Australian e-Health Research Centre

Developing Robust Clinical Text Deep Learning Models – a "Painless" Approach

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Background

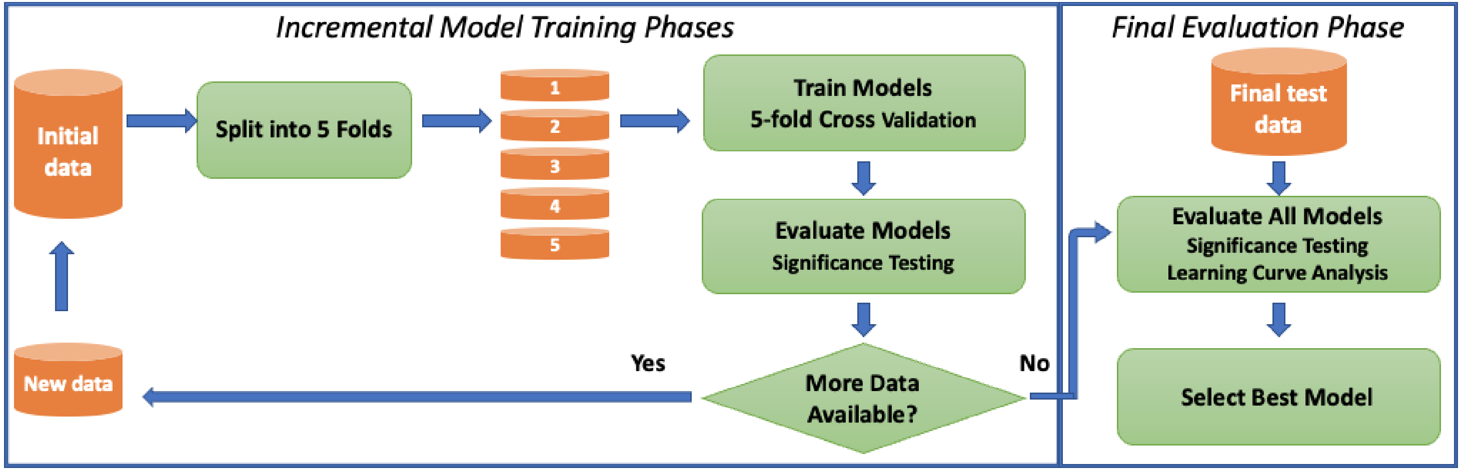
- Deep learning relies on large-scale labeled training data
- Labelling clinical data is costly and labour-intensive, requiring highly trained annotators
- Data scarcity hinders deep learning in health/clinical applications

Objectives

- Develop robust clinical text deep learning models with limited labeled data
- Determine sufficient dataset sizes for training-validation-testing
- Understand trade-offs between model performance and resource cost (training set size, learning time, model size)

Methods

A ***generalised incremental multiphase methodological framework*** was used to develop and robustly assess clinical text classifiers.



Methods

Learning curve analysis was conducted on diverse deep learning model architectures to:

- Generalize findings
- Identify performance-resource trade-offs
    - Due to varying parameters, computational costs, and domain specificities

Data description – *Pain dataset*

- 10,000 randomly selected records
  - routinely-collected clinical information from adult patients at an Australian hospital ED between March 2018 and February 2021
- Two free-text data fields, completed by ED nurses when patient arrives
  - “presenting problem” and “nurse assessment”
- Annotated as “Pain” or “No Pain” by two ED nurses. Third nurse for adjudication if disagreement.
  - 5520 as “Pain”: patient presented with signs or symptoms of pain
  - 4480 as “No-Pain”
  - 957 records required adjudication

Problem formulation

- A **binary text classification** problem
  - Use concatenated triage nurse assessment (two free-text fields) to predict the pain outcome ("Pain" or "No-Pain")
- Research ethics was obtained from the Human Research Ethics Committee of the Royal Brisbane and Women's Hospital (LNR/2021/QRBW/72976) and the Queensland University of Technology (109147)

Deep learning models

Popular text classification models ranging from simple to complex deep learning architectures (including transformers).

- Fine-tuned ***BERT*** and ***Distilled-BERT***: large pretrained general domain Transformers[1] and its distilled version[2] with reduced parameter space
- Fine-tuned *domain-specific* ***BlueBERT*** and ***Distilled-BlueBERT***: large biomedical domain variant of BERT[3] and its distilled version with reduced parameter space
- ***AttRNN-BERT*** and ***AttRNN-BlueBERT***: attention-based RNN models utilizing BERT/BlueBERT as word embeddings with RNN layer[4, 5]

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Results

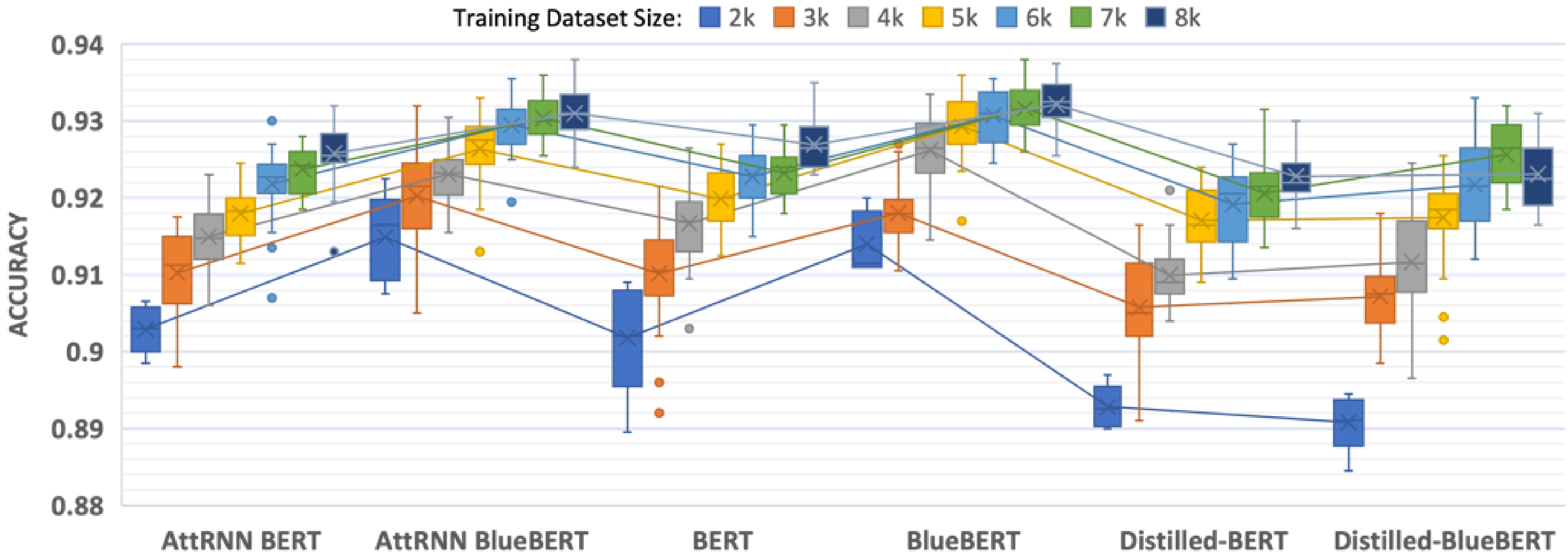

Figure 2. Learning curves of deep learning models evaluated on the final evaluation dataset.

Results

- Health domain-specific pre-trained models showed superior classification performances compared to general language models (p-value < 0.05)
- Distilled models, although not as competitive as uncompressed versions (p-value < 0.05), offer utility in low-resource settings by achieving good performance with much smaller parameter sets

Conclusions

- Incremental multiphase framework effectively generates learning curves to capture performance trends and variability across models and dataset sizes
- Significance testing quantifies robustness and identifies ‘optimal’ dataset sizes
- Results confirm importance of domain-specific pre-training and distilled models in low-resource settings
- Framework is flexible, can adapt to different learning methods that require less supervision and can continuously update the models with new labeled data.

References

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Thank you

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