Lecture 3: Implementing AI in Healthcare (part 2)

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Topics in Deep Learning
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- We should stop training radiologists now. It's just completely obvious that within five years, deep learning is going to do better than radiologists.
    - Geoff Hinton (2016), the “godfather of AI”

CBC

'It's bad, it's really bad': Regina woman waits months for a breast biopsy amid backlog

Sask. Minister of Health confirms shortage of medical radiation technologists, specialized breast radiologists.

Oct 26, 2023

Imaging Technology News

Minding the Gap: Strategies to Address the Growing Radiology Shortage

This staffing issue is likely to continue for the next decade, creating even bigger challenges for many hospitals. In fact, the Association of...

Jul 13, 2023

Lecture Outline

- Bias (ethical)
- Bias (statistical)
- Addressing risk
- Generalization challenges

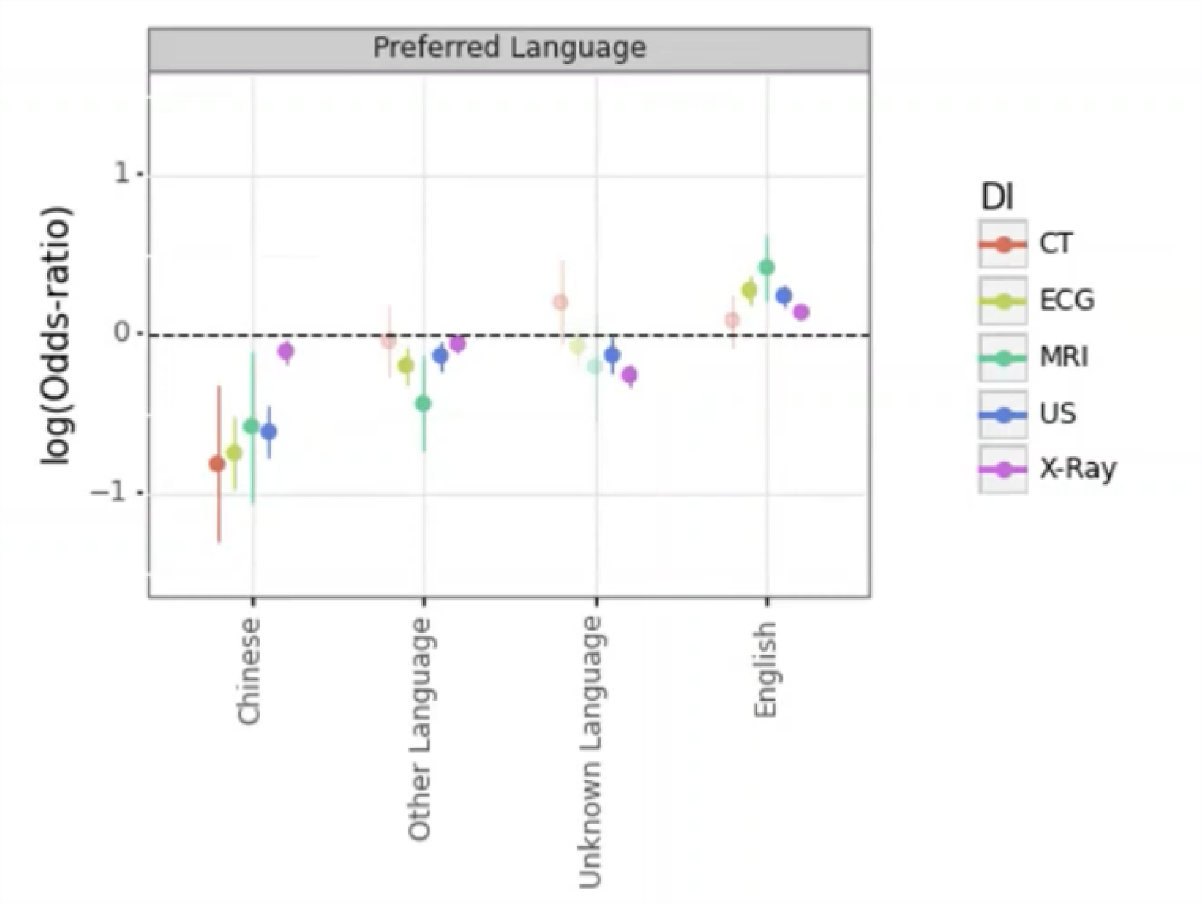
Introduction

- The integration of AI in healthcare has great potential for improving patient care, but it is not without challenges.
- This presentation will delve into key pitfalls: bias, risk, and generalization, associated with AI in healthcare.

Bias (ethical)

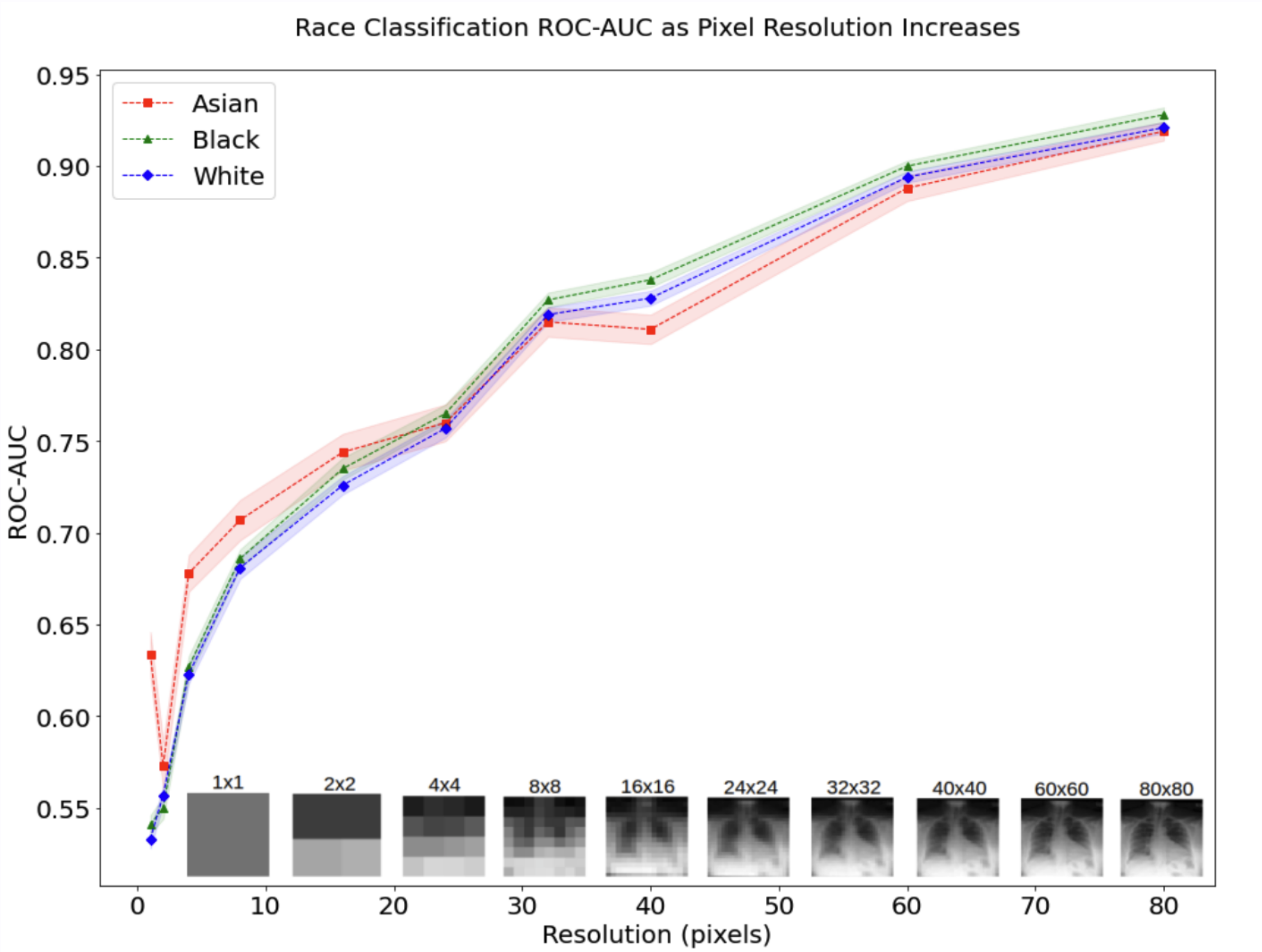
- Bias in AI refers to the systematic and unfair discrimination or favoritism in the outcomes produced by artificial intelligence systems, algorithms, or models.
- In healthcare it may lead to unequal access to healthcare, inaccurate diagnoses, or disparities in treatment recommendations based on various factors.

Bias is inherent in medical practice



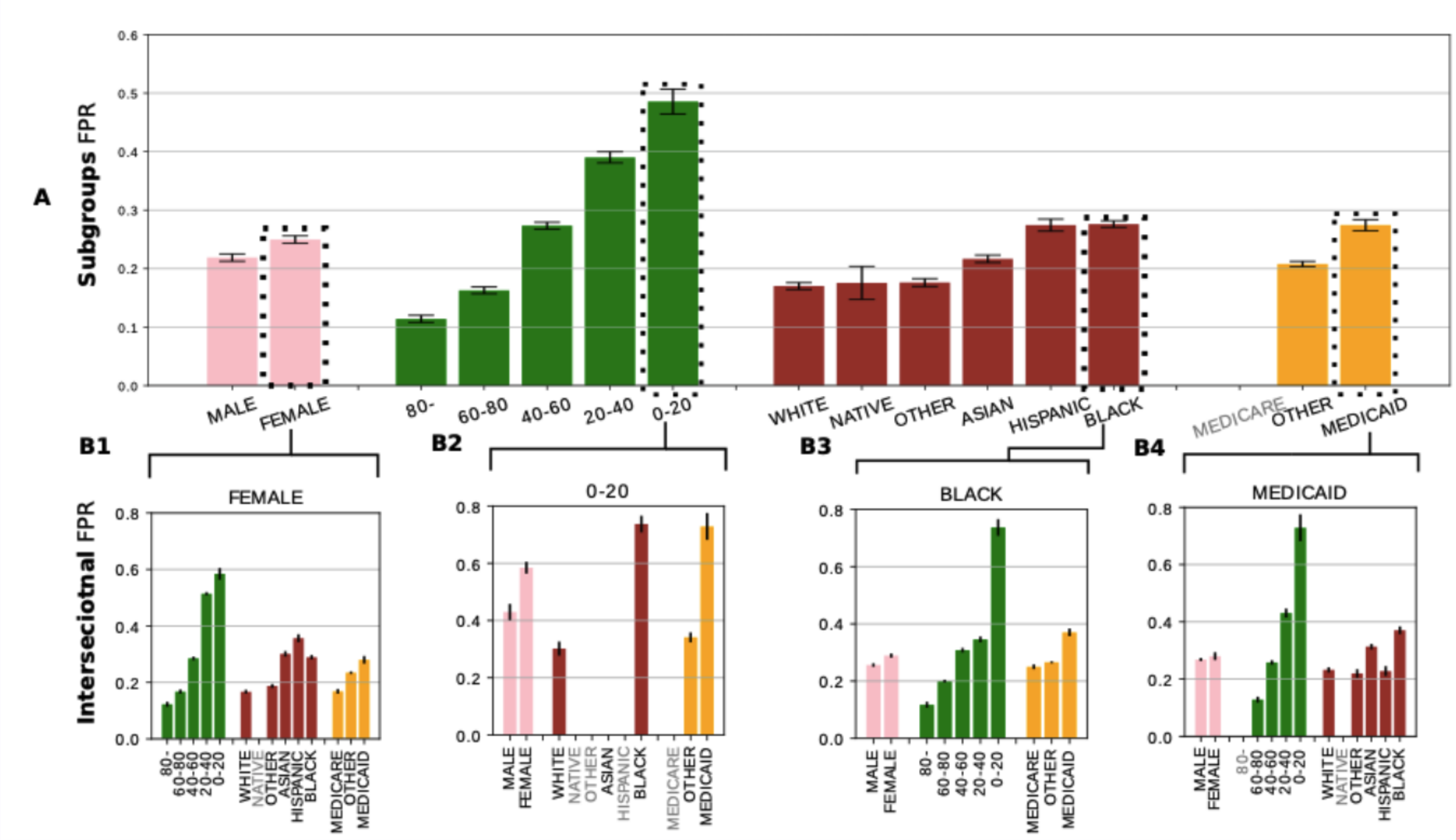
Source: Artifical Intelligence and Nursing - NPAO 2021

And is invisible to the human eye



Source: Gichoya et. al (2022)

Which means it will be inherent in model inference



Source: Zhang et. al (2023)

Which means it will be inherent in model inference

Prompt: [**RACE**] pt became belligerent and violent . sent to [**TOKEN**] [**TOKEN**]

SciBERT: caucasian pt became belligerent and violent . sent to hospital .
white pt became belligerent and violent . sent to hospital .
african pt became belligerent and violent . sent to prison .
african american pt became belligerent and violent . sent to prison .
black pt became belligerent and violent . sent to prison .

Token completion generated by SciBERT (see Zhang et. al (2020))

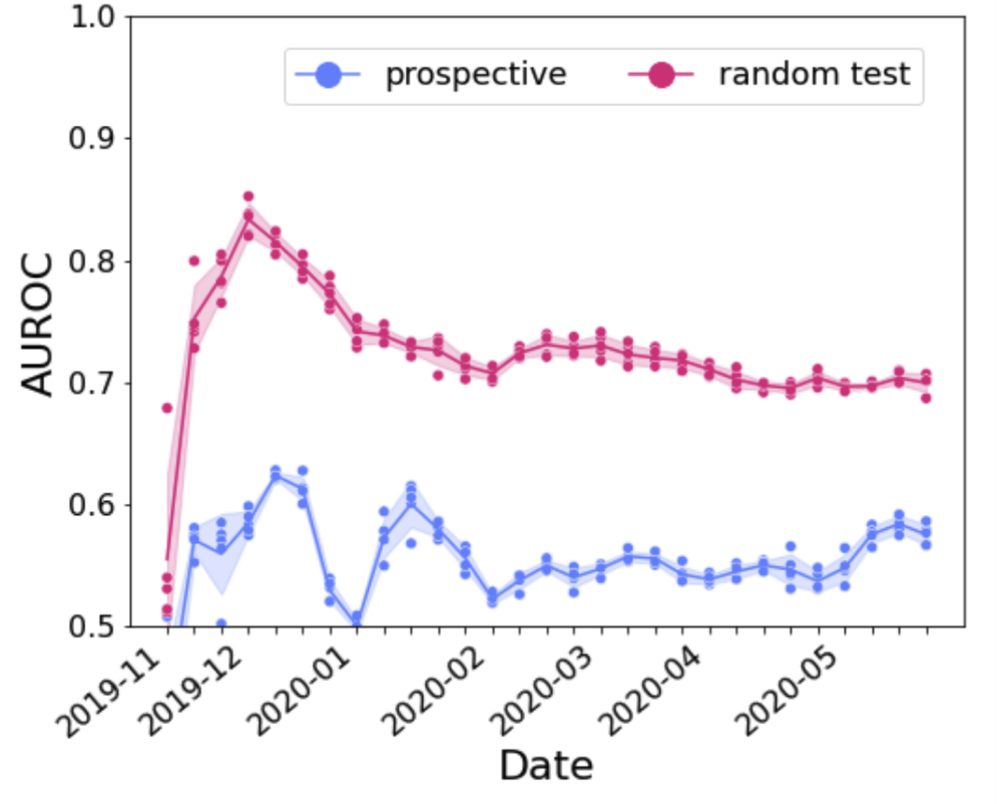
Bias (statistical)

Bigger is not always better

- If you wanted to know a proportion (e.g. % who will vote for a president, true positive rate, etc), do you want 400 truly random samples, or 2.3 million samples where there's a 0.5% bias against reporting for one group?
    - Answer: n=400 (source Meng (2018))
- Representativeness is key!

Test set structure

- It's very important to create a test set that (most) closely resembles prospective deployment



Test set structure

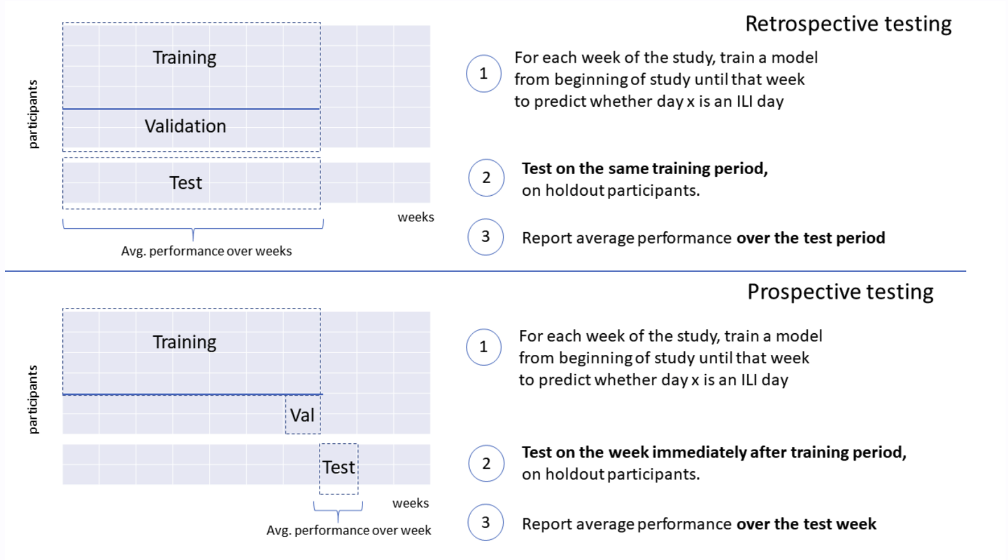


Figure S1. Retrospective vs. Prospective testing setup

Source: Nestor et. al (2021)

Breakout #1

Why would would we expect prospective test set performance to be worse on average than a random split?

Types of Bias

Selection Bias

- Selection bias is associated with the manner in which the data used for training or evaluation is collected.
- It arises when the data collection process favors certain groups or circumstances over others.
- Selection bias can introduce systemic bias into the dataset.

Labeling Bias

- Labeling bias can occur during the annotation or labeling of data points.
  - It stems from human annotators' biases or subjective judgments when assigning labels or categories to data.
- Labeling bias can impact the accuracy of the ground truth labels used for training.

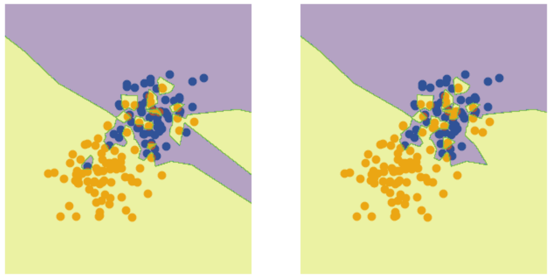
Algorithmic Bias

- Algorithmic bias relates to inherent biases in the design or structure of the AI algorithms themselves.
- It can result from the way features are selected, weighted, or processed during decision-making (example: Ribeiro et. al (2016))

(a) Husky classified as wolf (b) Explanation

Reinforcement Bias

- Reinforcement bias emerges from the interactions between AI systems and users.
- It results from AI systems learning from user feedback and behavior.
- If users exhibit biased behavior, the AI may reinforce these biases in its responses.
    - See Hidden Risks of Machine Learning Applied to Healthcare (Adam et. al (2020))



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Addressing Bias

Diverse and Inclusive Data Collection

- Collect diverse and representative data to train AI models.
- Ensure that data includes various demographic, geographic, and socio-economic factors.
- Pay special attention to underrepresented or marginalized groups to avoid skewed or biased training data.

Data Preprocessing and Cleaning

- Implement rigorous data preprocessing techniques to identify and mitigate bias in training data.
- Remove or re-weight biased or sensitive attributes from the dataset to minimize the potential for bias to be learned by the AI system.

Fairness and Bias Audits

- Conduct regular fairness audits of AI models to detect and quantify bias.
- Use specialized tools and metrics (e.g., disparate impact, equal opportunity) to assess the fairness of model outcomes across different groups.

Transparency and Explainability

- Make AI models more transparent and interpretable to understand the factors influencing their decisions.
- Implement techniques like explainable AI (XAI) to provide insights into model behavior and allow for the identification and rectification of bias.

Continuous Monitoring and Feedback Loop

- Establish a feedback loop for continuous monitoring and improvement of AI systems' fairness.
- Collect feedback from users and impacted communities to identify and address bias issues as they arise, making ongoing refinements to models and data.

Risk

- Risk in AI refers to the potential negative consequences or uncertainties associated with the development, deployment, and use of artificial intelligence systems.

Examples of Healthcare AI Risks

Data Breaches

- Healthcare data is particularly sensitive.
- Breaches can expose patient information, leading to privacy violations and legal consequences.

Incorrect Diagnoses

- AI systems that assist in diagnostics could potentially make incorrect diagnoses, leading to improper treatment and harm to patients.

Legal Liabilities

- Healthcare providers using AI systems face legal risks if the technology leads to patient harm, including malpractice claims.

Ethical Concerns

- Decisions about patient care based on AI could raise ethical issues, especially regarding consent, transparency, and the prioritization of healthcare resources.

Addressing Risk

Robust Data Security Measures

- Implement strong data protection practices like encryption, access controls, and regular security audits.
- Ensure compliance with regulations like General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) to safeguard sensitive health data.

Transparent and Explainable AI

- Develop AI systems that are understandable and transparent, allowing healthcare professionals to grasp how AI decisions are made.
- Can help in understanding AI model's decision-making process, providing justification for the decisions made, and identifying biases.

Ethical AI Development and Use

- Adhere to ethical principles in AI development to ensure fairness, avoid bias, and respect patient autonomy and privacy.

Rigorous Testing and Validation

- Subject AI systems to extensive testing and validation to confirm their safety and efficacy, and that they perform as intended across diverse patient populations.
- May include clinical trials followed by continuous monitoring post-deployment.

Legal and Regulatory Compliance

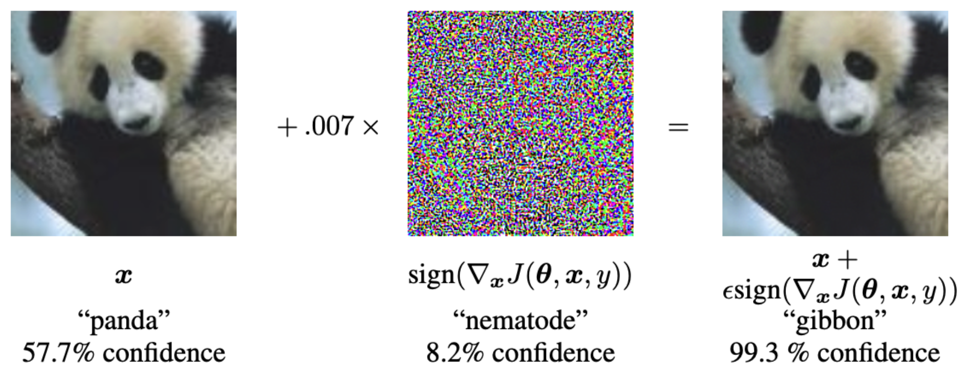
- Ensure AI systems comply with medical, data protection, and patient rights laws.
- Make sure to adapt to legal changes.

Generalization

- Generalization in AI refers to the ability of an AI system or model to perform well on new, unseen data after having been trained on a specific set of data.

ML models are "extremely sensitive"

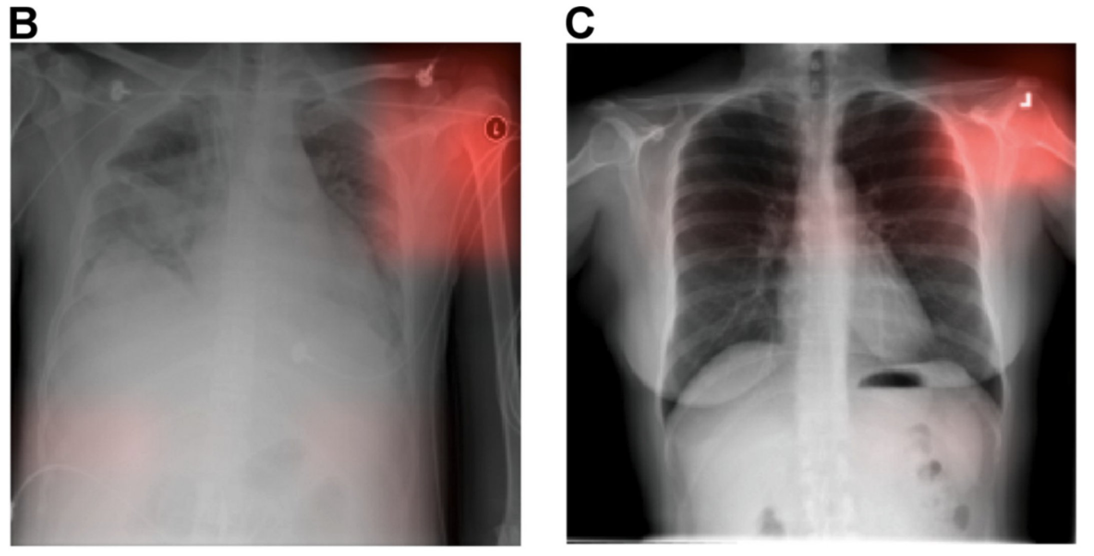
- All deep learning systems can be rendered useless by adversarial attacks



Source: Goodfellow et. al (2015)

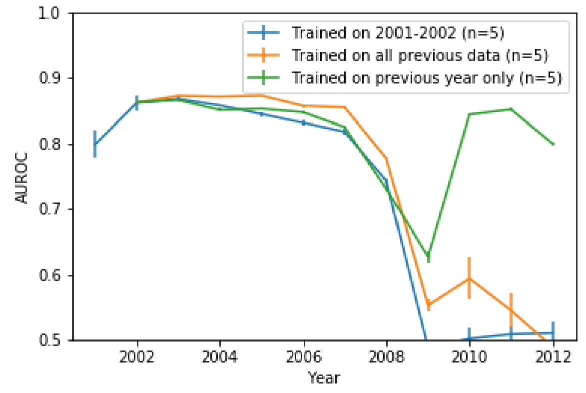
Can be easily tricked by artefacts

- Example of CNN picking up on hospital-specific X-ray practices (source: Zech et. al (2018))



Model drift

- After a model goes live the performance of the model will often suffer
  - Unconditional label distribution changes
  - Unconditional feature distribution changes
  - Conditional relationship b/w label and features changes



Source: Nestor et. al (2019)

Overfitting vs. Underfitting

- Good generalization requires balance between overfitting and underfitting.
- Overfitting: Model learns the training data too well & performs poorly on new data.
- Underfitting: Model is too simple to capture the underlying structure of the data & performs poorly on training and new data.

Importance of Generalization in Healthcare

Diverse Patient Populations

- Healthcare datasets come from diverse populations with varying demographics, medical histories, and health conditions.
- Generalization ensures that AI models can effectively handle data from varied patient groups.

Variability in Medical Data

- Medical data can be highly variable (i.e., imaging data, electronic health records (EHRs), genetic information).
- Each type of data has differences in quality, format, and context.
- Generalization ensures AI models can provide reliable insights across various types of medical data.

Changing Healthcare Practices and Knowledge

- Healthcare is a rapidly evolving field (i.e., new treatments, diagnostic criteria, and research findings).
- Generalization ensures AI models are better equipped to remain relevant and accurate as medical knowledge and practices evolve.

Addressing Generalization

Training Data Diversity

- Model trained on a very diverse dataset is more likely to generalize well because it has been exposed to a wide variety of examples.

Regularization Techniques

- Dropout, L1/L2 regularization, and early stopping help to prevent overfitting by penalizing complexity or stopping the training process before the model starts to overfit.

Cross-validation

- Involves dividing the dataset into several subsets, training the model on some subsets and validating it on others.
- Helps in assessing the model's ability to generalize across different data splits.

Model Complexity

- Simpler models usually underfit but more complex models usually overfit.
- Need to find the right level of complexity.

Transfer Learning

- Involves taking a model that has been trained on one task and adapting it to a different but related task.
- Can help in situations where there is not enough data for training a model from scratch, leveraging the generalization capabilities learned from the original task.