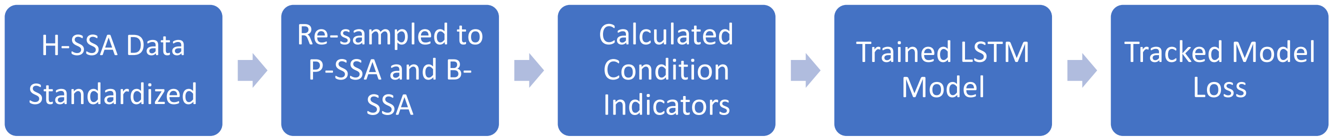

Figure 1: Data Analysis Steps

The set of 9 CIs were calculated for each of the 4 accelerometers, for a total of 36 CIs in each of the datasets (H-SSA, Pinion-SSA, Bevel-SSA). The CIs collectively enable a comprehensive assessment of the gearbox's condition, allowing for the detection of anomalies and the tracking of fault progression.

Following the calculation of the CIs, we implemented a LSTM model for anomaly detection [5]. The model was deliberately designed with a minimalistic architecture, featuring short time steps, a limited number of layers, and fewer epochs. This setup was chosen to increase the model's sensitivity to deviations from the baseline condition, allowing it to effectively capture changes in the dataset. The model was trained on the first 10% of the data, which is assumed to represent the gearbox in a normal operational state. The model looks at 36 features made up of CIs from the 4 vibration sensors on the gearbox. Based on the CI values from current and previous time steps, the model predicts the next values of all the CIs for the next time step. This training enabled the model to predict future condition indicator values as long as they remained similar to these initial conditions.

The loss output by the LSTM model is defined as the average of the mean squared error between the predicted CI values and the actual CI values. The median value of the loss is plotted in Figure *2* for each of the 3 datasets (H-SSA, Pinion-SSA, Bevel-SSA). The median is calculated using the individual loss values from each SSA file recorded on a given day. This method provides a clearer view of the general trend of the loss over the entire test period by minimizing fluctuations in the loss and impact of outliers. As the data began to deviate from the baseline condition of the gearbox system, the model struggled to adapt to these changes due to its intentionally limited complexity. This difficulty was reflected in the rising loss values, corresponding to a deviation from the baseline state, i.e. the formation and growth of a crack. The model's approach is particularly advantageous because it evaluates time steps encompassing all features simultaneously, which provides a comprehensive overview of all sensors and CIs. The median loss of each day is determined and plotted to identify trends in the crack growth, shown in Figure 2. This analysis ensures that any significant departure from the expected pattern, indicative of potential faults, is captured effectively, making it a useful tool for early fault detection and trending in complex systems.

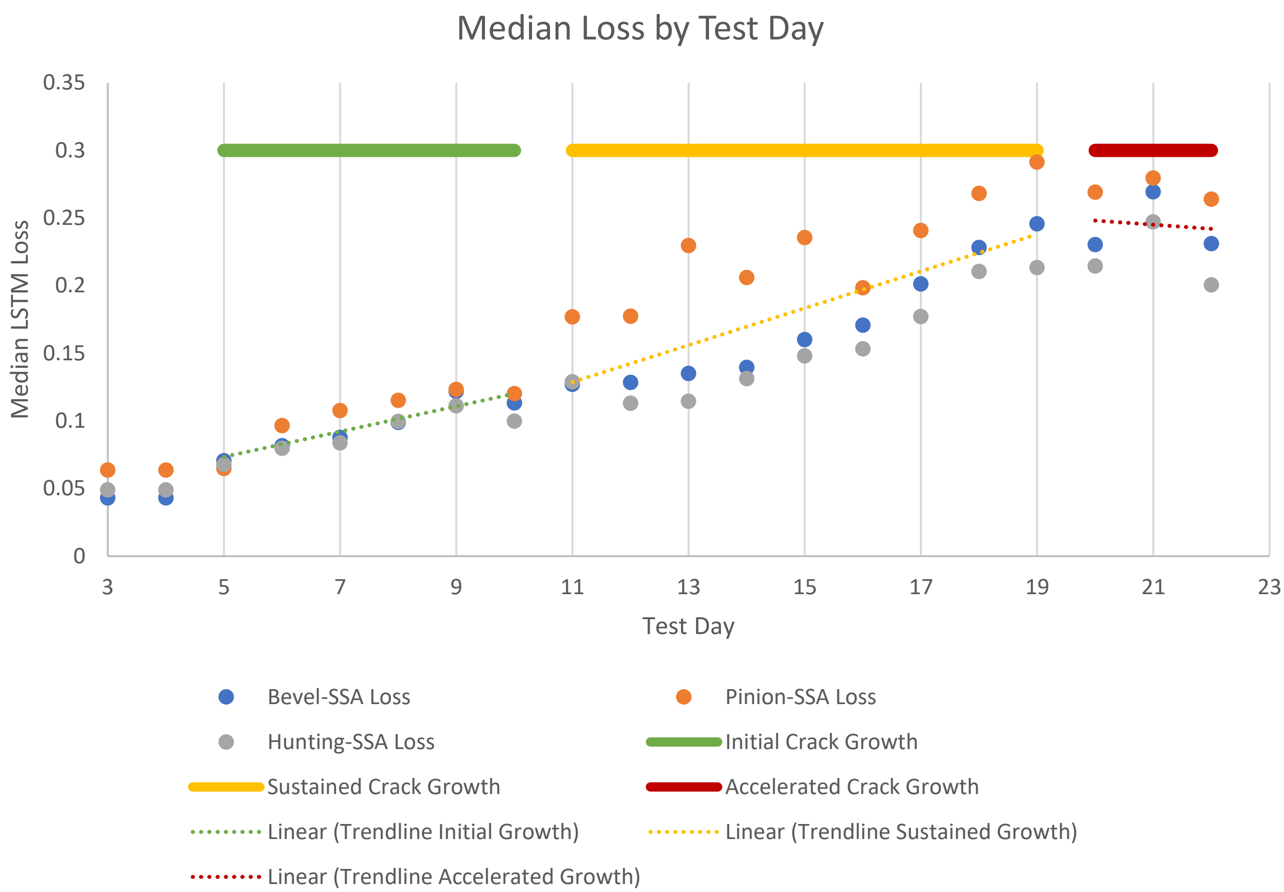

Figure 2: Estimated Crack Growth Trend using LSTM Model Loss

3. Key Fault Characteristics for Early Detection

The gearbox casing crack, a rare and critical fault, was identified through distinct variations in the trend of condition indicators across multiple vibration channels, reflecting its presence on a non-rotating casing structure. The analysis of the LSTM model output revealed variations in the median loss over different sections of time leading to our key fault characteristics.

From Figure 2, initially, the steady, linear increase in the slope of the loss could be an indication of a gradual accumulation of damage in the gearbox casing, where the crack begins to form and slowly propagate. This constant slope suggests that the crack propagation is steady. As the crack advances into the sustained growth region, the slope of the loss becomes steeper, accompanied by significant variation in the data points, particularly in the pinion-SSA loss. This increased variability could suggest intensified mechanical stress and irregular vibration patterns, highlighting a more dynamic and erratic phase of crack progression. In the accelerated crack growth region, a sharp, unexpected change in the slope could point to a rapid escalation in structural damage, indicating that the crack is expanding at a much faster rate. Based on the analysis of the model's loss, the initial detection of the crack is therefore on Day 5, which marks the start of the initial crack growth phase. Day 11 begins the sustained crack growth phase, and Day 20 marks the start of the accelerated crack growth phase. These observations in the loss collectively illustrate how changes in slope and variability could serve as an indicator of different phases of crack growth, providing insight into the structural health of the gearbox casing.

4. Fault Progression Trending Curve

The progression of the gearbox casing crack was monitored by observing changes in the LSTM model's loss over time, which was divided into three distinct phases. Referring again to Figure 2, during the initial crack growth phase, spanning from Day 5 to Day 10, there was a steady increase in loss values indicating a gradual, yet consistent, development of the crack. It is important to note that the loss for Days 3 and 4 is the validation training loss, as this data was utilized for model training of the baseline conditions.

This initial phase was succeeded by variations in the pinion-SSA data, marking the start of the sustained crack growth phase from Day 11 to Day 19. During this period, the loss continued to increase at a faster rate, reflecting the crack propagation as mechanical stress and vibrations become more pronounced.

In the final phase, from Day 20 to Day 22 of the test period, the loss exhibited an unusual decrease in growth rate. This anomaly correlating with severe structural damage and rapid crack expansion, indicated a transition into what we labeled the accelerated crack growth stage. This stage represents a critical point where the integrity of the gearbox casing was severely compromised, resulting in the end of the gearbox testing.

These phases are illustrated in Figure 2. The visual representation of these model trends distinguishes different stages of crack growth, providing an overall view of the fault's progression. The fault detection trend is attributed to the comprehensive analysis performed by the model, which integrates data from all four sensors and evaluates all condition indicators simultaneously. This approach ensures that any changes in model loss are due to substantial shifts in a majority of features, rather than isolated incidents. This approach demonstrates the capability of data-driven analytics and LSTM models to potentially detect early faults and provide insight on the dynamics of crack propagation through a gearbox system.

5. Supplementary Information

References:

[1] Sawalhi, N.; Wang, W.; Blunt, D. (2025) "The HUMS2025 Data Challenge Dataset." Melbourne: Defence Science and Technology Group (DST Group), 2025.

[2] Sawalhi, N.; Wang, W.; Blunt, D. (2024) "Helicopter Planet Gear Rim Crack Diagnosis and Trending Using Cepstrum Editing Enhanced with Deconvolution." Sensors 2024, 24, 2593. https://doi.org/10.3390/s24082593.

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[5] Neptune AI. (2023) "Anomaly Detection in Time Series: A Comprehensive Guide." Neptune AI Blog. Available online: https://neptune.ai/blog/anomaly-detection-in-time-series.