



Exceptional service in the national interest

The Use of AI in Public and Animal Health Preparedness

Sandia National Laboratories

J. Bradley Dickerson, PhD

Senior Manager, Global Chemical and Biological Security
Sandia National Laboratories

SAND2023-13302C

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.





Efforts with Relevance to Public and Animal Health Preparedness



- Using AI to Calibrate and Validate Epi Models
 - Makes more efficient use of epidemiological data to produce more accurate results
- AI-based Standoff Disease Detection and Surveillance
 - Facilitates clinical data collection in populations to identify abnormal animals
- Deep learning models improve identification of highest risk patients
 - Enables identification and compilation of indicators to trigger a response based on risks
- ADAPT: Automated Data-driven Assistant for Patient Triage
 - During response with multiple casualties and/or injuries an AI driven system can help first responders prioritize injuries based on clinical condition to enhance survival and optimize use of first responders



AI for Public Health Preparedness and Response:

Opportunities and Challenges

Example Opportunities:

Predictive Modeling: AI to forecast disease spread and plan interventions

Disease Surveillance: AI to detect emerging disease outbreaks early, before they spread widely.

Personalized Medicine: AI to tailor medical interventions to individual patient disease trajectories

Anticipatory Diagnosis: AI to predict rapid decompensation in ERs and ICUs, giving medics and docs precious time to avert systemic crashes and fatal outcomes.

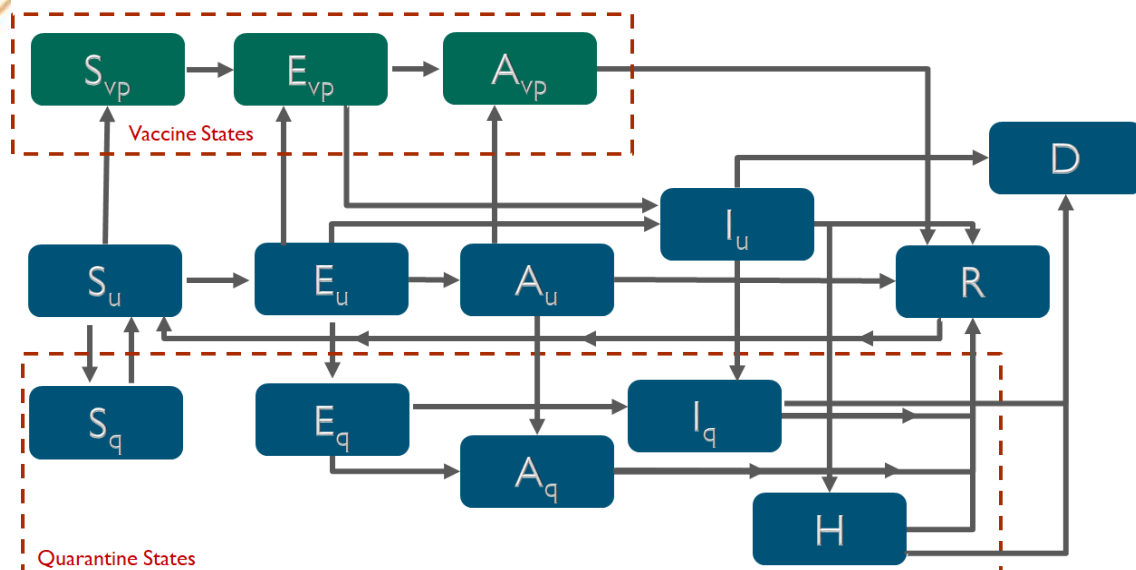
Challenges:

- AI Credibility
- Data Security
- Privacy
- Bias and Equity
- Interoperability
- Data Availability
- Regulatory Hurdles
- Public Trust
- Workforce Disruption
- Ethical Implications
- Scale with Events

Parallel research thrusts to field impactful AI applications AND address major challenges



Using AI to Calibrate and Validate Epi Models



Sandia's Adaptive Recovery Model (ARM)

- Current disease models cannot effectively adjust to different locations, populations, or variants
- We have proven that traditional calibration falls apart with more than four parameters.
- Sandia and MIT developed AI-based calibration method (UDE) that enables fast and accurate calibration of complex epi models

S_* : Susceptible

E_* : Exposed

A_* : Asymptomatic-Infectious

I_* : Infectious-Symptomatic

R : Recovered

H : Hospitalization

D : Disease-related Deaths

Intervention Strategies

- Vaccination strategies
- Quarantine
- Use of PPE
- Contact tracing
- Random testing

Force of Infection: $\lambda(t) = \beta\kappa(1 - \rho) \frac{\eta_A A(t) + I(t) + \eta_H H(t)}{\text{Total_Pop}}$

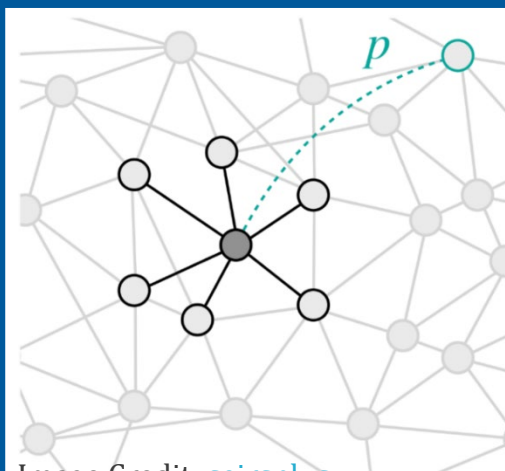
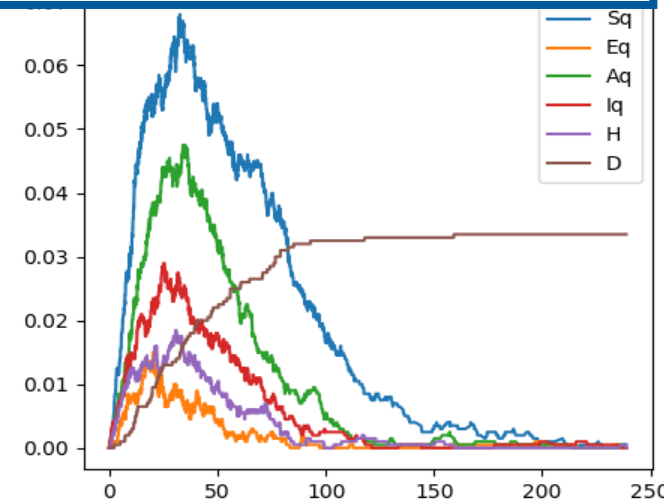


Image Credit: [seirsplus](#)

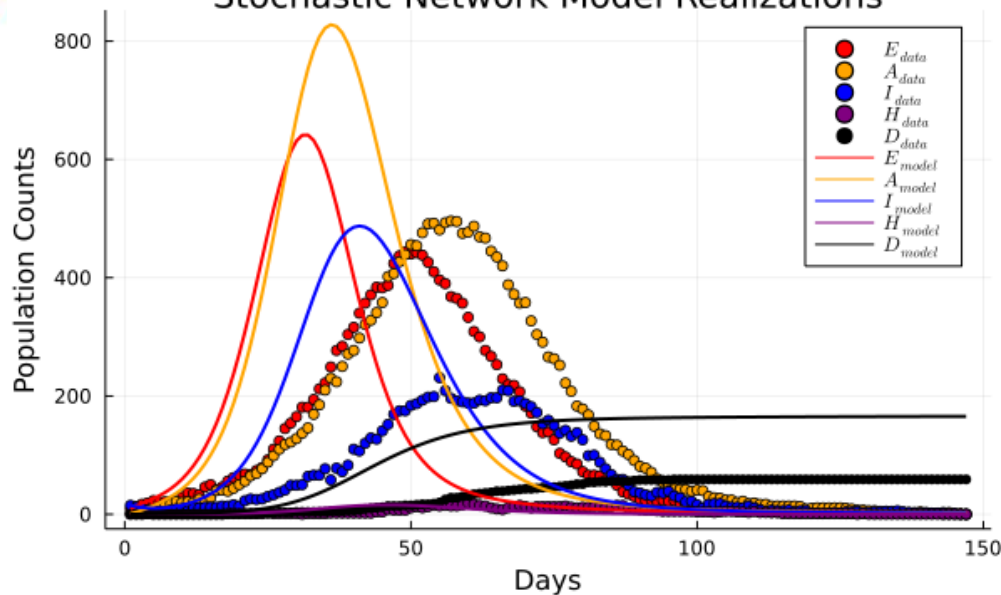




Epi Models Calibrated with AI maintain prediction accuracy



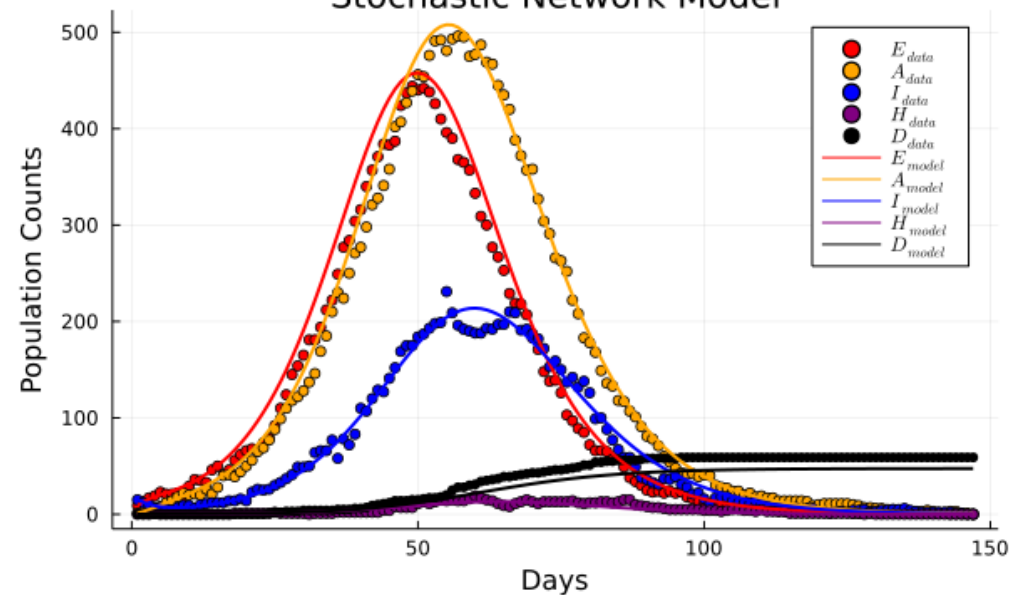
Compartmental Model Initialization to Stochastic Network Model Realizations



Traditional calibration of 17-parameter model (solid lines) doesn't match ground truth (dotted lines)

Initial	Param	UDE
0.114	β	0.086
5	κ	4.96
0.75	η_A	0.71
0.01	η_H	0.102
0.25	τ_{EA}	0.19
0.117	τ_{AI}	0.09
0.05	τ_{AR}	0.068
0.007	τ_{IH}	0.012
0.15	τ_{IR}	0.162
0.01	τ_{ID}	0.004
0.188	τ_{HR}	0.275
0.012	τ_{HD}	0.005
(...)	(...)	(...)

UDE Surrogate for Stochastic Network Model

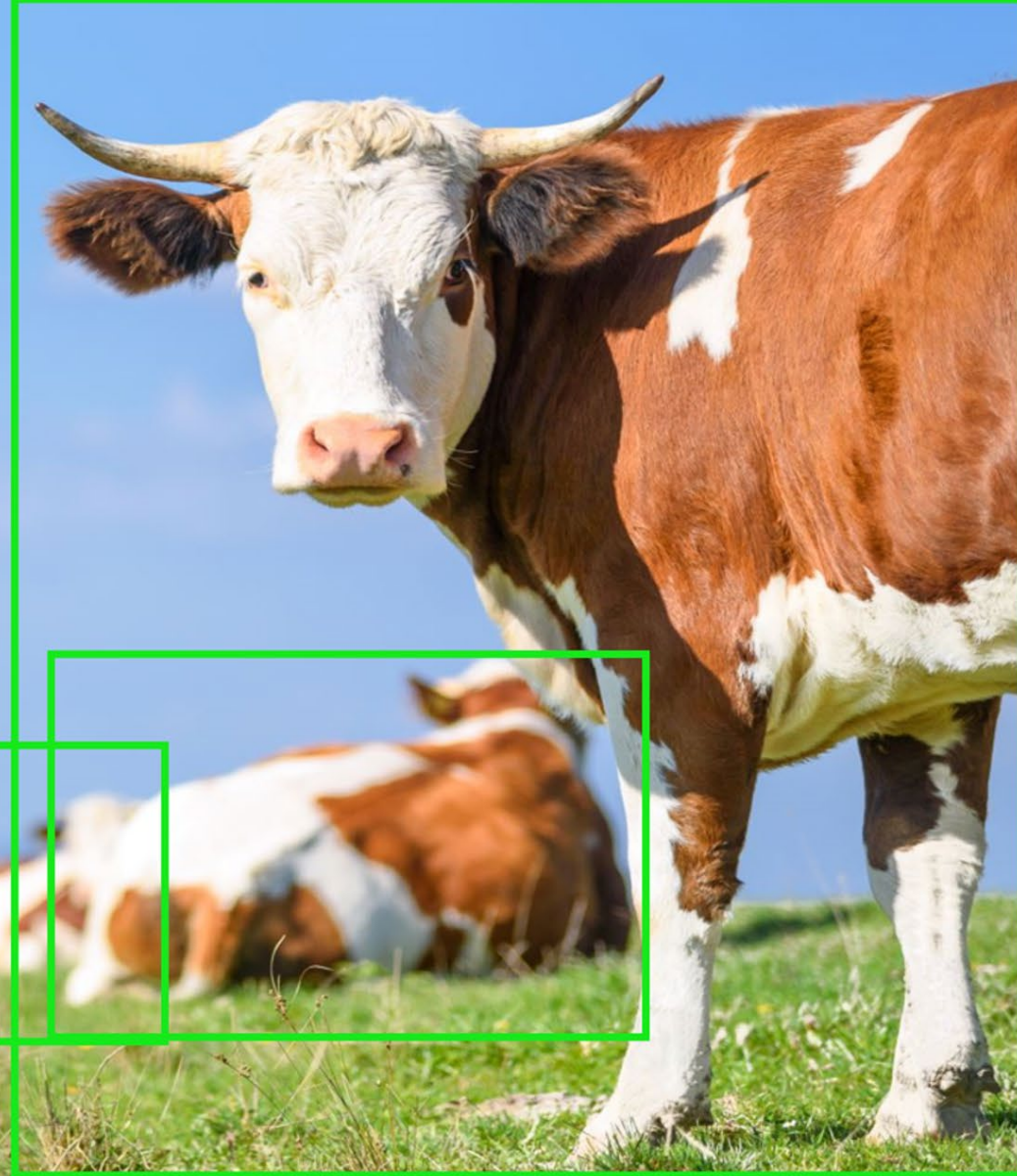


AI-based calibration of input parameters enables model predictions to conform to ground truth case counts effortlessly

Traditionally, epi models were laboriously hand calibrated to fit different populations and regions, often producing inaccurate predictions. Current research funded by CDC and DOE implements this AI calibration alternative for the nation's next generation of epi models for future outbreaks

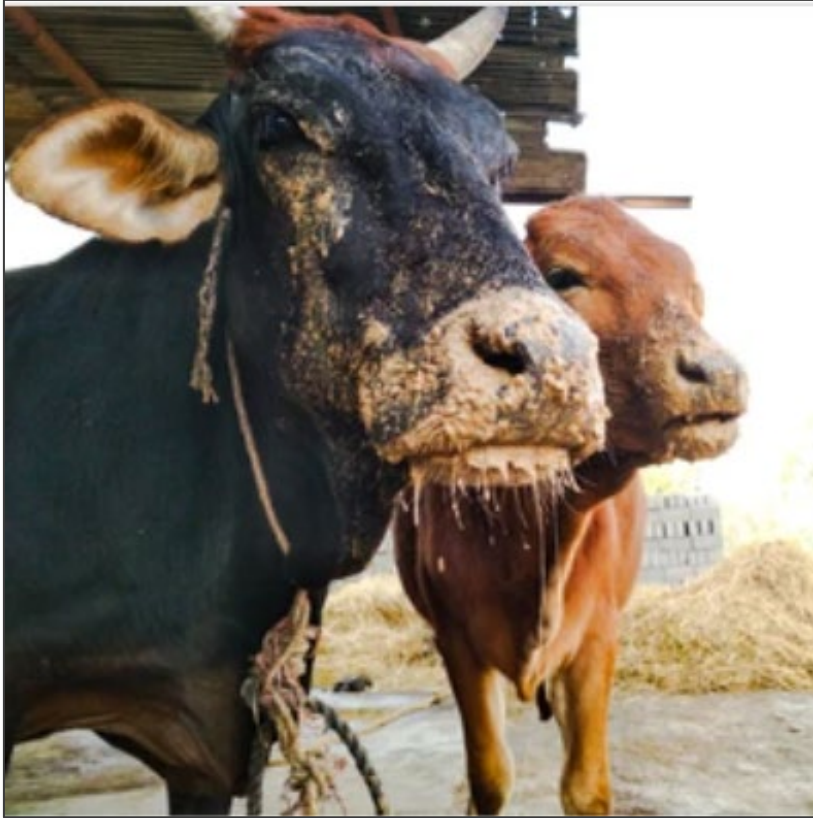


What do Cows
have to do with AI?





Livestock and Wildlife Surveillance Now and the Future



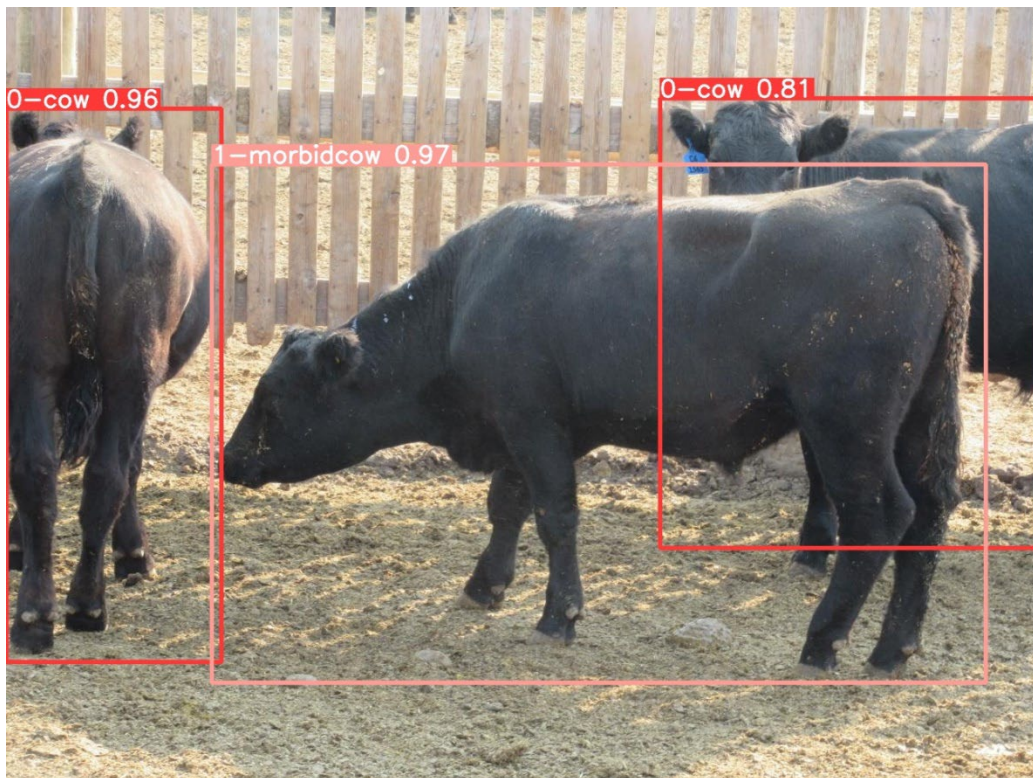
Deadly human diseases
often involve animal hosts



Can AI/ML and UAV based global disease
surveillance help prevent outbreaks?



Detection Requires AI-based fusion of multimodal sensor data



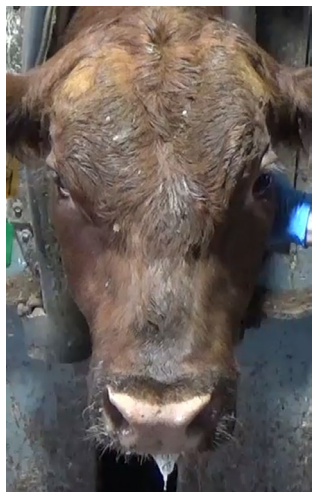
Static image classification yields 85% accuracy telling sick from healthy cattle



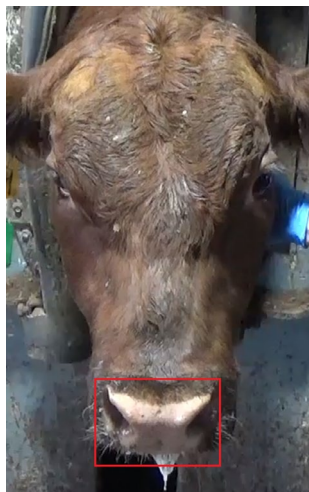
Including heart rate, O2Sat, temperature, gait changes, lethargy and other dynamic features increases accuracy to 95%



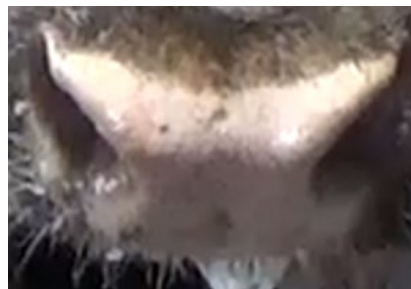
ML Detection of Heart Rate from Drone



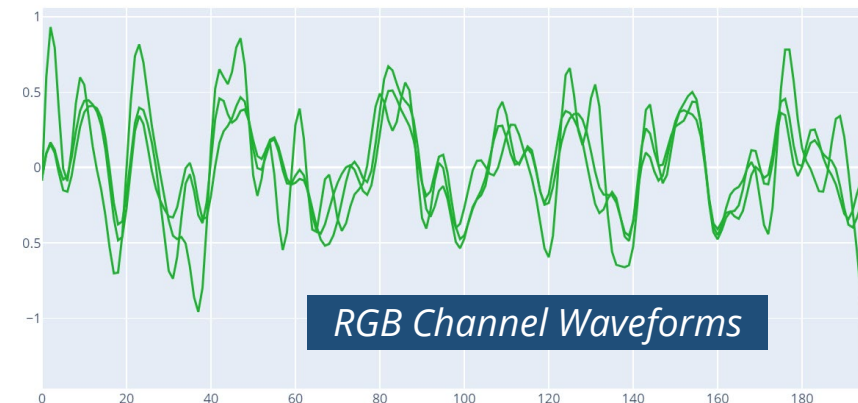
24 fps video of animal



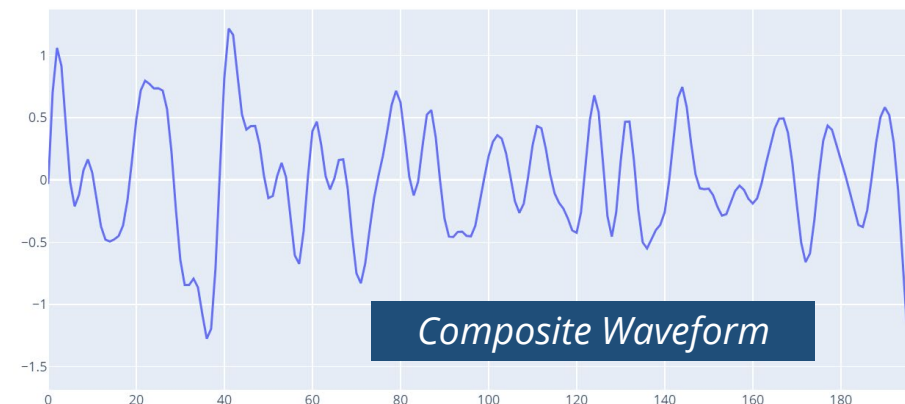
Detect nose on each frame



1. Isolate skin pixels
2. R,G,B channels
3. Detect changes over 8-sec RGB window
4. Analyze waveforms



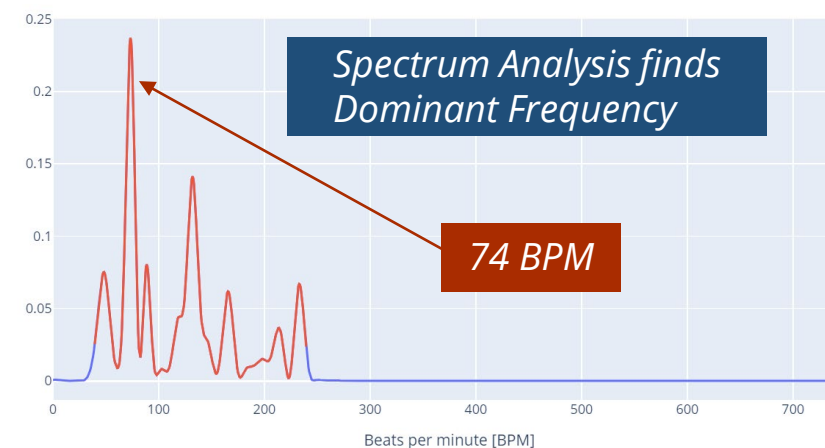
RGB Channel Waveforms



Composite Waveform

Standoff measurement of pulse from live video

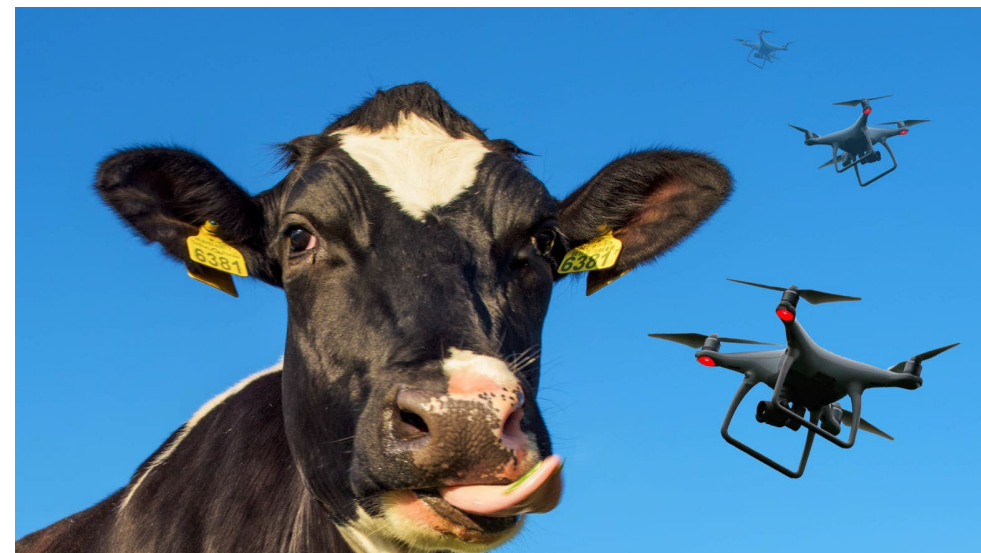
- Leverage spectral absorbance contrast of oxygenated and de-oxygenated hemoglobin
- Change in skin pixel color occurs with each heartbeat
- AI model converts pixel colors to Heart Rate
- Tested from fully Autonomous UAV at 20m altitude





Standoff sensing for High-Throughput Public Health Screening

- In addition to herd health, Sandia's animal health research illustrates possible directions for reliable, contactless health screening for public health planning and response
- Our research showed that dynamic analysis of individual movement and physiological signals required for accurate health screening.
- Animal Health algorithms designed to be unbiased to skin tone, sex, and breed, mirroring AI Challenges outlined earlier.
- Does not rely on face recognition or other privacy concerning methods.



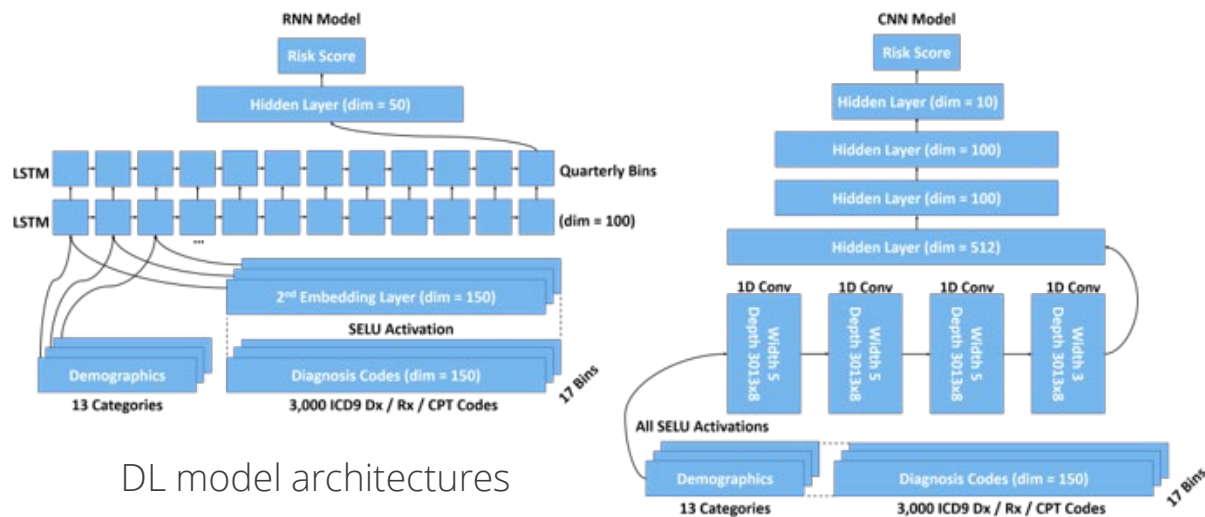
Sarah Rogers / The Daily Beast



Deep learning models improve identification of highest risk patients

Goal: Given longitudinal patient data, predict risk of a suicide attempt in the next year

Result: Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) outperform linear regression and logistic regression algorithms when measured by concentration of risk of a suicide attempt in highest scoring tiers of patients.



DL model architectures

Risk concentration results on inflated test set of ~9M patients

	Risk Tier	0.01%	0.1%	1.0%
3 Months	Lin. Reg.	29.6 (2.0)	20.0 (0.4)	11.7 (0.1)
	Log. Reg.	29.9 (1.6)	18.2 (0.4)	10.4 (0.1)
	RNN	30.4 (2.7)	22.9 (0.7)	11.9 (0.1)
	CNN	83.1 (3.7)	33.0 (0.4)	14.1 (0.0)
6 Months	Lin. Reg.	25.9 (2.2)	18.3 (0.4)	10.5 (0.1)
	Log. Reg.	28.6 (1.4)	17.7 (0.4)	10.0 (0.1)
	RNN	34.0 (2.3)	24.5 (0.4)	12.5 (0.1)
	CNN	75.6 (4.3)	31.8 (0.5)	13.7 (0.1)
1 Year	Lin. Reg.	21.1 (1.6)	15.6 (0.3)	9.0 (0.1)
	Log. Reg.	25.3 (1.2)	16.3 (0.4)	9.6 (0.0)
	RNN	30.4 (2.7)	22.9 (0.4)	11.9 (0.0)
	CNN	66.5 (3.7)	29.7 (0.4)	12.8 (0.0)

CNN predicts risk scores consistent with time to event; patients who attempted suicide within 3 months were assigned higher risk scores than those who made a suicide attempt in later months.

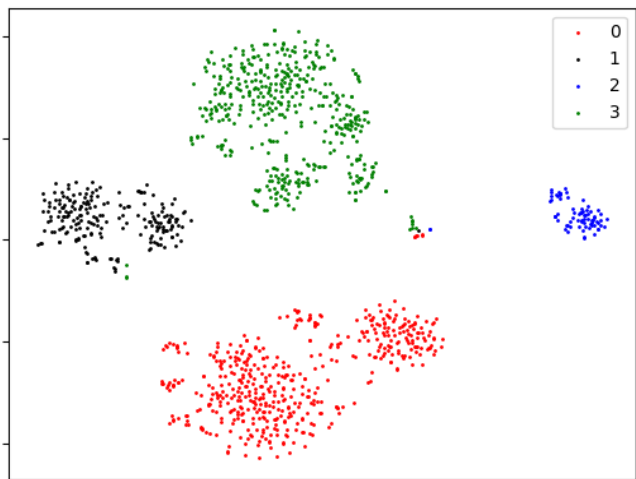


Explanations provide insights about individual risk scores and subgroups

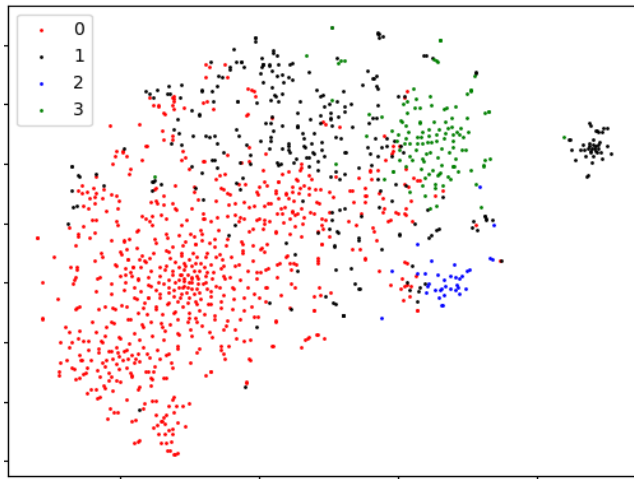
SHAP values for each patient highlight the most impactful features contributing to their predicted risk score. Larger positive SHAP values indicate which features increase risk score for a particular patient.

Clustering by SHAP values displays patient subgroups identified the CNN model and produces higher quality clusters than those generated using raw patient data (feature values). Subgroups may demonstrate distinct trajectories that lead patients towards suicide.

Top 1% of Patients by Risk Score

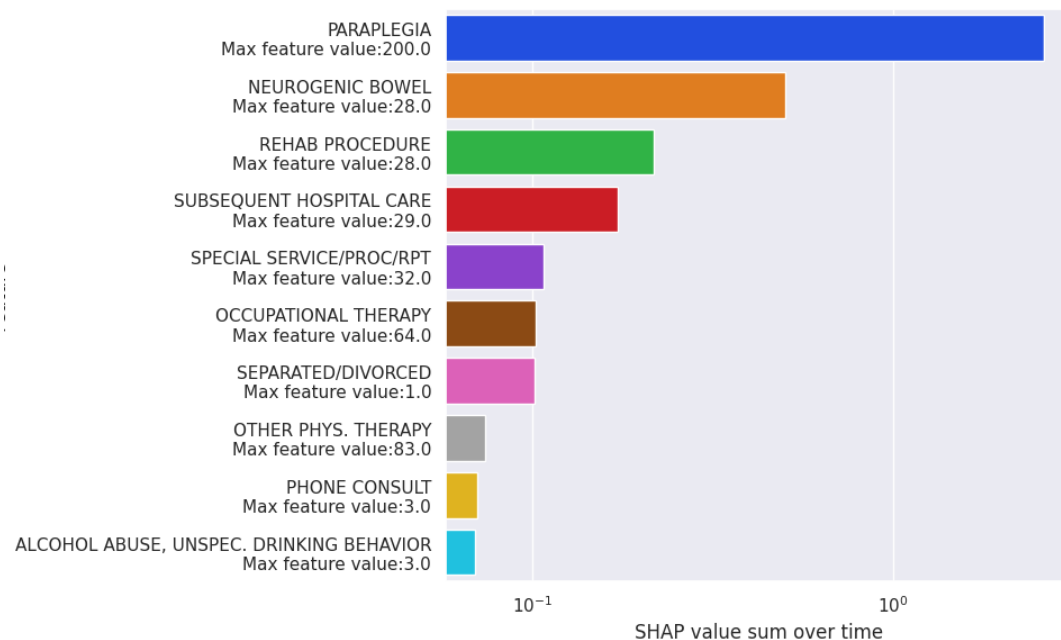
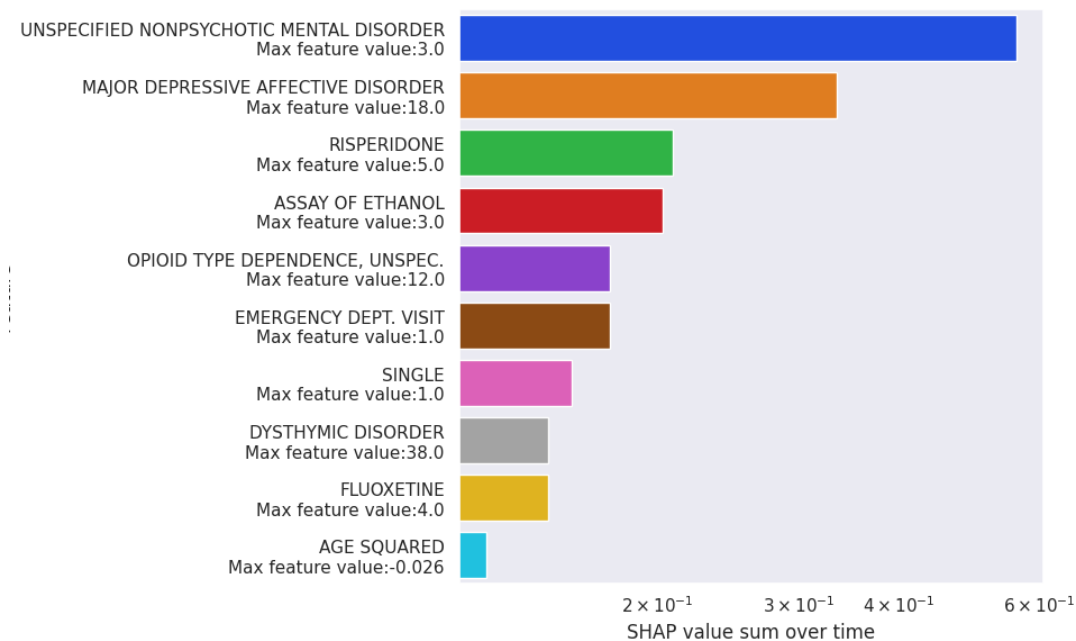


Clusters formed from SHAP values



Clusters formed from feature values

SHAP values for 2 individuals in highest risk tier





ADAPT: Automated Data-driven Assistant for Patient Triage

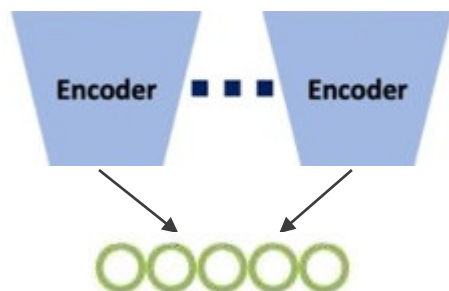
Sandia National Laboratories (Drew Levin), University of New Mexico

Graphical Abstract

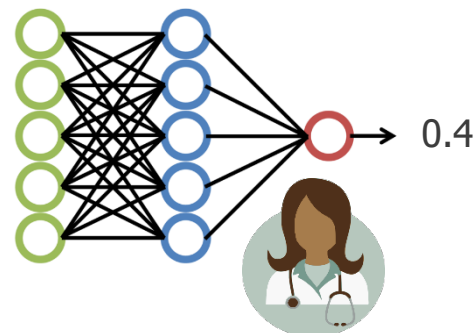
Collect data



Create encoded representation



Train model with data & expert knowledge



Explain model predictions

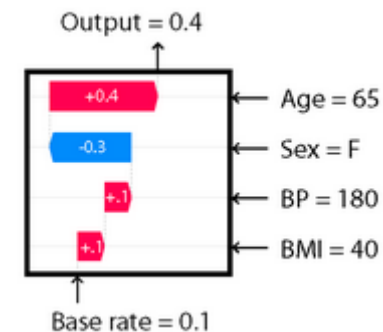


Image: SHAP documentation

Team Members

Sandia National Laboratories

University of New Mexico Department of
Emergency Medicine

Technical Approach

Our approach will comprise 3 main thrusts:

- **Data Preprocessing:** We will fuse data from diverse sensor modalities into a single representation which can serve as input to a machine learning model. The representation must be robust to missing or erroneous values and able to incorporate additional information (e.g., demographics) as available.
- **Machine Learning Models:** We will experiment with training various models to predict a patient's time to death with and without a given LSI. We will also integrate expert medical knowledge into the models, drawing on physics-informed machine learning approaches.
- **Model Explanations:** We will use local explainability techniques such as Shapely Additive Explanations to determine the features which most influence the models' prediction for each patient.

☐ Human Use / ☐ Animal Use



Summary

- AI can be used to automate and optimize preparedness and response
- The projects presented are only examples of the impact that AI can have on public and animal health
- These AI platforms are presented in the context of specific exemplars but are flexible and can be adapted to address other public and animal health challenges