MEDINFO23

8 – 12 JULY 2023 | SYDNEY, AUSTRALIA

Harnessing Artificial Intelligence to Improve Patient Safety

Prof Farah Magrabi
Macquarie University

Dr Ying Wang
Macquarie University

Dr Yang Gong
University of Texas Health Science Centre at Houston

Dr Zoie Wong
St. Luke's International University

Allan Fong
MedStar Health National Center for Human Factors in Healthcare

AIDH IMIA

Using AI to Identify Patient Safety Incidents by Type and Severity

@yingwang_chi

Dr Ying Wang

Research Fellow

Centre for health informatics

Macquarie University

The problem and the current solutions

MACQUARIE University
AUSTRALIAN INSTITUTE OF HEALTH INNOVATION

Patient safety incident report		
ID Date Time Incident type ? Severity assessment code ?	*Episode label X for patient X was placed incorrectly onto the specimen that belongs to patient Y*	
contributing factors	actions taken	patient outcome
incident minimization factors	results of review	steps for prevention

SAC Matrix

		CONSEQUENCE				
		Serious	Major	Moderate	Minor	Minimum
LIKELIHOOD	Frequent	1	1	2	3	3
	Likely	1	1	2	3	4
	Possible	1	2	2	3	4
	Unlikely	1	2	3	4	4
	Rare	2	3	3	4	4

Every incident assessed against the Severity Assessment Code Matrix should be scored separately for both their actual and potential consequence or outcome

NSW HEALTH

By applying supervised ML methods based on NLP and text mining, we can:

1. Identify **10 primary patient safety incident types**;

2. Classify **four levels of risk** associated with incidents, Severity Assessment Code (SAC) categories

(i/ extreme; ii/ high; iii/ medium; iv/ low);

The proposed AI algorithms

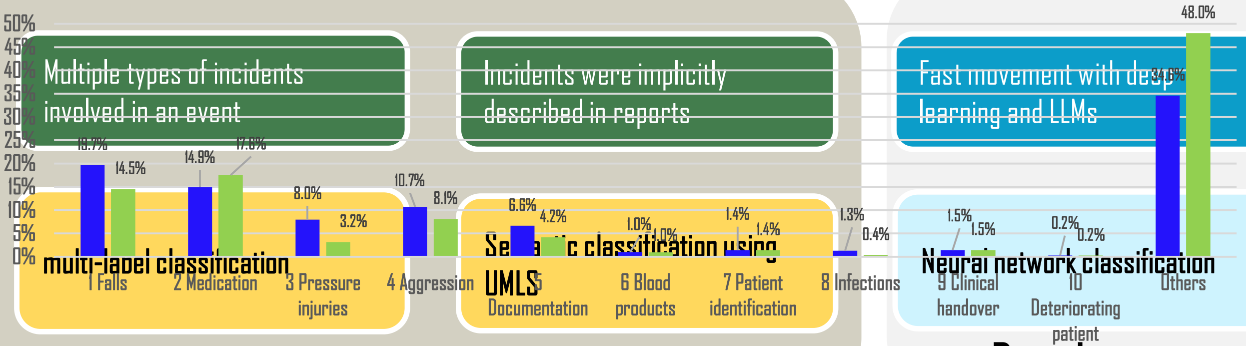
MACQUARIE University
AUSTRALIAN INSTITUTE OF HEALTH INNOVATION

Challenges

- Unbalanced datasets with limited labels
- Multiple types of incidents involved in an event
- Incidents were implicitly described in reports
- Fast movement with deep learning and LLMs

Solutions

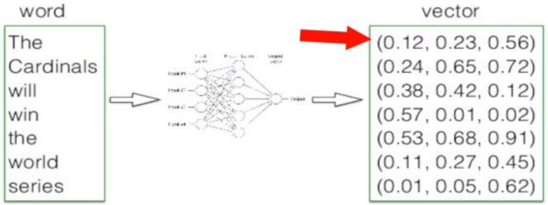
- Stratified classifiers; Multi-class classification
- Multi-label classification
- Semantic classification using UMLS
- Neural network classification

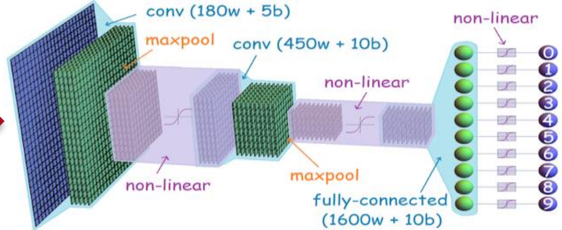


Classic Machine learning

Deep learning

Data processing → Feature engineering → Model training /validation → Model testing





NSW GOVERNMENT | CLINICAL EXCELLENCE COMMISSION

riskman

Looking Back, Looking Ahead

AUSTRALIAN INSTITUTE
OF HEALTH INNOVATION

Automating the Identification of Safety Events Involving Machine Learning-Enabled Medical Devices

Health data science and AI

@11AM, Monday, 10 July

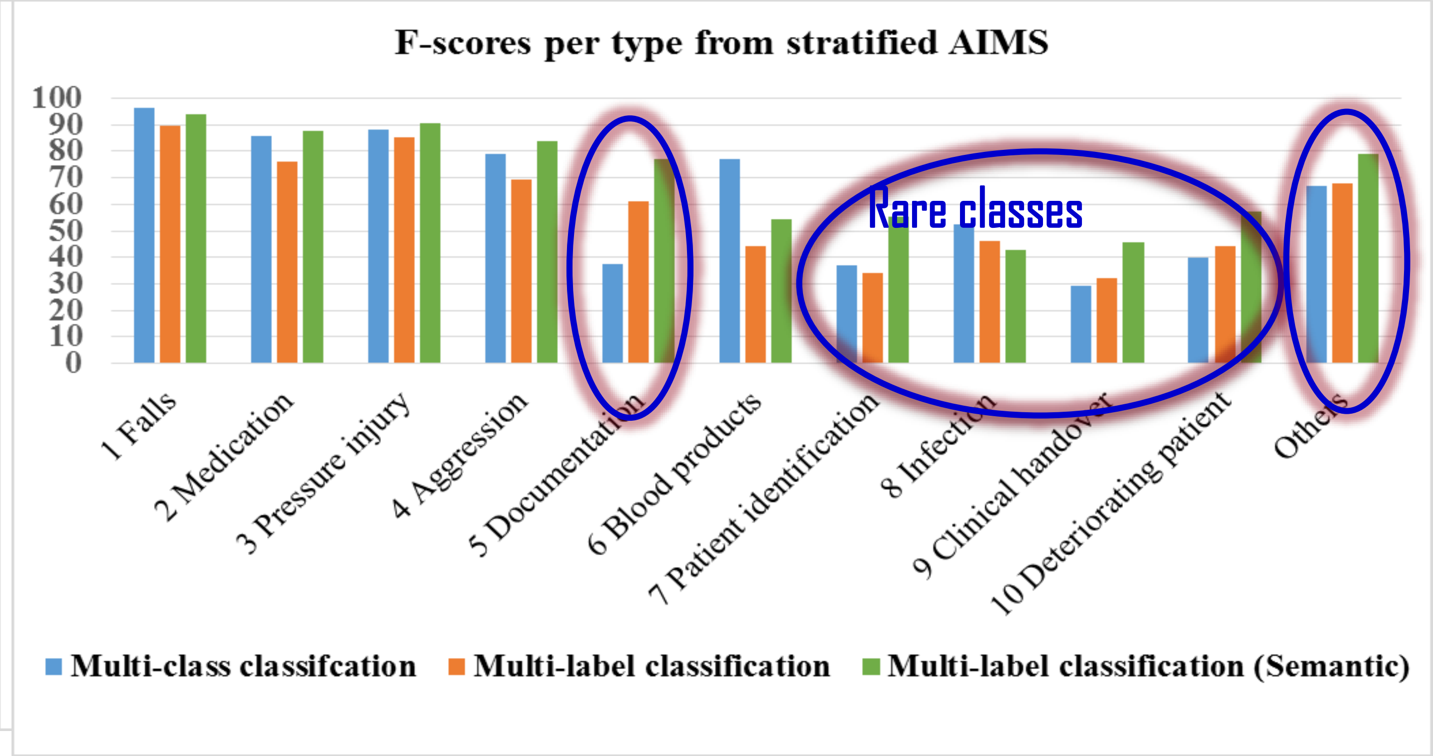
Looking ahead:

1. Evaluate the transportability of AI algorithms across various safety event reporting systems.
2. Ensure safe implementation and use of AI algorithms in real world settings.

Algorithms evaluation across datasets and reporting systems

MACQUARIE University
AUSTRALIAN INSTITUTE OF HEALTH INNOVATION

- Classic machine learning methods

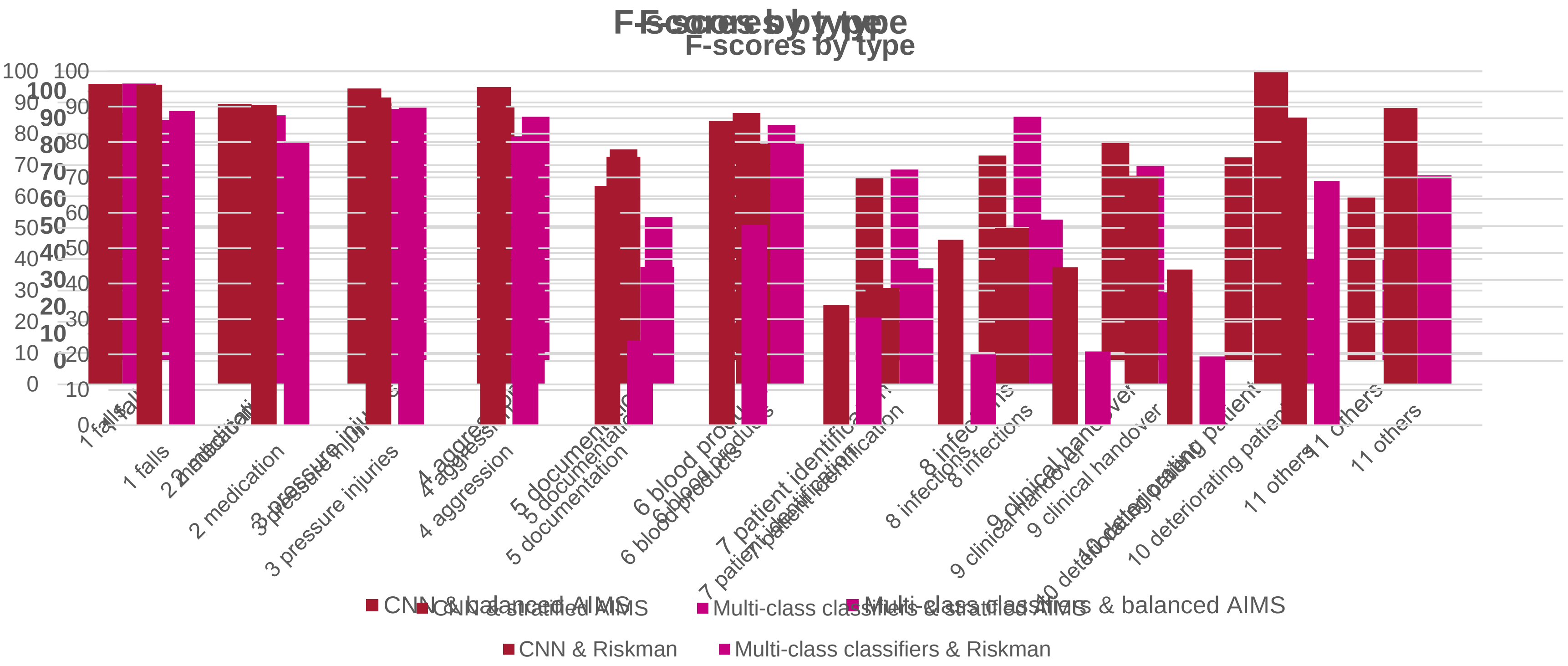


Algorithms evaluation

Deep learning vs Classic machine learning

MACQUARIE University

AUSTRALIAN INSTITUTE OF HEALTH INNOVATION



Leveraging FDA MAUDE Database To Identify Health IT Incidents

UTHealth Houston
McWilliams School of Biomedical Informatics

@gngyng

Yang Gong

MD, PhD, FIAHSI

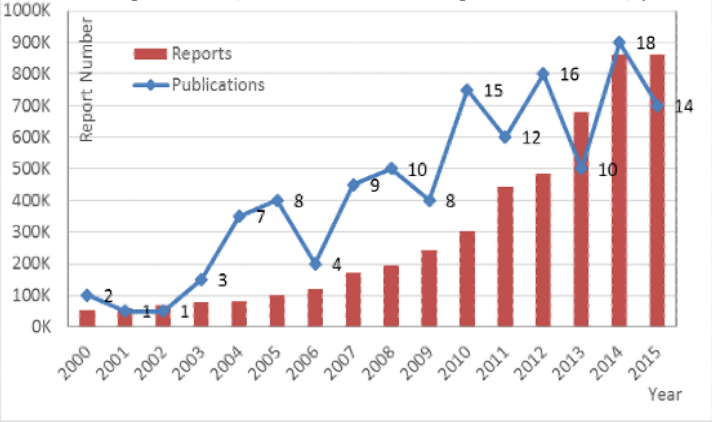
UThealth Houston

Learning from Health IT Events

"THE ELECTRONIC MEDICAL RECORD PROGRAM EPIC FUNCTION OF AUTO-VERIFICATION MISSED THAT AN ORDER FOR PLAVIX WAS ALREADY ORDERED. THERE WERE TWO ORDERS FOR XXXX. THE DOUBLE ORDER WAS CAUGHT WHILE SUPPLYING DRAWER OF DRUGS FOR PATIENT. EVENT DID NOT REACH PATIENT."

- Definition of HIT
  - Use of information and communication technology in healthcare to support the delivery of patient or population care or to support patient self-management.
- Collecting HIT event reports is challenging
  - Health IT errors could happen in any department
    - Medication events are involved with HIT
  - Lacking identification strategy and reporting classifications
- MAUDE
  - ~ 8,000,000 events involving medical devices,
  - ~ containing 0.7% HIT

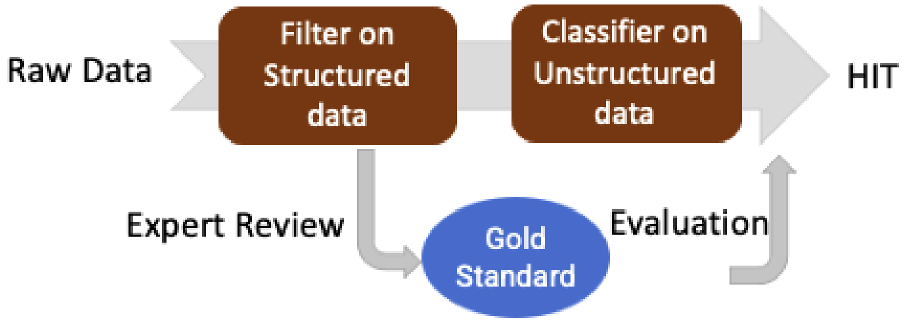
MAUDE reports (bars) and MAUDE-related publications (line) year

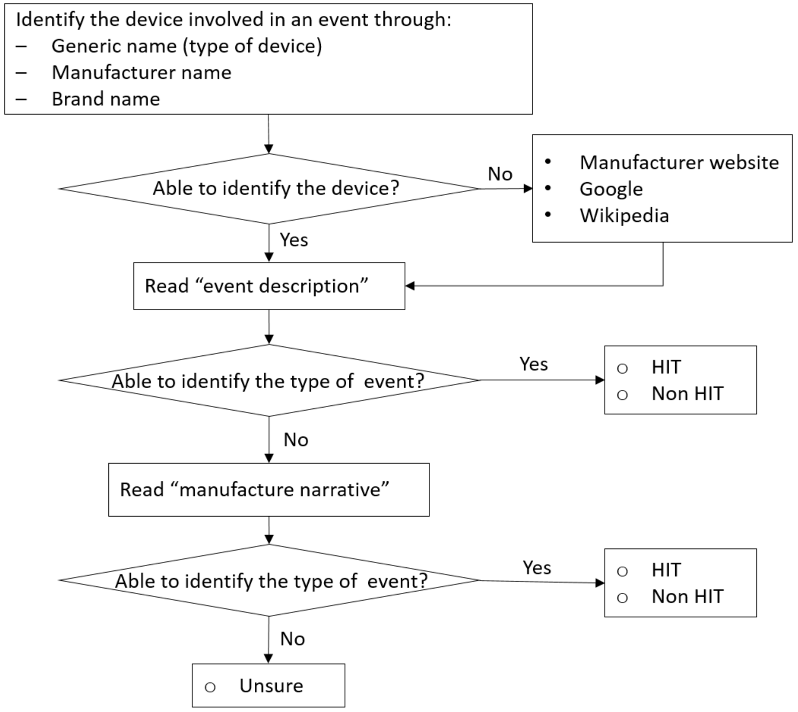


Approaches to identifying HIT events from MAUDE

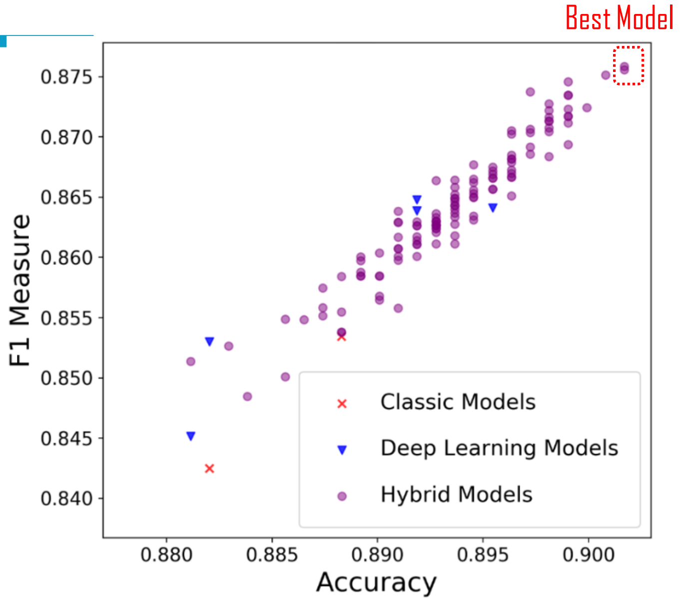
NLP and ML

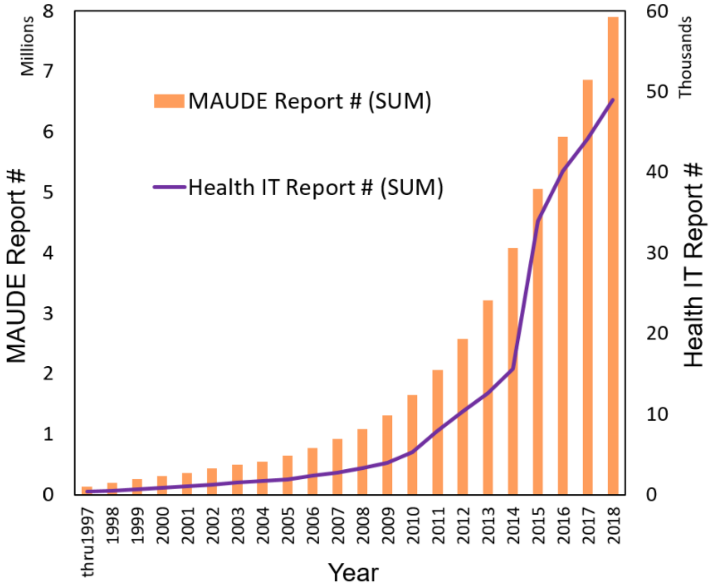
- Classic models (SVM, logistic regression, random forest, Naïve Bayes)
- Deep learning models (CNN, RNN, RNN_att, H_RNN, H_RNN_att)





The First Database (Publicly Available) for Health IT Events

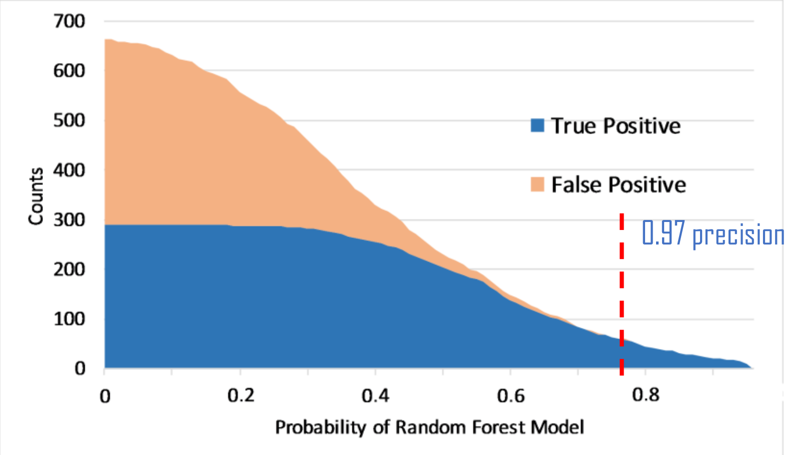




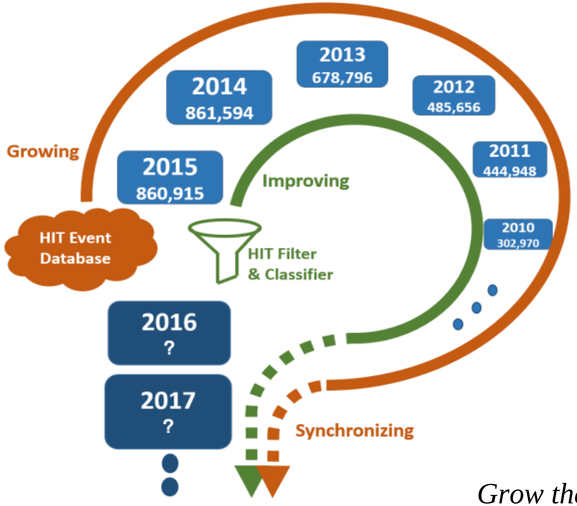
- Best model: Accuracy = **0.903** AUC = **0.954** F_1 = **0.876**
- Established the first database for health IT events **48,997** reports

Raw Data → Filter on Structured data → Classifier on Unstructured data → HIT

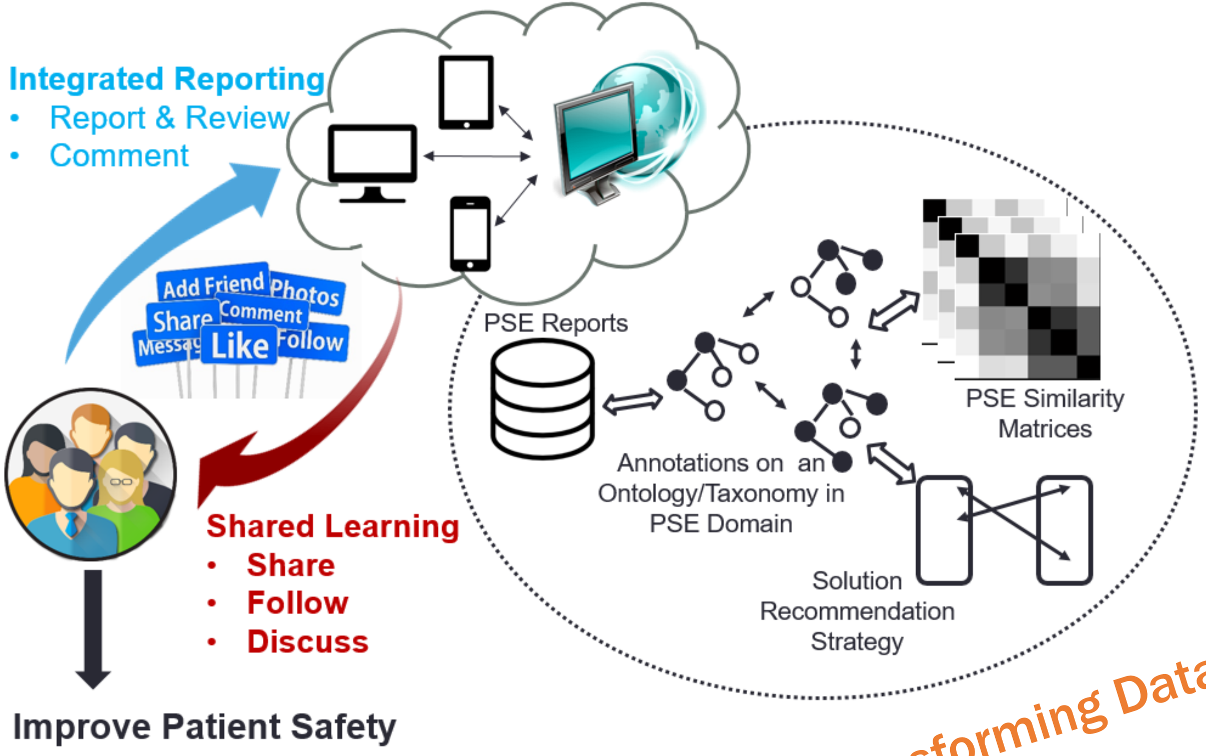
Proportion of HIT events: 0.4~0.9% → 50% → 97%

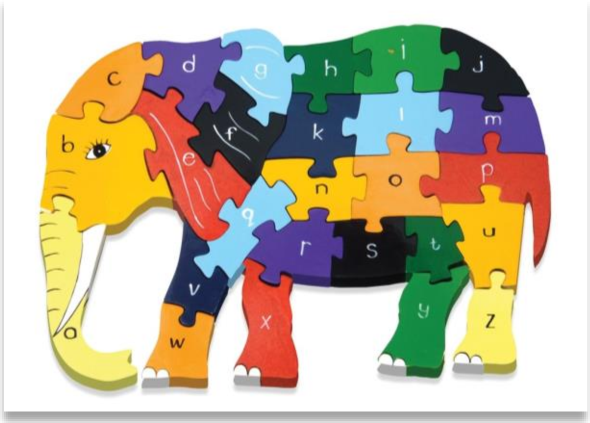


Trade off between precision and recall



Grow the HIT database





Transforming Data to Improve Patient Safety

MEDINFO23
8 – 12 JULY 2023 | SYDNEY, AUSTRALIA

Extracting structured data from incident reports

@zoiesywong

Zoie SY Wong

Associate Professor
St. Luke's International University

https://www.aiforpatientsafety.com/

From narrative incident reports to structured format

- A series of interrelated research studies that aim to develop information retrieval solutions to extract actionable data from incident reports for medication errors
- Medication errors

Custom-Built Ontology:
Medication Errors' Concepts and Rules

→

NLP and AI:
Medication named entities and relation extraction via Deep Learning

→

Digital Tool:
Incident Reporting System's Innovation

Ontology for medication-related incident reports

Medication error concepts (named entities) - NER

- the 'things of interest' within medication related reports / the key units of information that need to be extracted.
- 'drug', 'form', 'strength', 'duration', 'timing', 'frequency', 'date', 'dosage' and 'route.'

Intention and factuality analysis (attributes) - I&F

- Discrepancies between the intended delivery from the upstream operation and what is actually delivered to the downstream operation.

Zhang HK, Sasano R, Takeda K, Wong ZSY, editors. Development of a Medical Incident Report Corpus with Intention and Factuality Annotation. LERC 2020; 2020; Marseille.
Wong, Z. S. Y. Gold Standard/Manual Reviewed Annotated Datasets for Technical Validation. figshare https://doi.org/10.6084/m9.figshare.23504922.v1 (2023).

Intended and actual medication | Intended medication

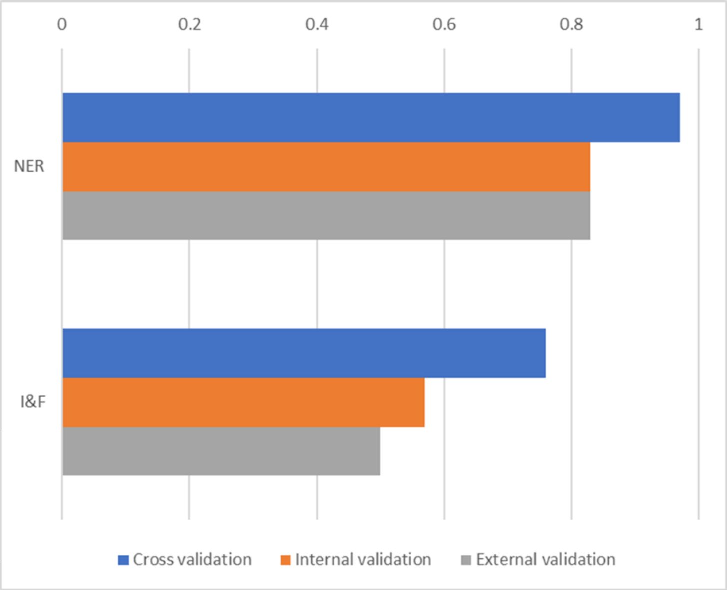
Loxoprofen 1 tablet × 50mg and Rebamipide 2 tablets × 100mg were prescribed, but Sennoside 2 tablets × 12mg was given instead of Rebamipide.

Actual medication | Intended medication

- Drug
- Dosage
- Strength_Amt

AI-empowered concept and relation extraction

GitHub



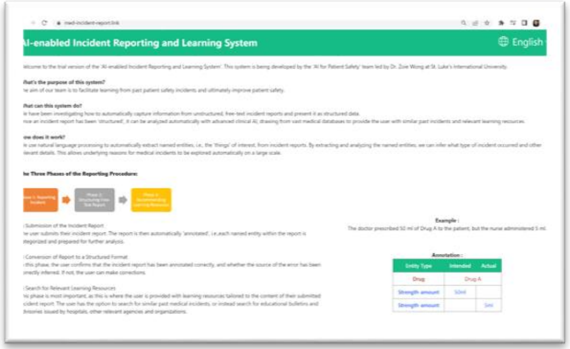
Wong, Z., Waters, N., Data Artist Team, Kuo, N. & Liu, J. Rule-based natural language processing pipeline to detect medication-related named entities: insights for transfer learning (accepted). Medinfo 2023 (2023).
https://github.com/aiforpatientsafety/machineannotator

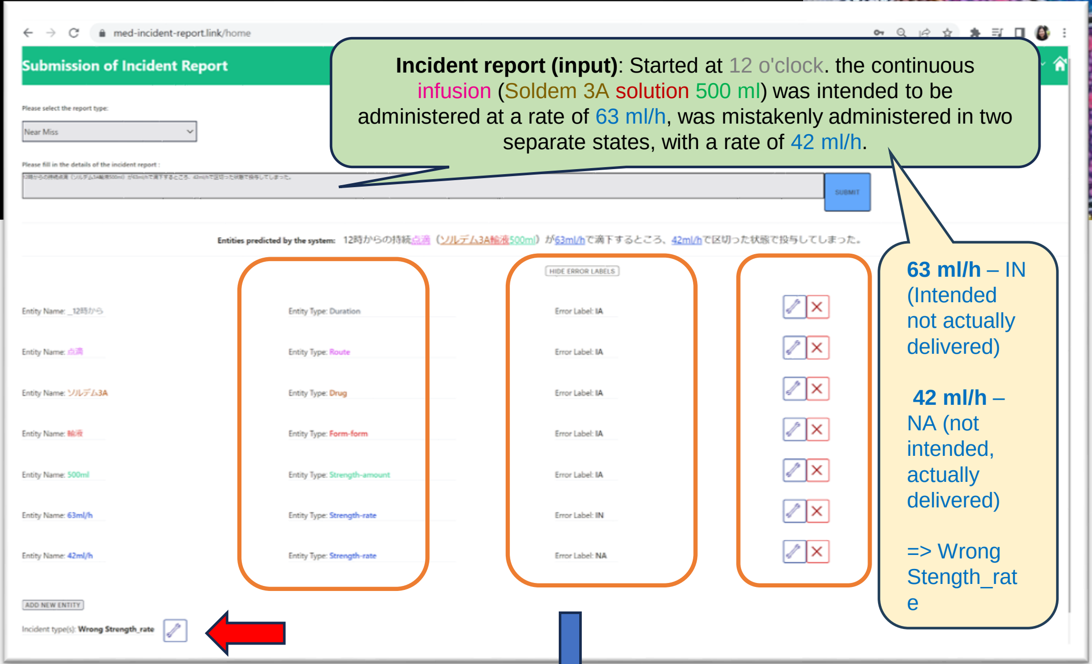
MEDINFO23

8 – 12 JULY 2023 | SYDNEY, AUSTRALIA

Proof-of-concept AI Incident Reporting System

https://med-incident-report.link/



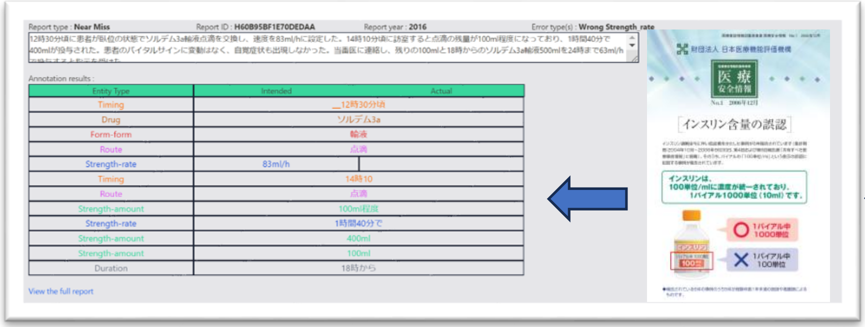


Incident report (input): Started at 12 o'clock. the continuous infusion (Soldem 3A solution 500 ml) was intended to be administered at a rate of 63 ml/h, was mistakenly administered in two separate states, with a rate of 42 ml/h.

63 ml/h – IN (Intended not actually delivered)

42 ml/h – NA (not intended, actually delivered)

=> Wrong Stength_rat e



@TheInstituteDH #MEDINFO23

Retrieve similar cases

Recommend relevant safety advisories

Users can correct mislabelled entries and register the report into structured format

MEDINFO23

8 – 12 JULY 2023 | SYDNEY, AUSTRALIA

Translating ML tools for incident management in real-world settings

Allan Fong

Senior Research Scientist

MedStar Health

MEDINFO23
8 – 12 JULY 2023 | SYDNEY, AUSTRALIA

Translating ML tools for incident management in real-world settings

Allan Fong

Senior Research Scientist
MedStar Health

Panel Discussion

Data
How to collect and share high-quality patient safety data?

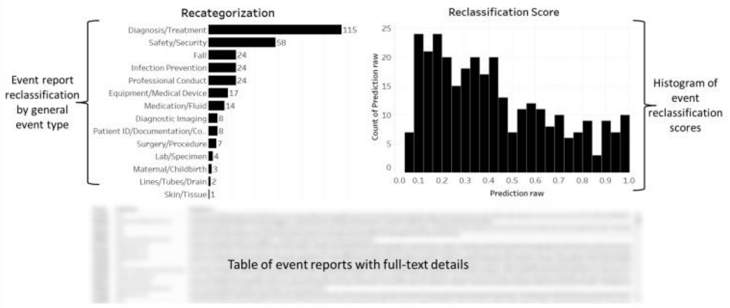
Model
How to develop more intuitive, advanced, and scalable ML methods?

Use
How to ensure effective transportability and implementation in real-world settings?

Two case studies

- Reclassify 'miscellaneous/other' events
- Prototype system to support review of FDA Adverse Event Reporting System (FAERS) reports

Reclassifying ‘miscellaneous/other’ reports



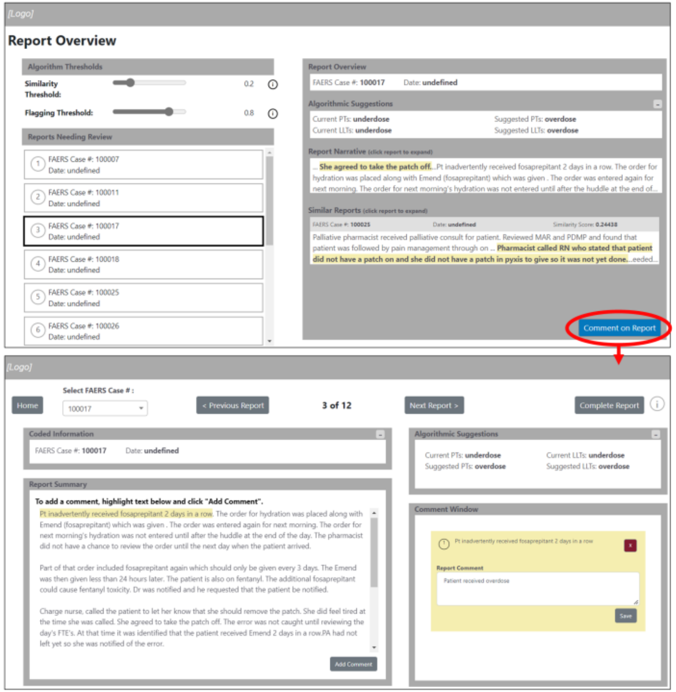
- Background
  - Event classification taxonomies used in many reporting systems can be complex and difficult to understand by frontline reporters
  - Many reports classified as ‘miscellaneous’ or ‘other’
- Method
  - Ensemble ML and NLP model to reclassify ‘miscellaneous/other’ reports
  - Integrated model into a clinical workflow dashboard
- Discussion
  - Different user thresholds suggests role-specific comfort levels of false positives and false negatives
  - Reclassification insights: against medical advice (AMA)
  - Can reduce aspects of workflow burdens

Fong, A., Behzad, S., Pruitt, Z., & Ratwani, R. M. (2021). A machine learning approach to reclassifying miscellaneous patient safety event reports. *Journal of Patient Safety*, *17*(8), e829-e833.

Supporting FAERS workflow

- Understand medication error categorization workflow for direct FAERS reports
- Framework to evaluate Artificial Intelligent (AI) integration opportunities

Evaluation components
Technical deployment (integrating an AI system into existing software systems would be a higher technical deployment cost compared to deploying a stand-alone AI system)
Process rigidity (Established workflows where end-users all follow the same process and use the same tools could show high process rigidity. Workflows where end-users can have more autonomy would be low process rigidity)
AI assistance (realized in time and resource savings or other measures of support)
Frequency (number of end-users and regularity of use)



Fong, A., Bonk, C., Vasilchenko, V., De, S., Kovich, D., & Wyeth, J. (2022). Exploring opportunities for AI supported medication error categorization: A brief report in human machine collaboration. *Frontiers in Drug Safety and Regulation*, *2*, 1021068.

Panel Discussion

Data
How to collect and share high-quality patient safety data?

Model
How to develop more intuitive, advanced, and scalable ML methods?

Use
How to ensure effective transportability and implementation in real-world settings?