Improving Patient Safety with Machine Learning and AI

Harnessing AI for Healthcare Quality Improvement

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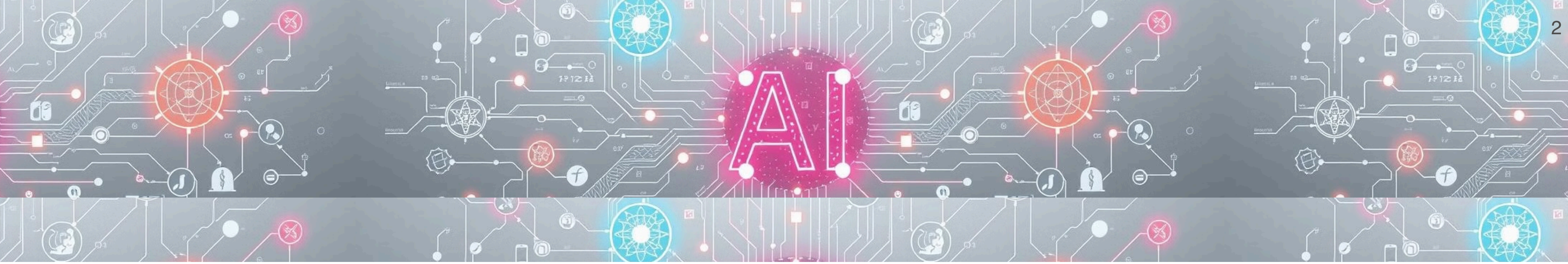

Understanding the AI Advantage

1. Data-Driven Insights

AI models can rapidly analyze vast troves of medical data to uncover patterns and anomalies that would be impossible for humans to detect.

2. Automated Workflows

AI-powered systems can streamline repetitive tasks, freeing up clinicians to focus on delivering personalized, high-quality care.

3. Predictive Capabilities

By learning from historical data, AI can forecast risks and complications, allowing healthcare teams to intervene proactively.

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AI Applications in Patient Safety

Automated detection of medication prescription errors

AI-assisted review of adverse drug events

Prediction of hospital-acquired infection risk

Early detection of sepsis using real-time vital signs

AI-generated treatment plans for complex cases

Computer vision for drug pill identification

Generation of patient-friendly discharge summaries

Personalized patient education materials using LLMs

Generation of material for HCW training

Automated clinical documentation from recordings

AI-powered analysis of diagnostics signals (e.g. radiology, pathology)

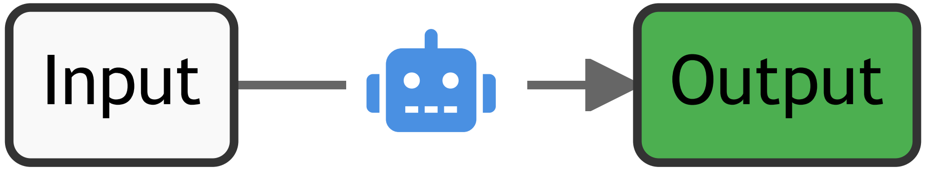
Named entity recognition from disease surveillance

Understanding Machine Learning

Machine Learning aims to predict outputs from inputs by learning patterns from data.

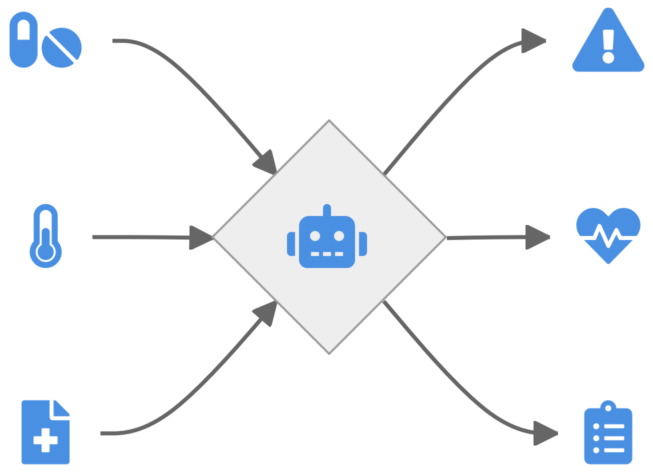
What ML Does

ML learns the relationship between inputs and outputs.



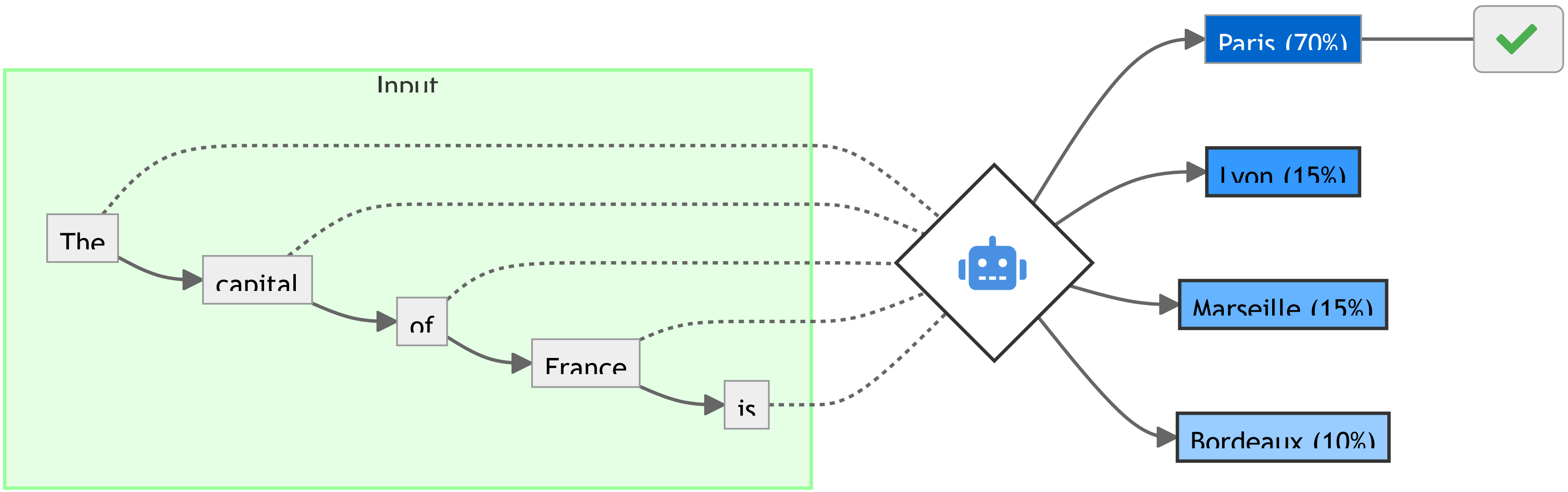
Example in Healthcare

ML models can process various medical data types to perform multiple tasks.



Understanding Generative AI

Generative AI models predict the next token based on learned patterns, enabling them to generate plausible text/images/sound/actions and adapt to various tasks.



Understanding Generative AI

Modern generative AI models are large language models (LLMs), also called foundation models, trained on vast amounts of data.

Allow easily to test innovative implementations of AI in new applications without new model development.

Key Concepts

- Learns patterns and relationships
- General knowledge of the world
- Generates contextually relevant outputs
- Adapts to various tasks with just prompt engineering
- Can be fine-tuned for specific tasks

Applications in Healthcare

- Patient-friendly discharge summaries
- Automated medical documentation and coding
- Personalized patient education
- Treatment plan generation assistance
- Clinical decision support
- etc…

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Implementing Generative AI in Healthcare

Modern generative AI is increasingly easy to deploy, with falling costs.

Generative AI models come in two main categories: open source and closed source, each offering unique advantages for healthcare applications

Open Source

Models with publicly available code, allowing for customization and transparency

- **Pros**: Customizable, transparent, potentially lower cost (not always true)
- **Cons**: Requires expertise, infrastructure, ongoing maintenance
- **Examples**: Meta LLaMA, Mistral, Cohere Command R+, many ad-hoc small models

Closed Source

Proprietary models offered as services by companies

- **Pros**: Ready-to-use, general purpose, regularly updated, often more powerful
- **Cons**: Less control, potential vendor lock-in, higher cost
- **Examples**: OpenAI GPT-4, Anthropic Claude, Google Gemini

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Implementing Generative AI in Healthcare

Deployment options range from on-premises solutions to cloud-based services, each with distinct advantages and considerations for data security, scalability, and integration.

In-House Deployment

- **Pros**: Full data control, customization, potentially lower long-term costs
- **Cons**: High initial investment, requires specialized team
- **Best for**: Large organizations with sensitive data

API-based Solutions

- **Pros**: Quick to implement, scalable, minimal maintenance
- **Cons**: Ongoing costs, potential data privacy concerns
- **Best for**: Smaller organizations, rapid prototyping

Use Cases

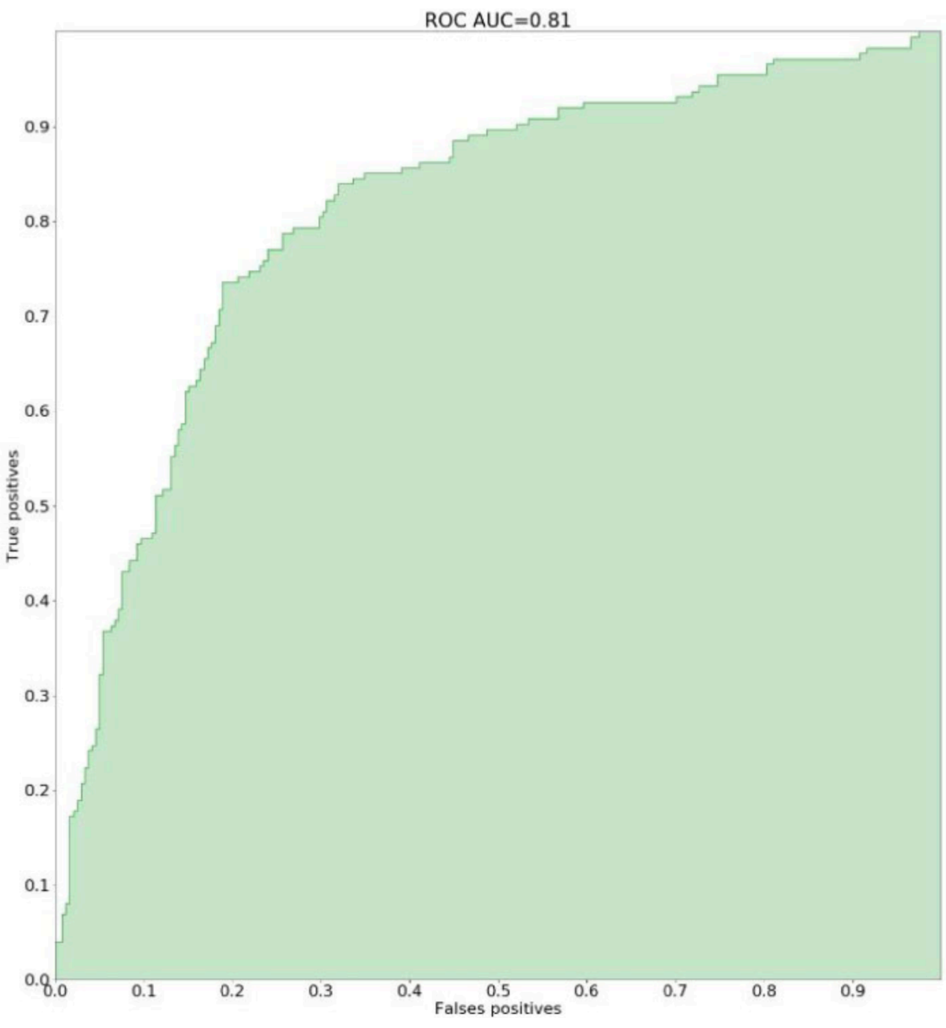
AI in Medical Error Reduction

- Automated prescription review and clinical history - drug interaction detection
- Identification of inconsistencies in medical records
- Real-time monitoring of patient data to flag potential errors
- Analysis of clinical notes for error patterns
- Detection of deviations from procedures and guidelines

Reducing Errors

Hybrid AI for Prescription Review (Corny et al., 2020)

AUROC curve



- Combined expert-defined rules with machine learning algorithms to analyze prescriptions.
- Trained on 18 months of real hospital data, including patient information, lab results, and 133,179 prescription orders.
- The system learned to predict which patients were most likely to need a pharmacist intervention due to potential prescription errors.
- This approach reduced false alerts by 26% compared to traditional methods, while still catching 74% of prescriptions that required intervention.

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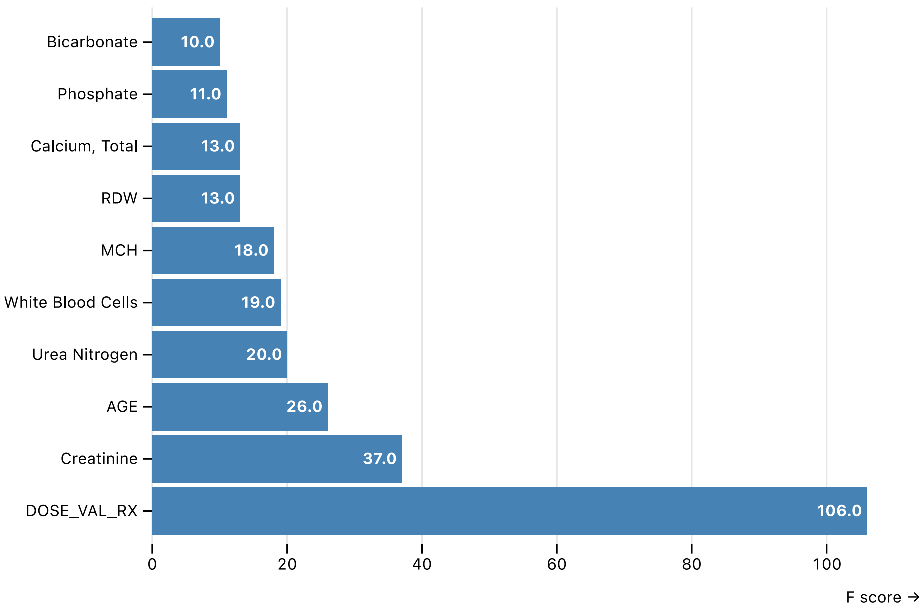
Reducing Errors

ML for Unsafe Prescription Detection (Ben Othman et al., 2023)

- Analyzed the MIMIC-III database, containing data from over 30,000 ICU stays, to learn patterns of safe prescriptions.
- Created artificial examples of problematic prescriptions by altering dosages and combinations in valid prescriptions.
- The system checks new prescriptions against learned patterns of safe prescriptions, flagging those that deviate significantly.
- It also identifies potential drug interactions by comparing new drug combinations to previously observed safe combinations.

Feature Importance



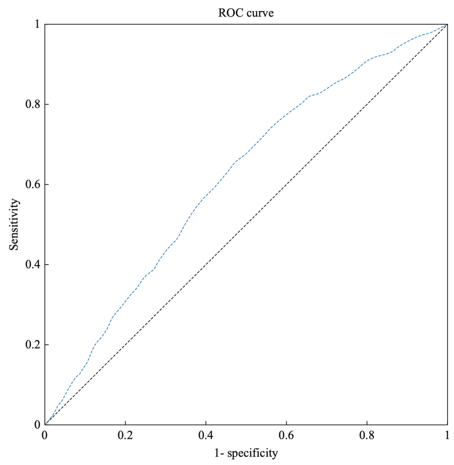
AI in Healthcare Risk Prediction

- Prediction of hospital-acquired infections
- Forecasting patient deterioration or complications
- Identification of high-risk patients for readmission
- Early detection of specific conditions (e.g., sepsis, acute kidney injury)
- Prediction of medication failure

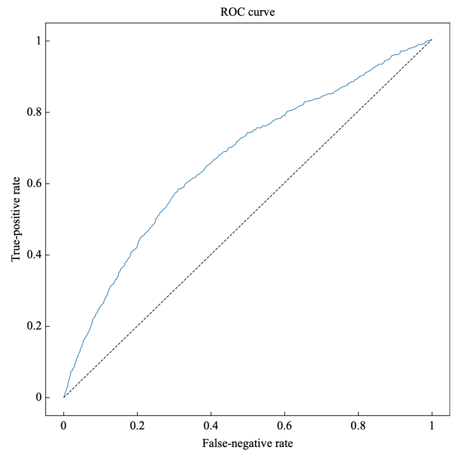
Risk Prediction in Healthcare Infections

HAI Prediction from ICU Surveillance Data (Barchitta et al., 2021)

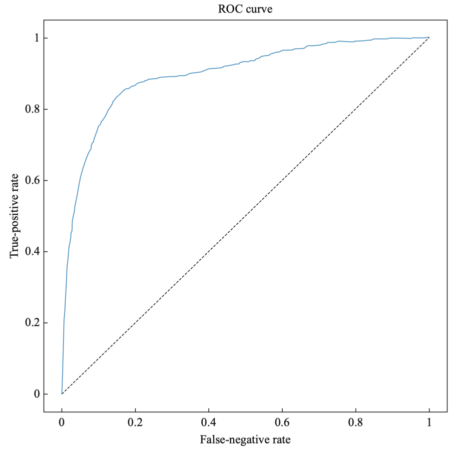
Only SAPS II score



ML without SAPS II score



ML with SAPS II score



- Used data from the SPIN-UTI project (Italian Nosocomial Infections Surveillance in ICUs)
- Utilized Support Vector Machines (SVM) on surveillance data from ICUs
- Analyzed patient characteristics at ICU admission
- Combined SAPS II score with other admission features
- Achieved high performance (AUC 0.90) for HAI risk prediction
- Demonstrated potential for early patient risk stratification

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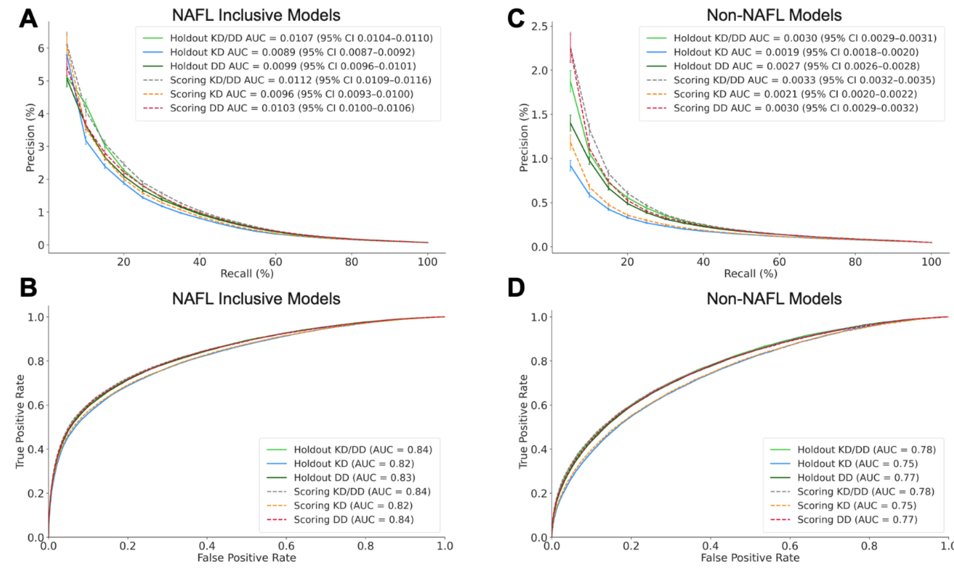
Risk Prediction in Healthcare Infections

Longitudinal Administrative Data for NASH Detection (Yasar et al., 2023)

- Used gradient-boosted decision trees on longitudinal claims data
- Analyzed 1,463,089 patients over multiple time points
- Predicted nonalcoholic steatohepatitis (NASH) in at-risk populations
- Achieved 60x improvement over baseline incidence at 10% recall
- Demonstrated value of longitudinal data in rare disease detection

Model performance



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Risk Prediction in Healthcare Infections

NLP and Deep Learning for HAI Detection from Clinical Narratives (Rabhi et al., 2019)

Relevant clinical features for HAI prediction

Document source extracts	Translation	Three-term sequences detected by CNN
En raison d'une <u>inflammation au dessus de la voie d'abord antérieur</u> de la cheville, incision et <u>prélèvements profonds avec écouvillon après lavage au sérum physiologique</u>. Résultats bastérios le [T + 36J]: <u>prélèvements positifs à enterobacter chloacae</u>. Antibiogramme: résistant à Augmentin, Cephalotine, Cephoxitine. A été mis sous <u>ATB</u>: <u>Fortum</u> IV 1 g toutes les 8 heures <u>Ciflox</u> 750 per-os 1 - 0 - 1	Because of the inflammation above the anterior channel of the ankle, incision and deep samples with swab after lavage with physiological serum *Basterios* results on [T + 36J]: positive samples to Enterobacter cloacae Antibiogram: resistant to Augmentin, Cephalothin, and Cefoxitin Has been put under ATB: Fortum IV 1 g for all 8 h Ciflox 750 per-os 1 - 0 - 1	['prelevement', 'profond', 'ecouvillon'] *('sample', 'deep', 'swab')* ['incis', 'prelevement', 'profond'] *('incision', 'sample', 'deep')* ['raison', 'inflamm', 'dessus'] *('because', 'inflammation', 'above')* ['basterios', 'prelevement', 'posit'] *('bacteriological', 'sample', 'positive')* [enterobact', 'chloaca', 'antibiogramm] *('enterobacter', 'chloacae', 'antibiogramme')* ['ã', 'augmentin', 'cephalotin'] *('ã', 'augmentin', 'cephalothin')* ['ciflox', 'per', 'os'] *('ciflox', 'per','os')*

Abbreviations: ATB, antibiotic; CNN, convolutional neural network.
Note: In the first column, the terms underlined are those highlighted by the annotator in the corresponding clinical note.

- Applied deep learning to French clinical narratives to predict HAI
- Compared CNN performance with conventional ML methods
- Achieved best F1 Score of 97.7% ± 3.6% using CNN
- Highlighted potential of NLP in automated HAI surveillance

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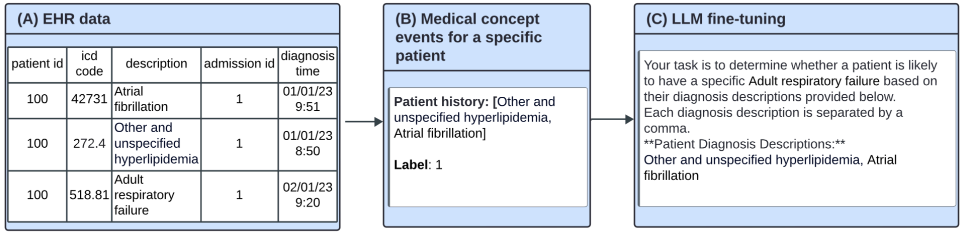
Risk Prediction in Healthcare Infections

Large Language Models for Clinical Prediction (Shoham et al., 2023)

- Large Language Models (LLMs) for clinical prediction
- Used Llama2 and BioMedLM on unstructured EHR data
- Predicted future diagnoses (e.g., kidney disease, respiratory failure) and hospital readmission
- Outperformed state-of-the-art models in disease and readmission prediction
- Fine-tuned LLMs for improved performance
- Demonstrated potential of LLMs in understanding clinical sequences

Model Fine-tuning



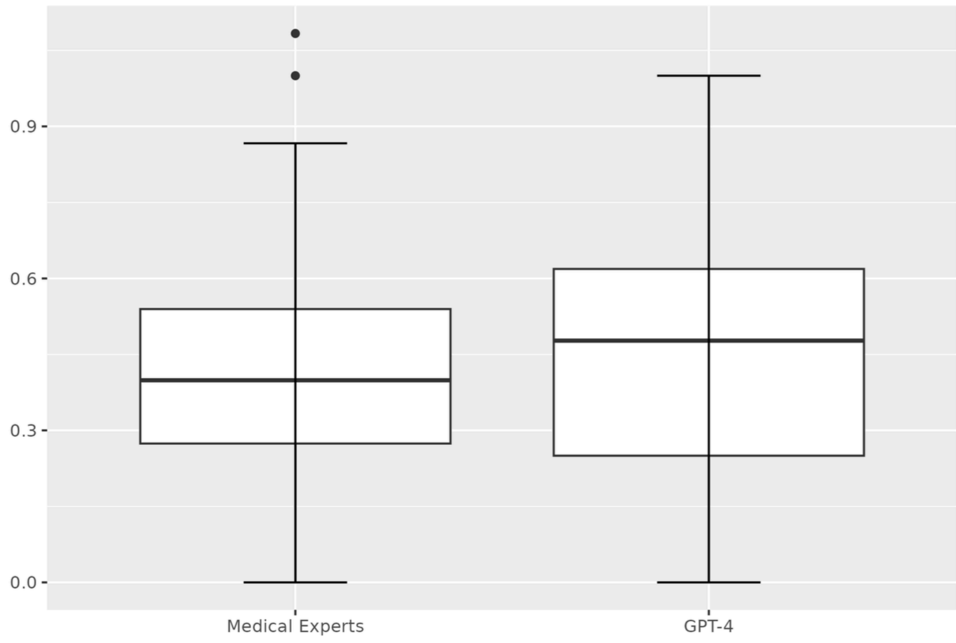
AI in Healthcare Decision Support

- Augmenting clinical judgment in complex cases
- Generating personalized treatment plans
- Assisting in medication management and safety
- Providing real-time clinical decision support at point of care
- Enhancing diagnostic accuracy through image and diagnostic signal analysis

AI in Healthcare Decision Support

Effectiveness and Safety of Large Language Model in Generating Type 2 Diabetes Management Plans (Mondal et al., 2024)

GPT-4 vs Expert Comparison



- Compared GPT-4-generated plans with those of medical experts
- Evaluated completeness, necessity, and dosage accuracy
- GPT-4 reduced unnecessary drug prescriptions
- Human experts excelled in plan completeness and safety
- Safety issues noted in 16% of GPT-4 generated plans

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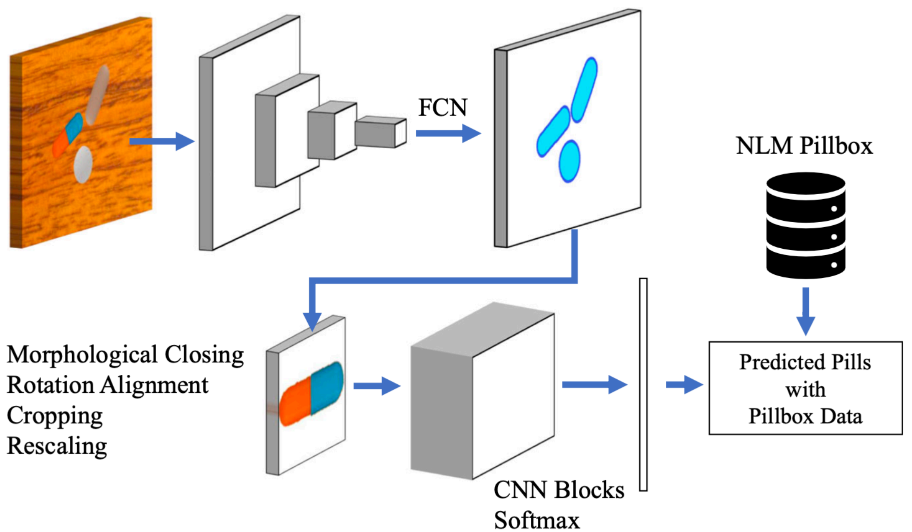
AI in Healthcare Decision Support

Fast and Accurate Medication Identification (Larios Delgado et al., 2019)

Pill Recognition System



- Developed deep learning model for pill recognition from images
- Achieved 94% accuracy within top-5 results
- Potential to reduce medication errors and improve patient safety
- Demonstrated real-time performance suitable for mobile applications

AI in Patient Support

- Generating patient-friendly discharge summaries
- Creating accessible patient education materials
- Simplifying complex medical information for better understanding
- Multilingual generation of discharge summaries and patient education materials
- Deployment of patient support chatbots
- Enhancing patient engagement and self-management

AI in Patient Support

Patient friendly discharge summaries (Zaretsky et al., 2024; Hanjae et al., 2024, Clough et al., 2024)

- AI can generate high-quality, standardized summaries
- Studies show AI summaries comparable to junior doctors'
  - 100% AI vs 92% doctor summaries accepted by GPs
  - AI summaries not easily distinguishable from human-written ones
- Benefits: consistency, time-saving, adherence to standards
- Limitations: potential for errors, lack of clinical reasoning
- Hybrid AI-human approach recommended for safety

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AI in Patient Support

Patient Education Materials Generated by AI (Hung et al., 2023; Armstrong et al., 2024)

- AI can rapidly generate patient education materials
- Readibility easiness can be tuned by prompt engineering
- Time-saving: AI generates in minutes vs. weeks for experts

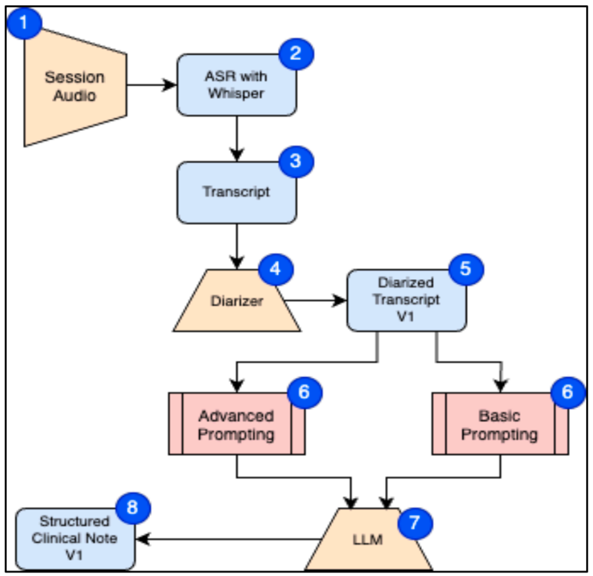
AI in Documental Support and Analysis

- Automatic transcription and analysis of patient-clinician interactions
- Generation of structured clinical notes
- Summarization of clinical records for clinical decision support
- Extraction of clinical information for research and analytics
- Coding and billing support

AI in Documental Support and Analysis

Transforming Medical Records and Consultations (Biswas & Talukdar, 2024; Basei de Paula et al., 2024)

Model Pipeline



Prompt Example

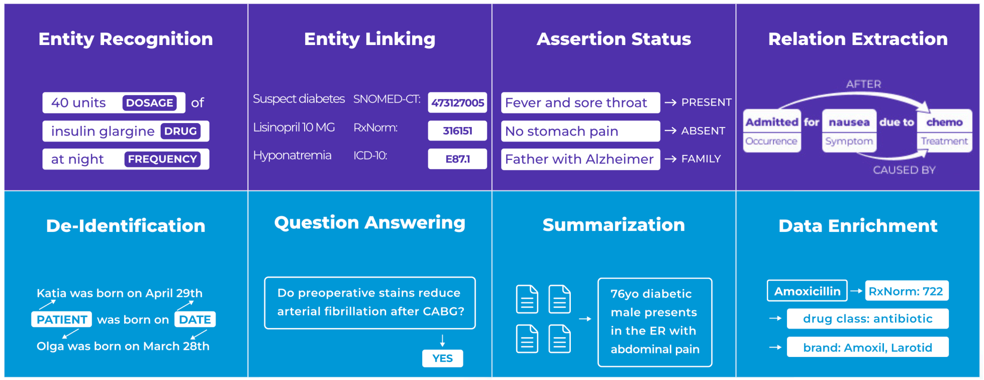
Example prompt

- **Formatting instructions**: {{ Detailed instructions on the SOAP/BIRP note structure and formatting, including the specific sections and the information to be included in each section }}
- **Transcript**:
  {{ Diarized transcript of patient-clinician interaction }}
- **Instructions**: Based on the above transcript and the provided example, please generate a SOAP/BIRP note following the specified structure and format. Ensure that all relevant information from the transcript is captured in the appropriate sections of the note. Maintain patient confidentiality by avoiding the use of any personally identifiable information.

- AI generates clinical notes from transcribed interactions
- Conversation-to-text tools convert audio to optimized clinical documents
- 6,380 anamneses generated, 891 users adopted over 3 months
- Show potential for improved documentation quality
- Time-saving allows more focus on patient interaction
- Challenges: data privacy, model reliability, human oversight

AI in Documental Support and Analysis

Automated Medical Record Analysis (John Snow Labs example)



- Extracts clinical information from unstructured text in patient records
- Identifies and disambiguates medical entities like symptoms, treatments, and drugs
- Maps medical terms to standardized codes for consistent data representation
- Performs document classification and contextual parsing of clinical notes
- Enables patient risk scoring based on information in clinical narratives
- Facilitates cohort retrieval using free-text prompts for precision population health management
- Improves accuracy of clinical text analysis through preprocessing techniques like summarization
- Supports multilingual processing of biomedical text without code changes

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Risks and Limitations

Risks and Limitations

Potential for inaccurate outputs, including “hallucinations”

Risk of perpetuating or amplifying existing biases

Concerns about data privacy, security, and patient consent

Regulatory and ethical challenges in evolving AI landscape

Possibility of clinical deskilling and overreliance on AI

Risks of automation bias and overreliance on AI

Challenges in explaining AI decision-making processes

Concerns about equitable access and benefits from AI

ECDC current work

ECDC Risk Prediction Model for HAI and AMR

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- Utilizes data from PPS third edition (2022-2023)
  - 1,851 hospitals across 29 EU/EEA countries
- Develops machine learning model to predict HAI and AMR prevalence
- Compares hospital-specific data to expected prevalence
- Allows for benchmarking against similar hospitals
- Aims to support targeted interventions and resource allocation
- Will be available online and offline

LLM-Powered Extraction to meet HAI case-definitions

Case definition example

Superficial incisional (SSI-S)
Infection occurs within 30 days after the operation and infection involves only skin and subcutaneous tissue of the incision and at least one of the following:

- Purulent drainage with or without laboratory confirmation, from the superficial incision.
- Organisms isolated from an aseptically obtained culture of fluid or tissue from the superficial incision.
- At least one of the following signs or symptoms of infection: pain or tenderness, localised swelling, redness, or heat, and superficial incision is deliberately opened by surgeon, unless incision is culture-negative.
- Diagnosis of superficial incisional SSI made by a surgeon or attending physician.

- Utilizes LLMs to extract clinical indicators from medical records
- Matches ECDC HAI-Net surveillance protocols case definitions
- Extracts specific clinical signs (e.g., fever, purulent drainage)
- Helps automate HAI surveillance
- Enables stable comparisons and easier validation
- Supports harmonized HAI surveillance across EU/EEA
- Limitations include hallucinations, data privacy concerns, processing large amounts of data, and multi-lingual support

Thank you for your attention!

HAI-net team: Diamantis Plachouras, Carl Suetens, Tommi Karki, Angelo D'Ambrosio, Aikaterini Mougkou