Enhancing smart monitoring in milling with automated deep transfer and continual learning

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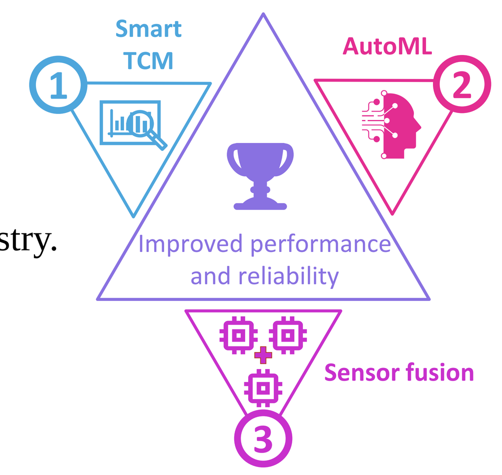
INTRODUCTION

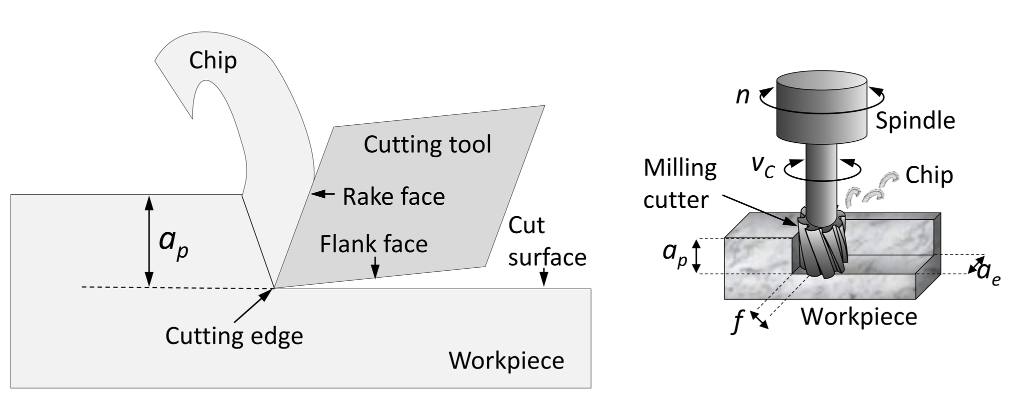
- Smart tool condition monitoring (TCM) in machining:
  - Optimisation of tool performance and prevention of tool failure.
- Focus on tool wear.
- Limitations related to:
  - Data availability.
  - Machine learning (ML) and deep learning (DL) models.
  - Gap between research and industry.
- Automated machine learning (AutoML) pipeline:
  - Automated search of optimal architectures.
  - Synthetic augmented data.
  - Transfer and continual learning.
- Sensor fusion.



BACKGROUND & LITERATURE REVIEW

Machining

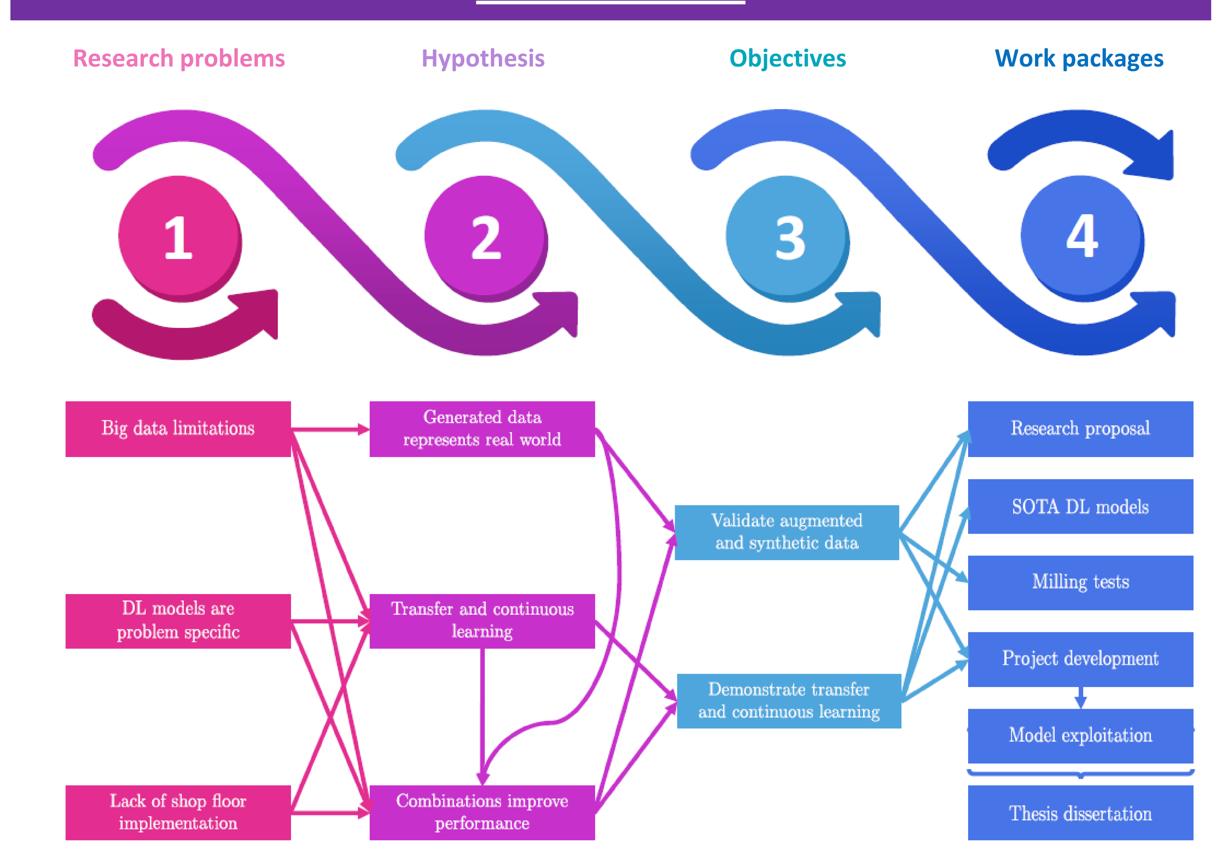
- Material removal by cutting



Literature review – Gaps identified

- Lack of big data:
  - Varying cutting conditions and materials.
  - Unlabelled or unavailable.
- DL models trained with milling data:
  - Problem specific and lack of DOE.
  - Lack of systematic analysis of suitable scientific variables.
- DL models rarely implemented:
  - Machining shop floors and testbeds.

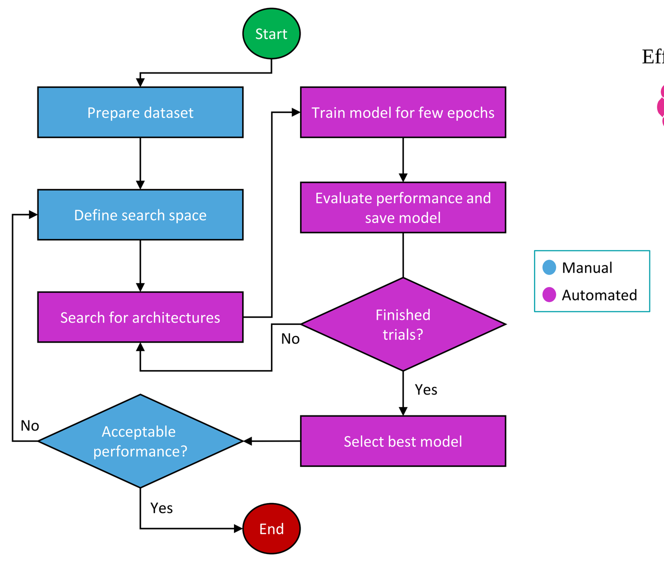
OBJECTIVES

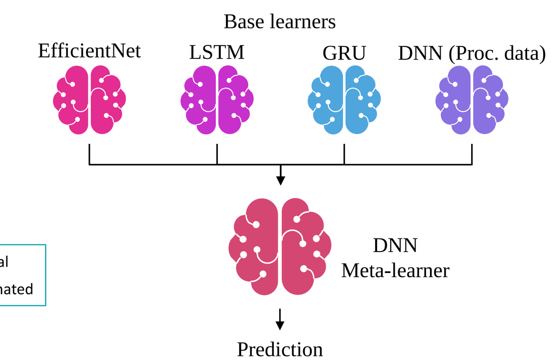


METHODOLOGY

1. AutoML meta learner

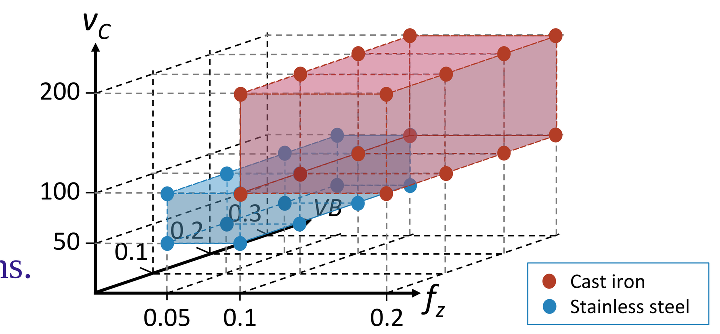
- Search for optimal architectures and hyperparameters.
- NASA Ames/UC Berkeley milling dataset [1].
- Library: AutoKeras

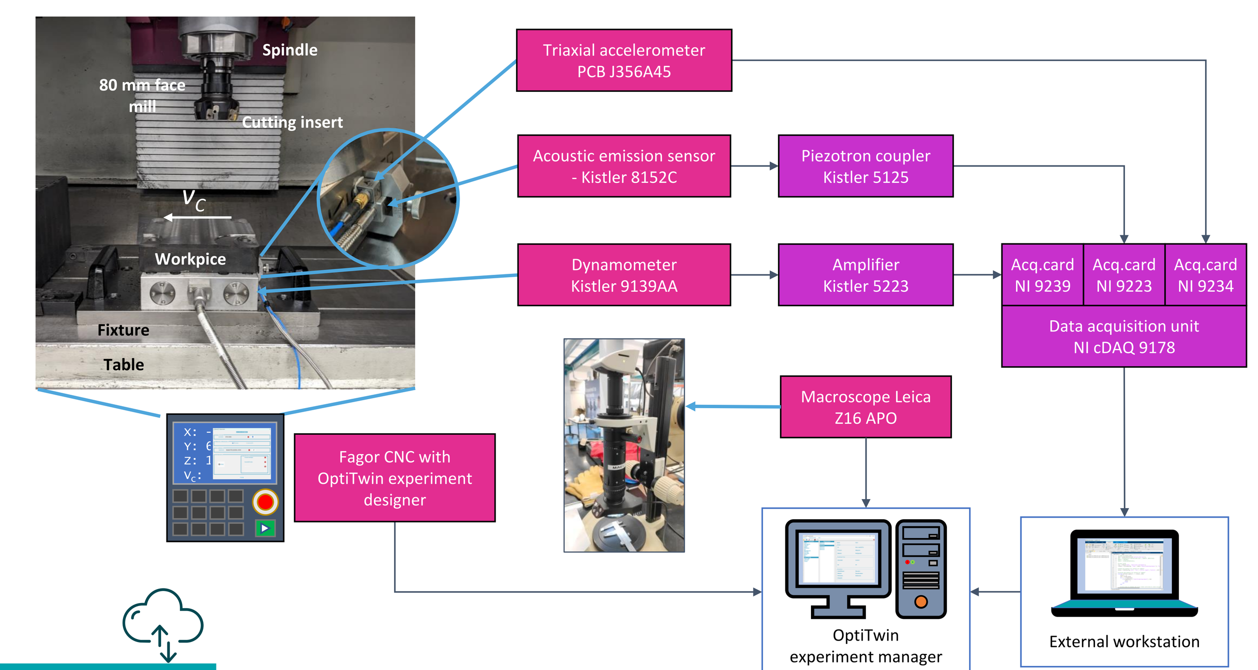




2. Face-milling experiments

- 80 mm face-milling tool holder with 1 cutting insert.
- DOE:
  Full factorial (2^3 x 4) x 2 repetitions.





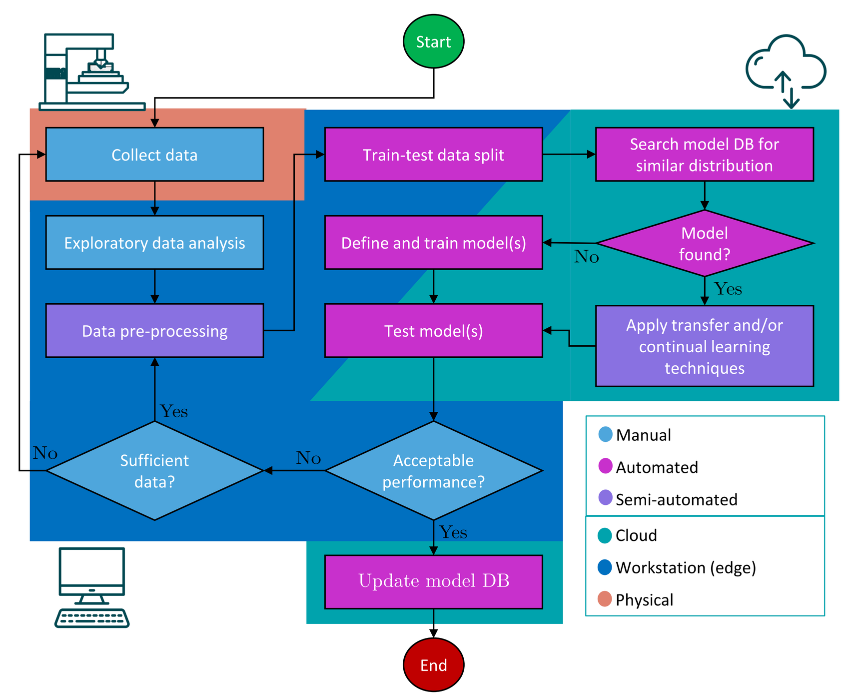
3. Transfer and continual learning

Transfer learning:

- Extrapolate model knowledge:
  - Model-based transfer (task adaptation).
  - Feature-based transfer (domain adaptation).
- Library: Transfer-Learning-Library

Continual learning:

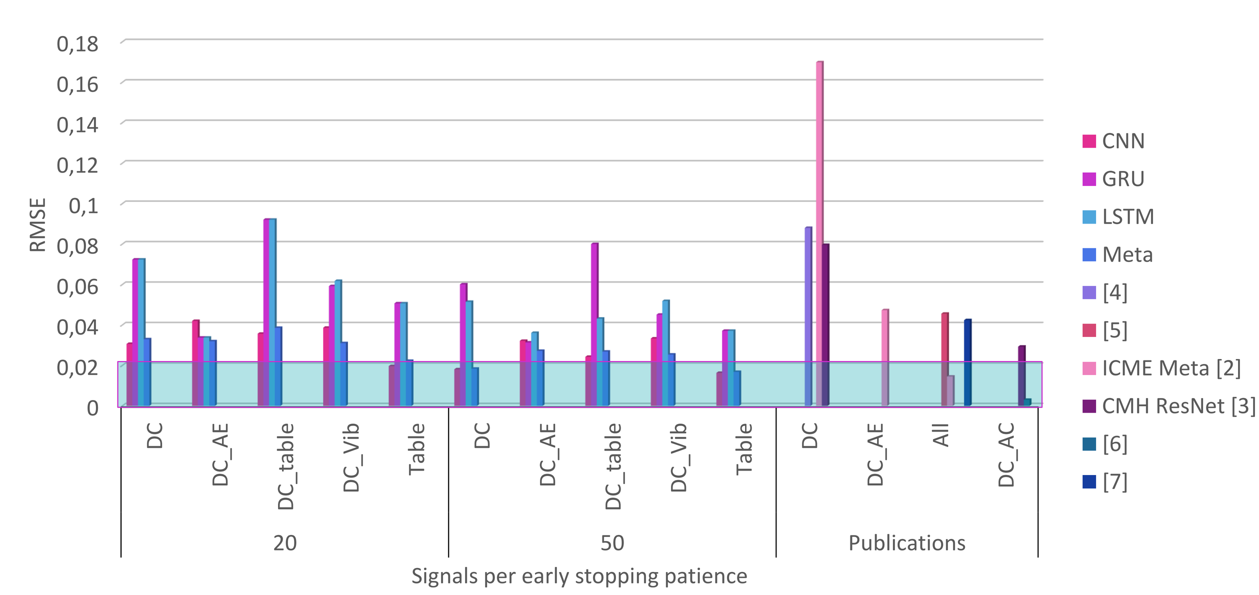
- Update model with new data:
  - Model retraining.
  - Model fine tuning.
- Library: Avalanche



RESULTS THUS FAR

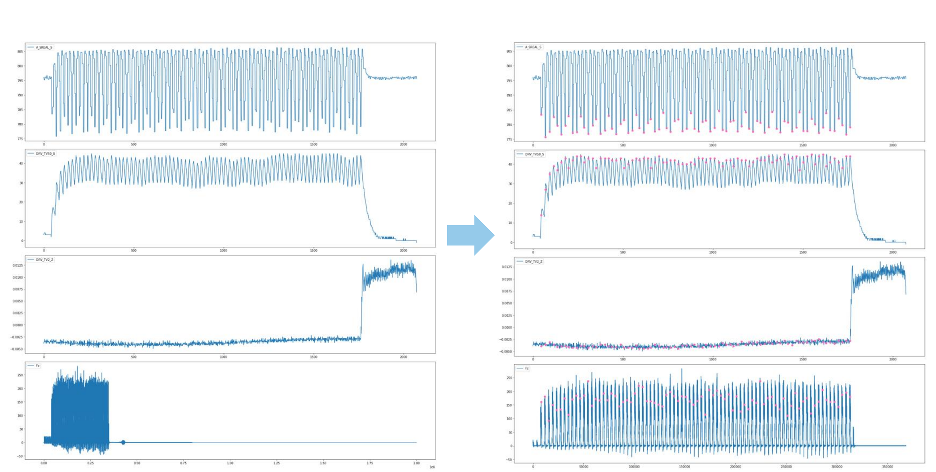
DL models trained with NASA Ames/UC Berkeley milling dataset [1]

- AutoML used to improve meta-learning DL model.



Face-milling experiments performed.

- 67 cuts performed – 22.3 GB.
- External signal could not be synchronized with CNC → Manually synchronized.
- Sampling frequency seems to be higher than programmed (under revision).



CONCLUSIONS

- DL models with high performance were found with AutoML.
- Dataset is almost ready for training models.
  - Sampling frequency validation.
  - Exploratory data analysis pending.
- Future work:
  - Finish validating and exploring signals.
  - Define transfer and continual learning strategies.
  - Apply strategies to all models using our dataset.
  - Validate and evaluate best performing strategies.

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