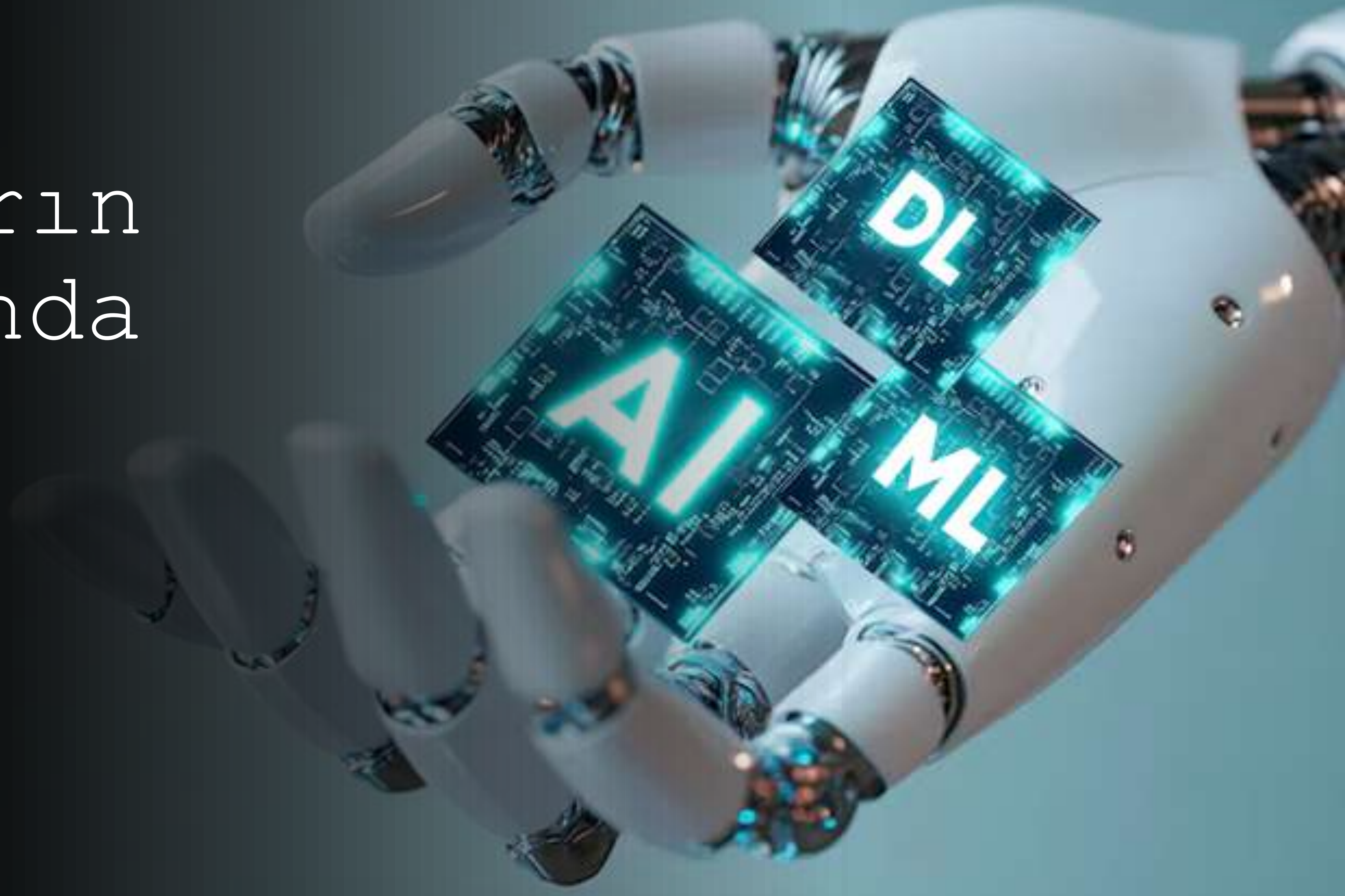
Postoperatif Infeksiyonların Erken Tanısında Yapay Zeka Modelleri



Bahar Madran

Koç Universitesi, Halk Sağlığı

Dr. Öğr. Üyesi

İçerik

- Postoperatif enfeksiyonlara erken müdahalenin önemi
- Yapay zeka destekli risk ve erken tanı modelleri
- Klinikte yayınlanmış yapay zeka çalışmaları
- Gelecekte nasıl olmalı

Postoperatif enfeksiyonlar

- Morbidite, mortalite, yatış gün sayısı, maliyet
- Tanıda gecikme

- Post op 2. gün; Ateş yok, Crp hafif
- Post op 5. gün sepsis, yb ihtiyacı

CAE tanısı konduğunda zaten **geç** kalmış oluyoruz!

Daha erken müdahale mümkün mü & bize ne kazandırır?

Klasik yöntemler neden yetersiz?

- Klinik belirti & bulgular
- CRP&PCT
- Kültürler
- Mevcut skorlar

Yapay zeka bize ne vaat ediyor?

Çok değişkenli verilerden **erken risk sinyali**!

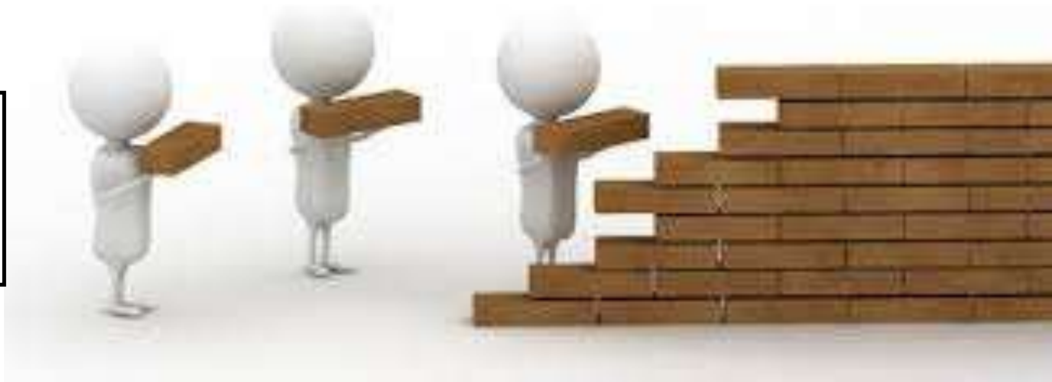
Vital bulgular

Lab dinamikleri

CAE risk skorlama adımları (süre, ASA, yara sınıfı)

Elektronik sağlık kayıtları

Bu verileri aynı anda, hızlı ve doğru bir şekilde yorumlamak. Dinamik değişimleri açırmak



Yapay Zeka Modelleri

Klasik Machine Learning (Klasik makine öğrenimi)

- Klinisyenin düşünme biçimini taklit eder, anlaşılır, şeffaf, küçük veri ile çalışır.

Deep Learning (Derin Öğrenme)

- Klinisyenin henüz bilmediği, fark etmediği örüntüleri yakalamaya çalışır, daha karmaşık, daha büyük yapıyı kullanan yapılardır. Erken sinyalde daha güçlü veri sağlar.

Klasik makine öğrenimi (Classical Machine Learning)

- Klinik uzman önemli değişkeni seçer.
- Model bu seçilen veriye göre riski hesaplar.
- Daha anlaşılır, şeffaf bir yapı.

Örneğin; Ateş, CRP artışı, uzun operasyon süresi, temiz-kontamine cerrahi,

re-operasyon; CAE riski çok yüksek !!!

ML Destekli Sürveyans Programı

Amaç

- Enfeksiyonları izlemek
- Trendleri izlemek
- Riskli hastaları işaretlemek

Kime Hizmet Eder

- Enfeksiyon Kontrol Ekipleri
- Kalite birimi
- Hastane yönetimi

Odak

- Popülasyon

ESK tanır, çoklu veriyi analiz eder, erken tanı uyarısını sapyar,

Tanı koymaz, tedavi önermez.

Klinik Karar Destek Sistemi

Amaç

- Klinik olarak karar vermeyi desteklemek

Kime Hizmet Eder

- Hekim
- Hemşire

Odak

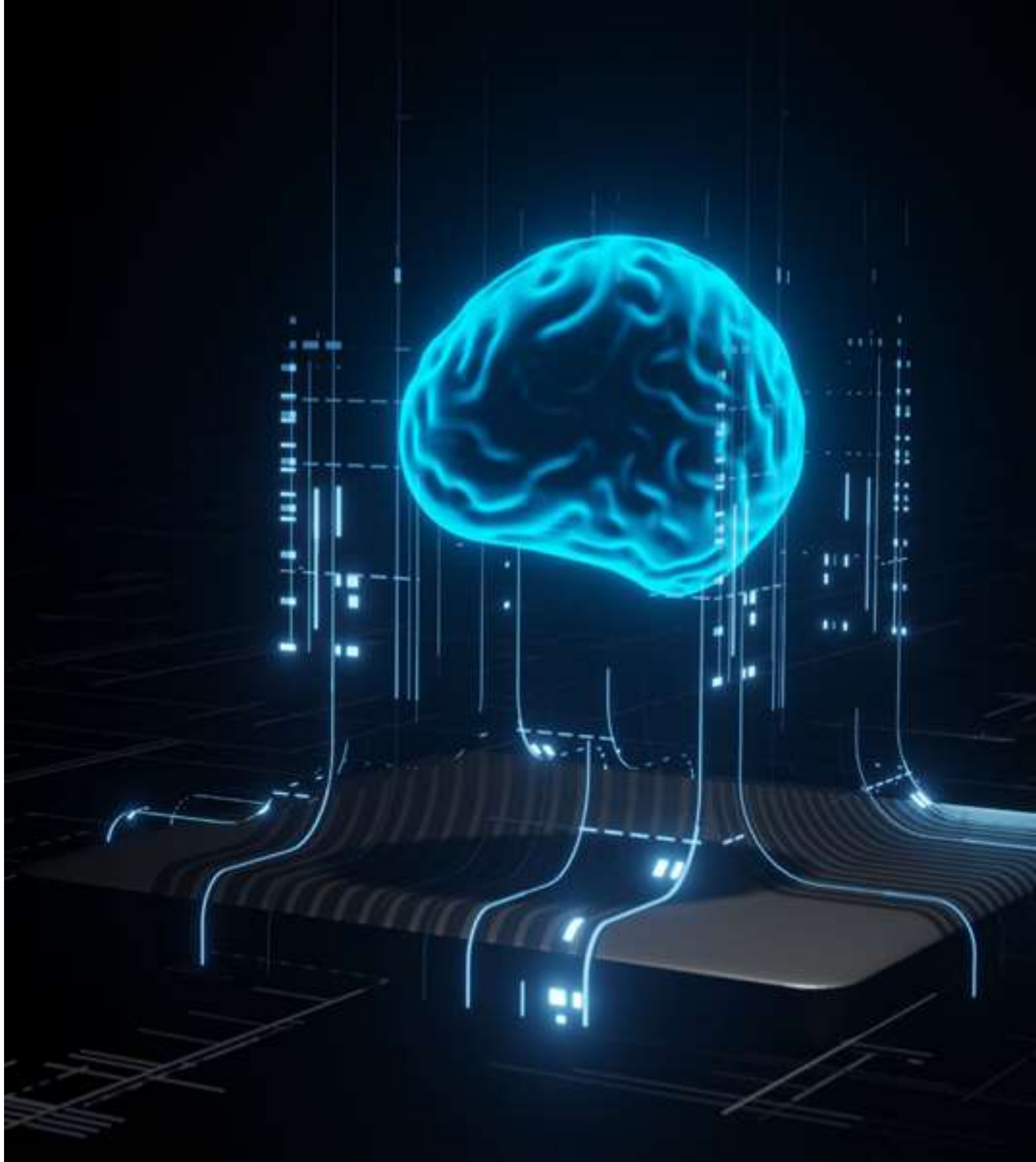
- Tek hasta, medikal durum

Tanı koyar, tedavi önerir, doz ayarlaması yapar, risk skorunu gösterir.

Doğrudan bakım kararına temas

Deep Learning

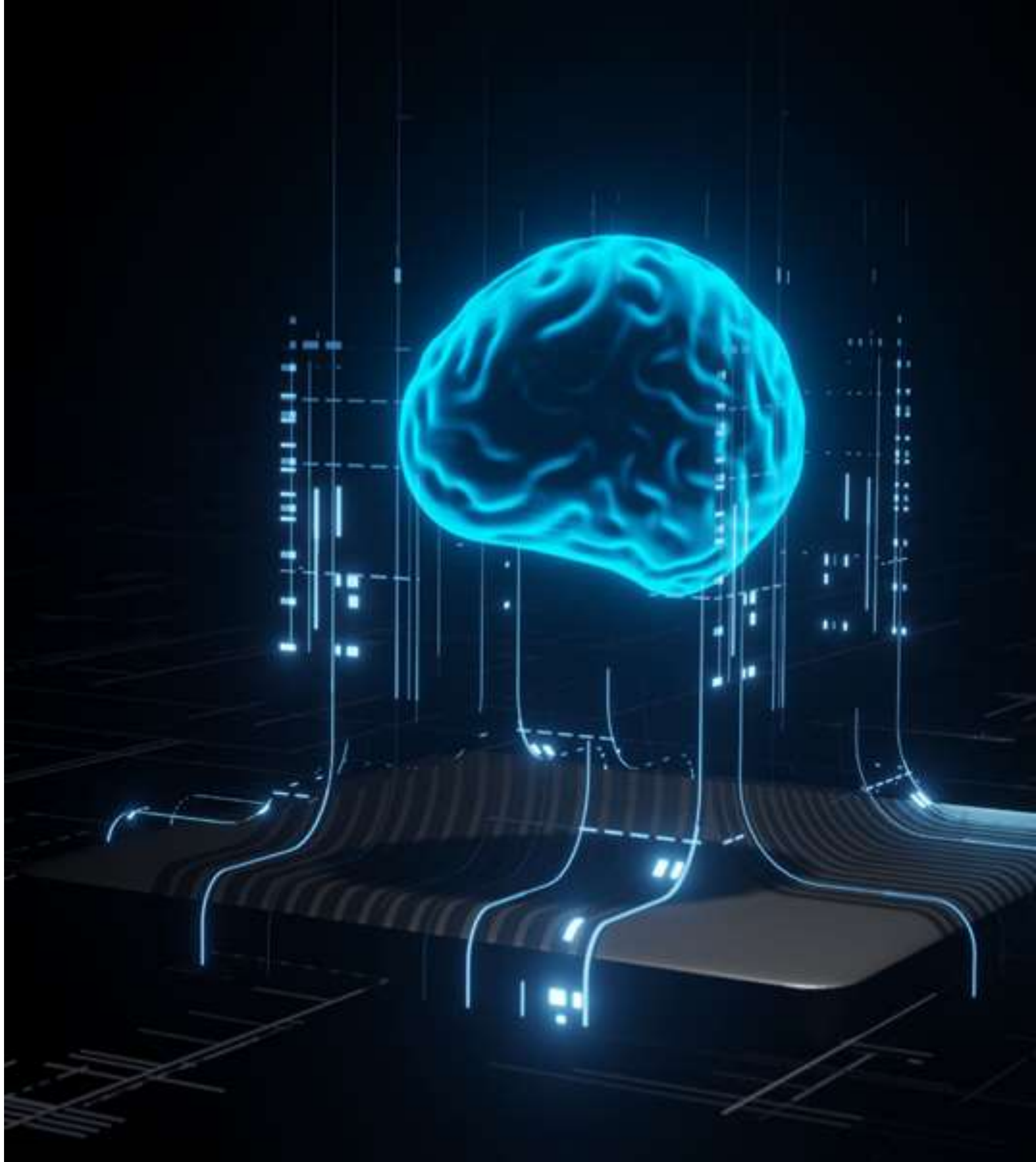
- Daha çok zaman kıtlığında, verinin ham olduğu durumlarda başvurulur.
- Yüksek boyutlu ham verilerden otomatik özellik çıkarımı yapabilir.
- Erken risk sinyali bulma konusunda daha başarılı.



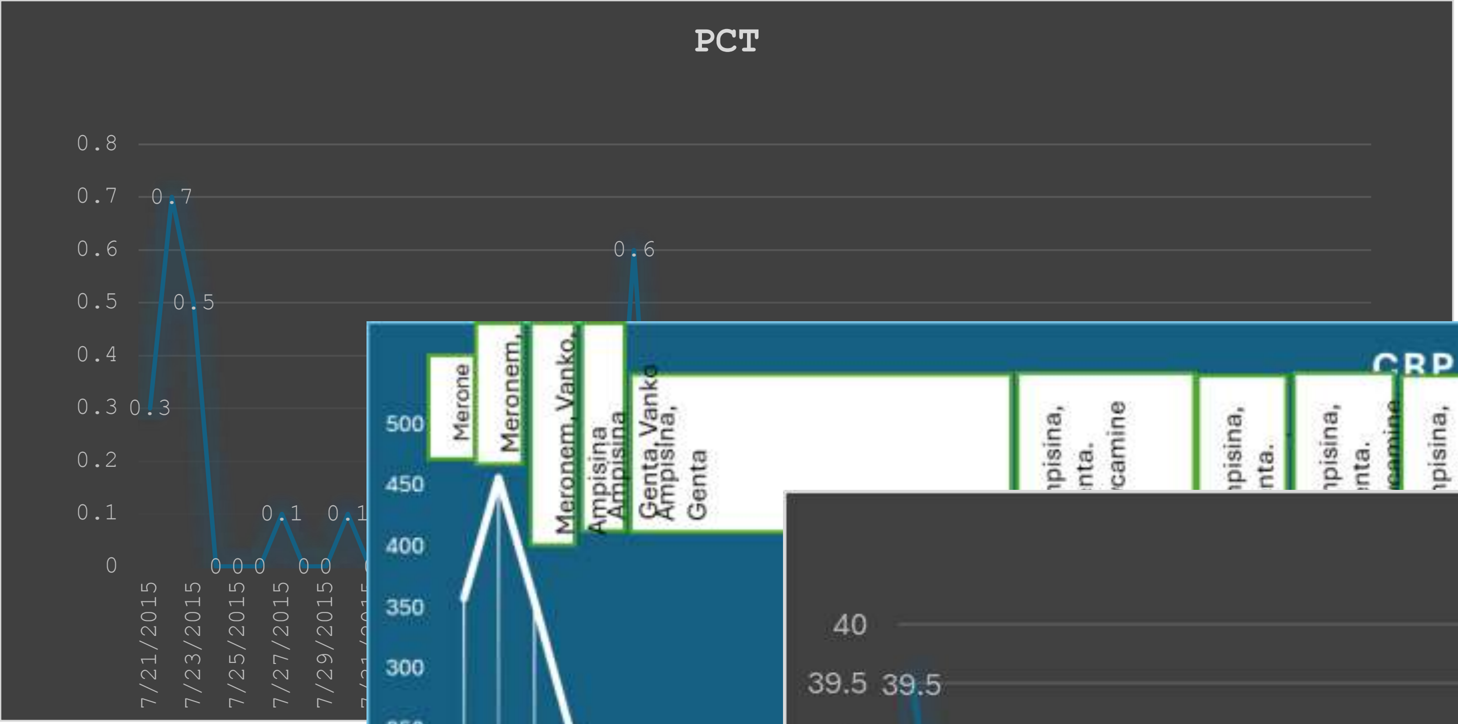
Deep Learning

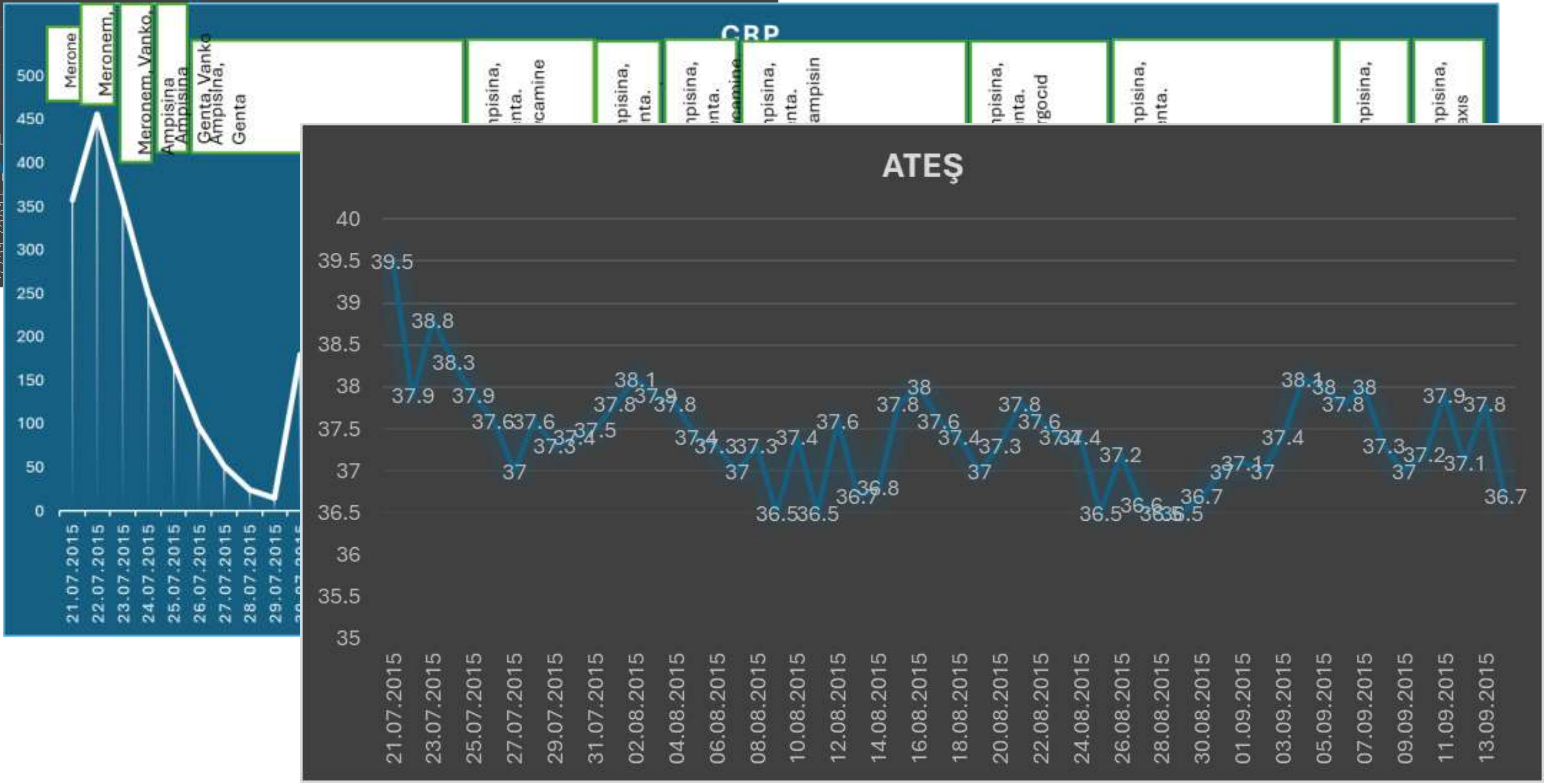
Literatürde;

- Multilayer Perceptron (MLP)
- Deep Neutral Network (DNN)
- Convolutional Neutral Network (CNN)
- Long Short-term memory (LSTM)
- Random forest
- Logistic regresyon
- ...
- ... vb



İlk ML Denememiz-Infogram





Klasik ML – Deep Learning Model Örnekleri

Modelin başarısı

***AUC:** Area Under The Curve, Sensitivity-Specificity arasındaki denge

! Tek merkezli çalışmalar, external validasyonu olmayan çalışmaların temsiliyeti düşük

! Bazı model uygulamaları kara kutu gibi

! Klinik işleyişi aksatmamalı

Klinisyene kaç gün kazandırdı?

Hastaya neler kazandırdı?

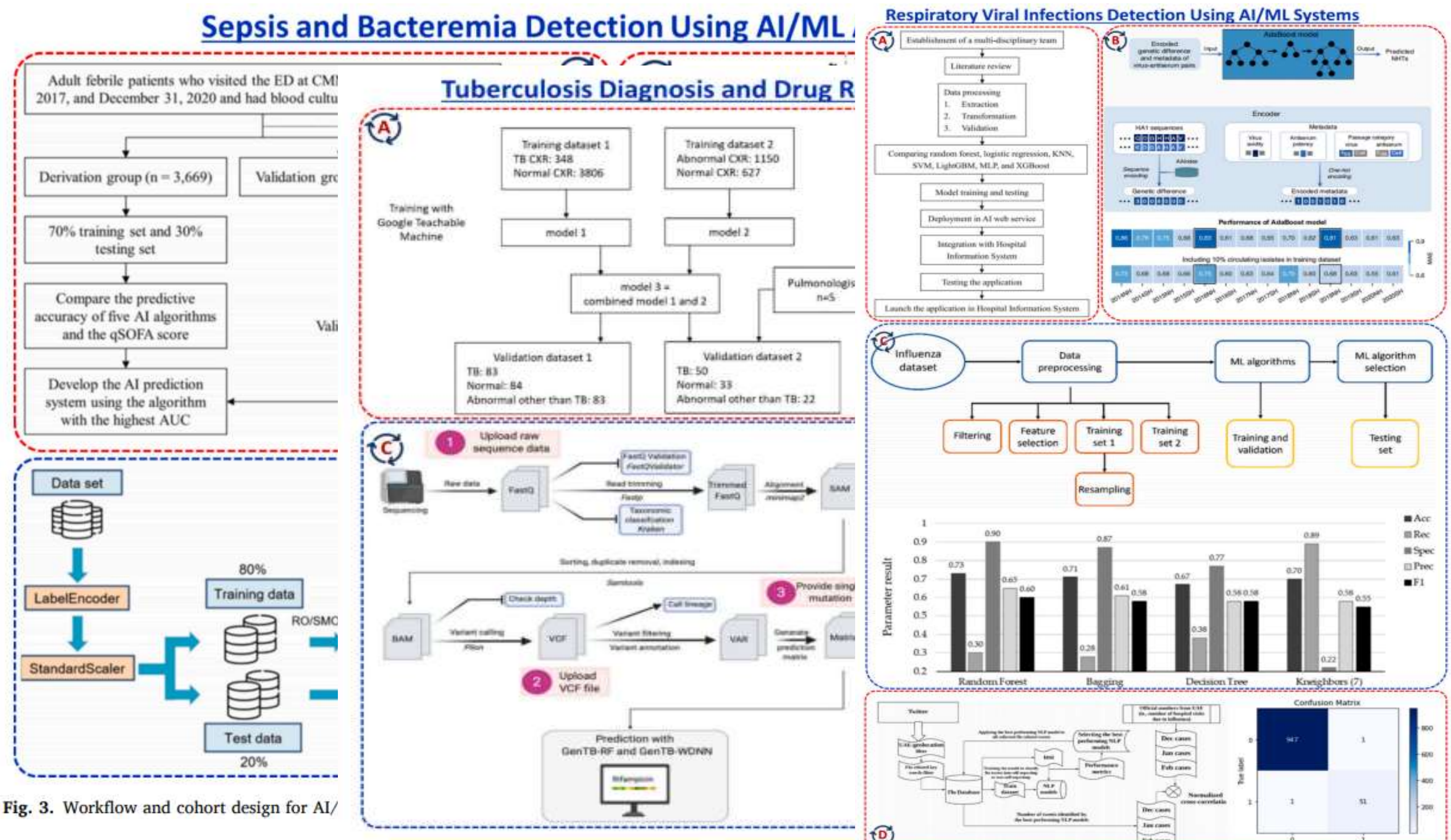


Fig. 3. Workflow and cohort design for AI/

Wang *et al. Journal of Intensive Care* (2023) 11:49
https://doi.org/10.1186/s40560-023-00695-y

RESEARCH

A deep learning mode multidrug-resistant or in critically ill patients

Yaxi Wang[1], Gang Wang[1], Yuxiao Zhao[1], Cheng Wa
Silong Gao[1*] and Xufeng Pang[3*]

Abstract

Background This study aimed to apply the backpro ing multidrug-resistant organism (MDRO) infection in

Methods This study collected patient information a of Qingdao University from August 2021 to January 2 set (80%) and a test set (20%). The least absolute shri were used to determine the independent risk factors on these factors. Then, we externally validated this m center. The model performance was evaluated by the specificity, and accuracy.

Results In the primary cohort, 688 patients were en tors for MDRO infection, as determined by the primar long-term bed rest, antibiotics use before ICU, acute before ICU, quantity of antibiotics, chronic lung disea dation set, including 31 (13.03%) MDRO infection pat of the training set, the test set and the validation set and 0.811 (95% CI 0.731–0.891), respectively.

Conclusions This study confirmed nine independen well and was potentially used to predict MDRO infect

Keywords Multidrug-resistant organism infection, B

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journal homepage:

Machine Learning Models Surgical Site Infection Aft Laparotomy

Michael D. Cobler-Lichter, MD, MSDS, Zoe M. Weiss, MD, Matthew Fastiggi, Nicole B. Lyons, MD, Luciana Tito Bu, Jonathan P. Meizoso, MD, MSPH, N. Brandon M. Parker, DO, and Kenneth

Division of Trauma & Surgical Critical Care, DeWitt Daug Center, University of Miami Miller School of Medicine, Mi

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Keywords:
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Infection
Laparotomy
Machine learning
Surgical site infection
Trauma

A B S T R A

Introduction:
infection (S
pothesized t
perioperativ
Materials an
Improveme
retrospectiv
hospital SSI
and organ s
relative sign
Results: Of 5
ment Projec
The model
curve of 0.8
model sligh
curve of 0.8
pactful vari
volume of p
Conclusions:
risk for SSI.
automatical
plans tailor

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Journal of Hospital Infection 154 (2024) 112–121

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Journal of Hospital Infection

journal homepage: www.elsevier.com/locate/jhin

Healthcare Infection Society

Leader

Clinically explainable machine learning models for early identification of patients at risk of hospital-acquired urinary tract infection

R.S. Jakobsen [a,b,*], T.D. Nielsen [c], P. Leutscher [a,d], K. Koch [a,e]

[a] *Centre for Clinical Research, North Denmark Regional Hospital, Hjørring, Denmark*
[b] *Business Intelligence and Analysis, The North Denmark Region, Denmark*
[c] *Department of Computer Science, Aalborg University, Aalborg, Denmark*
[d] *Department of Clinical Medicine, Aalborg University, Aalborg, Denmark*
[e] *Department of Clinical Microbiology, Aalborg University Hospital, Aalborg, Denmark*

A R T I C L E I N F O

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Received 21 February 2023
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Available online 31 March 2023

Keywords:
Clinical explainability
Feature selection
Hospital-acquired urinary tract infection
Machine learning
Risk prediction

S U M M A R Y

Background: Machine learning (ML) models for early identification of patients at risk hospital-acquired urinary tract infection (HA-UTI) may enable timely and targeted pr ventive and therapeutic strategies. However, clinicians are often challenged in t interpretation of the predictive outcomes provided by the ML models, which often rea different performances.

Aim: To train ML models for predicting patients at risk of HA-UTI using available data fr electronic health records at the time of hospital admission. This study focused on t performance of different ML models and clinical explainability.

Methods: This retrospective study investigated patient data representing 138,560 hospi admissions in the North Denmark Region from 1st January 2017 to 31st December 20 Fifty-one health sociodemographic and clinical features were extracted as the full da set, and χ^2 test and expert knowledge were used for feature selection, resulting in t reduced datasets. Seven different ML models were trained and compared between t three datasets. The SHapley Additive exPlanation (SHAP) method was used to supp population- and patient-level explainability.

Findings: The best-performing ML model was the neural network model based on the f dataset, with an area under the curve (AUC) of 0.758. The neural network model was a the best-performing ML model based on the reduced datasets, with an AUC of 0.7 Clinical explainability was demonstrated with a SHAP summary and forceplot.

Conclusion: Within 24 h of hospital admission, the ML models were able to identify patie at risk of developing HA-UTI, providing new opportunities to develop efficient strategies the prevention of HA-UTI. SHAP was used to demonstrate how risk predictions can explained at individual patient level and for the patient population in general.

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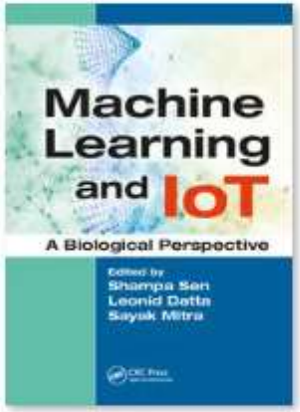

FULL ACCESS

Chapter

Machine Learning Based Hospita Acquired Infection Control Syste

By Sehaj Sharma, Prajit Kumar Datta, Gaurav Bansal

Book Machine Learning and IoT

Edition	1st Edition
First Published	2018
Imprint	CRC Press
Pages	23

Infection Control System

Sehaj Sharma, Prajit Kumar Datta,
and Gaurav Bansal

CONTENTS

A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis

Xiaoxuan Liu*, Livia Faes*, Aditya U Kale, Siegfried K Wagner, Dun Jack Fu, Alice Bruynseels, Thushika Mahendiran, Gabriella Moraes, Mohith Shamdas, Christoph Kern, Joseph R Ledsam, Martin K Schmid, Konstantinos Balaskas, Eric J Topol, Lucas M Bachmann, Pearse A Keane, Alastair K Denniston

Summary

Background Deep learning offers considerable promise for medical diagnostics. We aimed to evaluate the diagnostic accuracy of deep learning algorithms versus health-care professionals in classifying diseases using medical imaging

Lancet Digital Health 2019; 1: e271–97

Published Online

Lancet Digital Health;

2012-2019 yıllarında yayınlanmış, 82 çalışma-147 hasta kohortu (25 çalışma external validasyon)

DL ile Sensitivity, Specificity (87- 92.5%)
Manuel Sürveyans (86%- 90%)

Derin öğrenme, görüntü temelli tanıda insan kadar iyi olabilir; ancak klinik uygulama için henüz yeterince sağlam kanıt yok.

Funding None.

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Trust, London, UK (X Liu, L Faes MD, D J Fu PhD, G Moraes MD, C Kern MD, K Balaskas MD); Eye Clinic,

Infection Control & Hospital Epidemiology (2024), **45**, 604–608
doi:10.1017/ice.2023.224

SHEA

Original Article

Hospital-acquired infections surveillance: The machine-learning algorithm mirrors National Healthcare Safety Network definitions

Stephani Amanda Lukasewicz Ferreira RN, MSc[1], Arateus Crysham Franco Meneses BSc[1],

NHSN' nin aynı tanı kriterleri kullanılarak
ML ile desteklenmiş Yarı-Otomatik Sürveyans – Manuel Sürveyans sonuçları
6296 hasta kaydı, 447 değişken (yaş, cinsiyet, ateş, ateş gün sayısı, lökosit, crp, klt vb)

Manuel Sürveyans : 2.9% (183 SBİE, Özellikle VİP inf. kaçıyor)

ML Destekli Yarı-otomatik Sürveyans: 4.7% (299 SBİE)

considered 447 features for HAI classification. Among them, 148 features (33.1%) were related to infection signs and symptoms; 101 (22.6%) were related to patient severity status, 51 features (11.4%) were related to bacterial laboratory results; 40 features (8.9%) were related to invasive procedures; 34 (7.6%) were related to antibiotic use; and 31 features (6.9%) were related to patient comorbidities. Among these 447 features, 229 (51.2%) were similar to those proposed b

Conclusion: The ML algorithm, which include
Well-documented algorithm performances m
the drawbacks of traditional HAI surveillanc

ML ile daha tutarlı, daha az iş gücü

(Received 21 March 2023; accepted 16 September 2023; electronically published 11 January 2024)

Dosya incelemek zaman alıcı, iş gücü kaybı (Amaç erken tanı değil, kaliteyi artırma, iş gücü kontrolü).

Minesota
ESK - CAE süreyansı yapan ML destekli bir model geliştirilmiş.

Başka bir kurumda, farklı bir ESK ile denenmiş (external validation)

Her iki kurumun; **SSI AUC 0.80 – 0.90**

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

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Author manuscript
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Published in final edited form as:
J Am Coll Surg. 2021 June ; 232(6): 963–971.e1. doi:10.1016/j.jamcollsurg.2021.03.026.

Applying Machine Learning Across Sites: External Validation of a Surgical Site Infection Detection Algorithm

Ying Zhu, PhD, Gyorgy J Simon, PhD, Elizabeth C Wick, MD, FACS, Yumiko Abe-Jones, MS, Nader Najafi, MD, Adam Sheka, MD, Roshan Tourani, PhD, Steven J Skube, MD, Zhen Hu, PhD, Genevieve B Melton, MD, FACS, PhD
Institute for Health Informatics (Zhu, Simon, Tourani, Hu, Melton) and the Departments of Medicine (Simon) and Surgery (Wick), University of Minnesota, Twin Cities; Minneapolis, MN; and the Departments of Surgery (Abe-Jones, Najafi) and Medicine (Sheka, Skube, Melton), University of California San Francisco, San Francisco, CA

Abstract

Doğru tasarlanırsa sistem başka merkezde de çalışabilir!

NSQIP SSI detection of superficial, organ space, and total SSI within 30 days postoperatively were validated using area under the curve (AUC) scores and corresponding 95% confidence intervals.

RESULTS: For the 8,883 patients (Site A) and 1,473 patients (Site B), AUC scores were not statistically different for any outcome including superficial (external 0.804, internal [0.784, 0.874] AUC); organ/space (external 0.905, internal [0.867, 0.941] AUC); and total (external 0.855, internal [0.854, 0.908] AUC) SSI. False negative rates decreased with increasing case review volume and would be amenable to a strategy in which cases with low predicted probabilities of SSI could be excluded from chart review.

Pre-op **BT görüntüsünü** inceleyerek
Klinik veri, lab verisi, skor YOK

DL ile **SSI tahmini (AUC: 0.90)**

Operasyonun zorluğu (AUC: 0.57)

JAWS JOURNAL OF ABDOMINAL WALL SURGERY | EHS EUROPEAN HERNIA SOCIETY

ORIGINAL RESEARCH
published: 14 April 2025
doi: 10.3389/jaws.2025.14371

Development of Multicenter Deep Learning Models for Predicting Surgical Complexity and Surgical Site Infection in Abdominal Wall Reconstruction, a Pilot Study

William R. Lorenz[1], *Alexis M. Holland*[1], *Benjamin A. Sarac*[2], *Samantha W. Kerr*[1], *Hadley H. Wilson*[1], *Sullivan A. Ayuso*[1], *Keith Murphy*[3], *Gregory T. Scarola*[1], *Brittany S. Mead*[1], *B. Todd Heniford*[1] and *Jeffrey E. Janis*[2]*

[1]Division of Gastrointestinal and Minimally Invasive Surgery, Department of Surgery, Carolinas Medical Center, Charlotte, NC, United States, [2]Department of Plastic and Reconstructive Surgery, Ohio State University Wexner Medical Center, Columbus, OH, United States, [3]Department of Computer Science, University of North Carolina at Charlotte, Charlotte, NC, United States

Objective: Hernia recurrence and surgical site infection (SSI) are grave complications in Abdominal Wall Reconstruction (AWR). This study aimed to develop multicenter deep learning models (DLMs) developed for predicting surgical complexity, using Component Separation Technique (CST) as a surrogate, and the risk of surgical site infections (SSI) in AWR, using preoperative computed tomography (CT) images.

Methods: Multicenter models were created using deidentified CT images from two tertiary AWR centers. The models were developed with ResNet-18 architecture. Model performance was reported as accuracy and AUC.

Results: The CST model underperformed with an AUC of 0.569, while the SSI model exhibited strong performance with an AUC of 0.898.

Conclusion: The study demonstrated the successful development of a multicenter DLM for SSI prediction in AWR, highlighting the impact of patient factors over surgical practice variability in predicting SSIs with DLMs. The CST model's prediction remained challenging, which we hypothesize reflects the subjective nature of surgical decisions and varying institutional practices. Our findings underscore the potential of AI-enhanced surgical risk calculators to risk stratify patients and potentially improve patient outcomes.

Keywords: artificial intelligence, ventral hernia repair, quality improvement, prediction model, component separation, deep learning model

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***Correspondence**
Jeffrey E. Janis,
jeffrey.janis@osumc.edu

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Accepted: *02 April 2025*
Published: *14 April 2025*

Citation:
Lorenz WR, Holland AM, Sarac BA,

Multimodel ML destekli prtogram,

Amaç: Hedef **erken tanısı değil**, kliniğin iş akışını bozmadan tanıya **erken odaklanmak**, iş gücü kaybını önlemek.

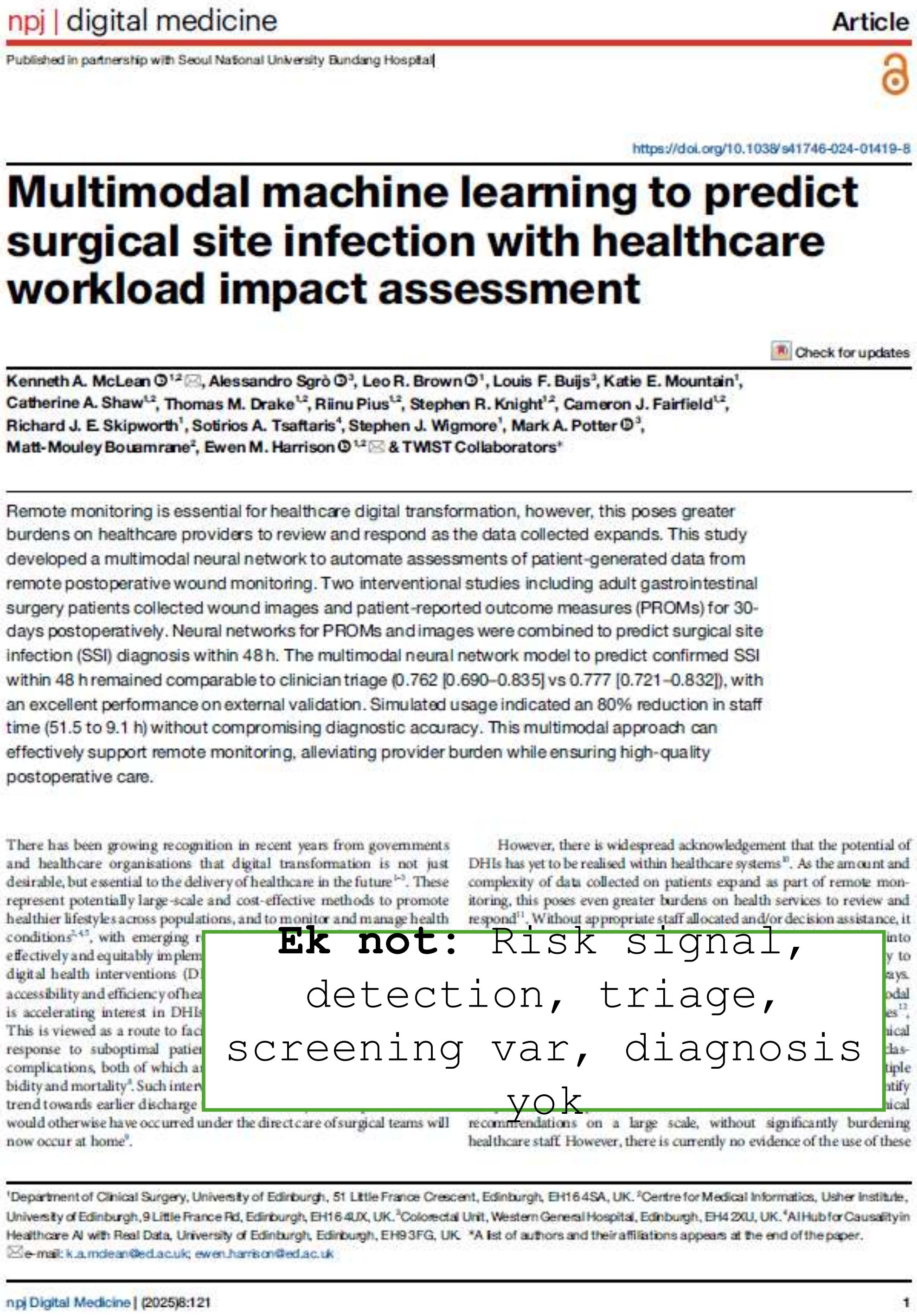
Post-op 30. günde, 423 hasta'dan,
1500 bildirim (Kızarıklık, ağrı , ateş, akıntı ?)
2600 **yara fotoğrafı**

Klinik semptom ve yara görüntüleri birlikte modellenerek erken uyarı geliştirildi.

AUC 0.76-0.83

Personelin tanı için ayırdığı süreyi 80% azaltıyor.
(51 saatten - 9 saate)

Tanı süresi (time-to diagnosis)ne kadar kısalmış?



npj | digital medicine

Article

Published in partnership with Seoul National University Bundang Hospital

https://doi.org/10.1038/s41746-024-01419-8

Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment

Check for updates

Kenneth A. McLean[1,2], Alessandro Sgrò[3], Leo R. Brown[1], Louis F. Buijs[3], Katie E. Mountain[1], Catherine A. Shaw[1,2], Thomas M. Drake[1,2], Riinu Pius[1,2], Stephen R. Knight[1,2], Cameron J. Fairfield[1,2], Richard J. E. Skipworth[1], Sotirios A. Tsaftaris[4], Stephen J. Wigmore[1], Mark A. Potter[3], Matt-Mouley Bouamrane[2], Ewen M. Harrison[1,2] & TWIST Collaborators*

Remote monitoring is essential for healthcare digital transformation, however, this poses greater burdens on healthcare providers to review and respond as the data collected expands. This study developed a multimodal neural network to automate assessments of patient-generated data from remote postoperative wound monitoring. Two interventional studies including adult gastrointestinal surgery patients collected wound images and patient-reported outcome measures (PROMs) for 30-days postoperatively. Neural networks for PROMs and images were combined to predict surgical site infection (SSI) diagnosis within 48 h. The multimodal neural network model to predict confirmed SSI within 48 h remained comparable to clinician triage (0.762 [0.690–0.835] vs 0.777 [0.721–0.832]), with an excellent performance on external validation. Simulated usage indicated an 80% reduction in staff time (51.5 to 9.1 h) without compromising diagnostic accuracy. This multimodal approach can effectively support remote monitoring, alleviating provider burden while ensuring high-quality postoperative care.

There has been growing recognition in recent years from governments and healthcare organisations that digital transformation is not just desirable, but essential to the delivery of healthcare in the future[1-3]. These represent potentially large-scale and cost-effective methods to promote healthier lifestyles across populations, and to monitor and manage health conditions[2,4,5], with emerging r… effectively and equitably implem… digital health interventions (D… accessibility and efficiency of hea… is accelerating interest in DHIs… This is viewed as a route to fac… response to suboptimal patie… complications, both of which a… bidity and mortality[8]. Such inter… trend towards earlier discharge… would otherwise have occurred under the direct care of surgical teams will now occur at home[9].

However, there is widespread acknowledgement that the potential of DHIs has yet to be realised within healthcare systems[10]. As the amount and complexity of data collected on patients expand as part of remote monitoring, this poses even greater burdens on health services to review and respond[11]. Without appropriate staff allocated and/or decision assistance, it … recommendations on a large scale, without significantly burdening healthcare staff. However, there is currently no evidence of the use of these

[1]Department of Clinical Surgery, University of Edinburgh, 51 Little France Crescent, Edinburgh, EH16 4SA, UK. [2]Centre for Medical Informatics, Usher Institute, University of Edinburgh, 9 Little France Rd, Edinburgh, EH16 4UX, UK. [3]Colorectal Unit, Western General Hospital, Edinburgh, EH4 2XU, UK. [4]AI Hub for Causality in Healthcare AI with Real Data, University of Edinburgh, Edinburgh, EH9 3FG, UK. *A list of authors and their affiliations appears at the end of the paper.
e-mail: k.a.mclean@ed.ac.uk; ewen.harrison@ed.ac.uk

npj Digital Medicine | (2025)8:121

1

Ek not: Risk signal, detection, triage, screening var, diagnosis yok

npj | digital medicine

Article

Published in partnership with Seoul National University Bundang Hospital

https://doi.org/10.1038/s41746-025-01989-1

Semi-automated surveillance of surgical site infections using machine learning and rule-based classification models

Américo Agostinho[1], Etienne Chalot[1], Daniel Teixeira[1], Davide
Stephan Harbarth[1,2] & Mohamed Abbas[1,2,3]

Surgical site infections (SSIs), among the most frequent hea
surveillance, but traditional methods are labour-intensive. W
rule-based models for the semi-automated detection of deep
prospective cohort of 3931 surgical patients. We assessed
(proportion of patients not requiring manual review) at a 0.5
under the receiver operating characteristic curve (AUROC) a
(AUPRC). The best-performing ML models (Naïve Bayes an
sensitivity up to 0.90, AUROC up to 0.968, AUPRC up to 0.24
rule-based model showed higher sensitivity (1.000) but low
reduction. Our findings suggest that semi-automated appro
SSI surveillance while reducing manual workload. Further v

ML ile desteklenmiş yarı otomatik sürveyans ile CAE 'nu takip edebilir miyiz?

Prospektif kohort

2016- 2022 / 3931 cerrahi hasta,

30-90 gün inceleme

CAE; 4.5%

Fraklı ML türlerini duyarlılığını incelemiş, hepsi AUC 0.85- 1.00 arası

İş gücü kaybını 90% önlüyor.

Algoritmaların performansı ne düzeyde?

Hangi veri türü daha iyi sonuç veriyor?

*Yapılandırılmış veri (lab, ICD vb.)
*Metin/verbal veri (klinik notlar)
*İkisi birlikte

Hangi yöntemler daha güçlü?

Annals of Medicine and Surgery 84 (2022) 104956

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journal homepage: www.elsevier.com/locate/amsu

Systematic Review / Meta-analysis

Performance of machine learning algorithms for surgical site infection case detection and prediction: A systematic review and meta-analysis

Guosong Wu[a,b,e,*], Shahreen Khair[a], Fengjuan Yang
Danielle Southern[a,b], Zilong Zhang[a], Yuanchao Feng
...astwood[a]

...ty Health Sciences, Cumming School
...Medicine, University of Calgary, Ca
...of Medicine, University of Calgary,
...monton, Alberta, Canada

32 çalışma,
108 algoritma
165.717 işlem,
6076 CAE
Hız 3.67%,

Makine öğrenmesi modellerinin ortalama performansı:
Sensitivity: 0.83, Spesifity: 0.95, AUC ≈ 0.92☞

***Kaçırma oranı orta düzey**
***Yanlış alarm düşük**
***Genel ayırt edicilik güçlü**

Sadece yapılandırılmış veri (lab, klinik veri vb) kullanılırsa **sensitivite: 0.56,**
Klinik notlar ve serbest notların ...lenmesi sensitivite yi **90% e çıkarıyor**

A B S T R A C T

Background: Medical resear...
algorithms to detect/predi...
mance of ML algorithms i...
systematic review and met...
prediction and to describ...
algorithms.
Methods: MEDLINE, EMBAS...
followed.

Machine learning
Algorithms
Systematic review
Meta-analysis

ML, Deep learning'den daha başarılı, çalışmaların çoğu tek merkezli, external validasyon yok,

Klinik uygulamaya entegrasyon aşamasında!

- Yönetimin desteğini al, ESK’nın yeterliliğini, BT’nin kapasitesini değerlendir.
- Hangi CAE türünü, hangi kriterler ile takip edeceksin karar ver.
- Hangi veriler bu algoritmaya dahil edilecek?
- Alarm hangi durumda çalışacak?
- Bildirim kime düşecek?
- Hangi klinik adımı tetikleyecek, hangi aksiyonlar alınacak?

Örneğin; Post-Op 2. günde, 78% risk,

- Klinik değerlendirme, görüntülme, hedefli kültür,

Belirsizlikler:

- Ne zaman geçilmeli?
- Geliştirmeli mi, satın mı alınmalı?

Riskler:

- Tek merkezli çalışmalarda verinin güvenirliği,
- External validasyon eksikliği,
- Yanlış pozitiflik riski,
- Alarm yorgunluğu.

Etik ve Güven

- Şeffaflık (kara kutu)
- Klinik sorumluluk kimde
- Yapay zaka bir destek aracıdır, **karar verici her zaman klinisyen** olmalıdır.

Gelecekte!

- Multimodal verilerin yaygın kullanımı (Lab verileri & görüntüleme& hekim notlarının entegrasyonu)
- Gerçek zamanlı HİS entegrasyonu,
- Aksiyonların AMY ile entegre olması, ortak çalışması

Özetle;

- Post-operatif vakalarda **erken tanı sinyali** kritik.
- Klinik uygulama ve yapay zeka işbirliği **klinisyenlere zaman** kazandırır,
- Hastalara **erken odaklanmayı** artırır,
- Uygulamanın **gelişmesi ve yaygınlaşması** ile birlikte yanlış pozitiflik azalır.

! Başarının anahtarı, BT&Klinik&Yönetim işbirliği, bu işe kendini adanmış

çalışanlar, kullanımın yaygınlaşması ve uygulamanın sürdürülebilir olmasıdır.

Sonuç olarak;

Yapay zekâ temelli araçlar CAE’larının **erken fark edilme**sinde destek sağlayarak sağlık personeline **zaman kazandırabilir**, bu nedenle **teknolojiden kopmadan** hasta takibini sürdürebilmek adına **bu platformların kontrollü şekilde denenmesi ve benimsenmesi** önemlidir.