

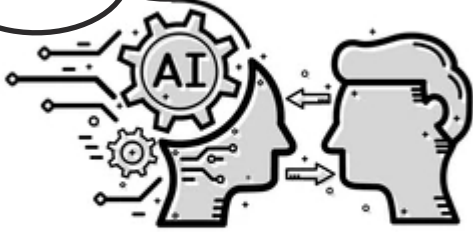
# Deep Learning for Time Series Data in Healthcare

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**November 16, 2024**  
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# Motivation: Healthcare Jarvis

Based on your current status and **time series data**, I **predict** that you have 50% chance of getting COVID. I have scheduled an appointment for you with Dr. Recovery tomorrow...

I am feeling tired and having a fever and a cough...



AI TECHNOLOGY ICON

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Healthcare Jarvis



Iron man's Jarvis

# Outline

- Background
- Neural Networks and Recurrent Neural Networks in Precision Healthcare
- Methods in Deep Learning Models
- Using Recurrent Neural Networks in Healthcare
- Conclusion and Future Directions

# BACKGROUND

# Introduction to AI in Precision Medicine

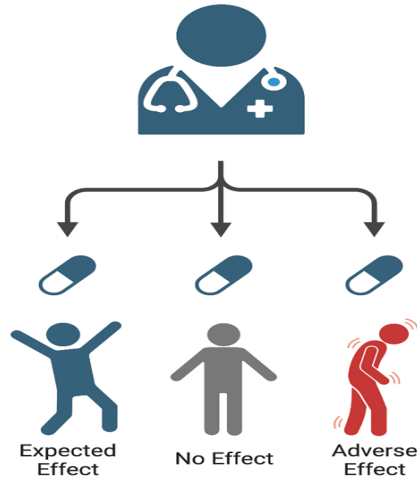
Transformative  
Effects of AI in  
Healthcare



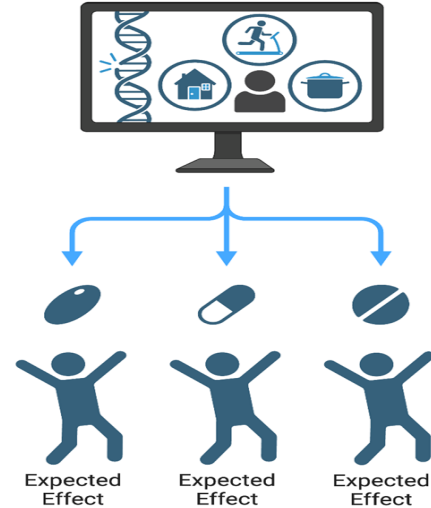
- AI, Artificial Intelligence in general enhances diagnostic accuracy.
- Personalized treatment plans are optimized using patient-specific data.
- Real-time AI monitoring tracks vital signs, alerting providers to critical changes.
- Faster responses and improved patient safety result from AI-driven insights.

# Difference between Personalized treatment and traditional treatment.

**Healthcare Professional  
One-Fits-All Treatment**



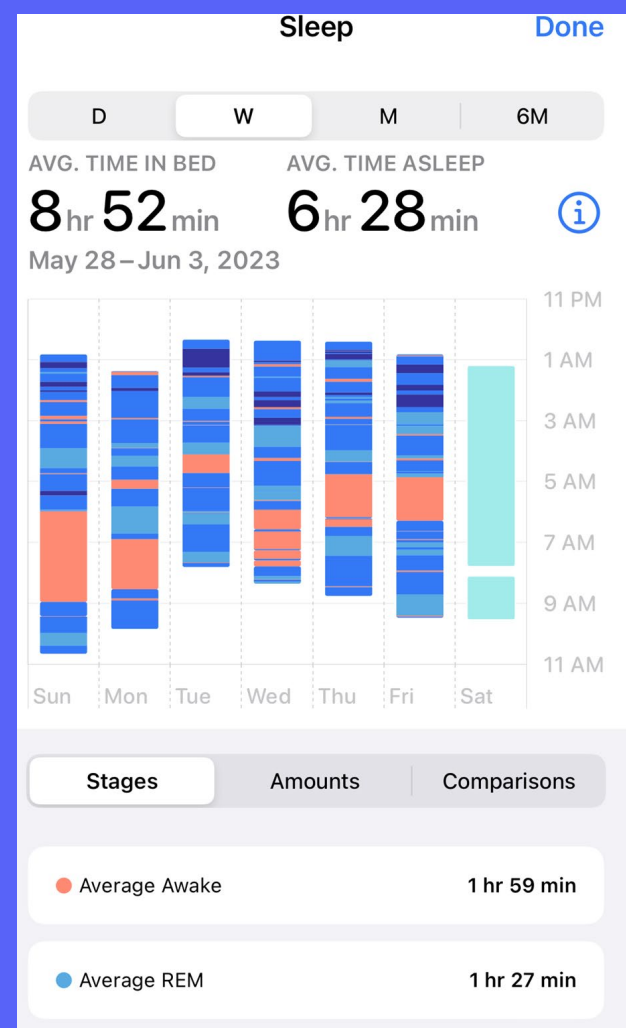
**AI-assisted  
personalized treatment**



**Personalized treatment, unlike traditional treatment take your personal medical history into account making it much more effective.**

## What is Time Series data

- Time series data is a type of data collected over time at regular intervals.
- Crucial for identifying trends and patterns over time.
- **Healthcare Applications:** Used to monitor vital signs (e.g., heart rate, blood pressure) in real-time and predict health outcomes.

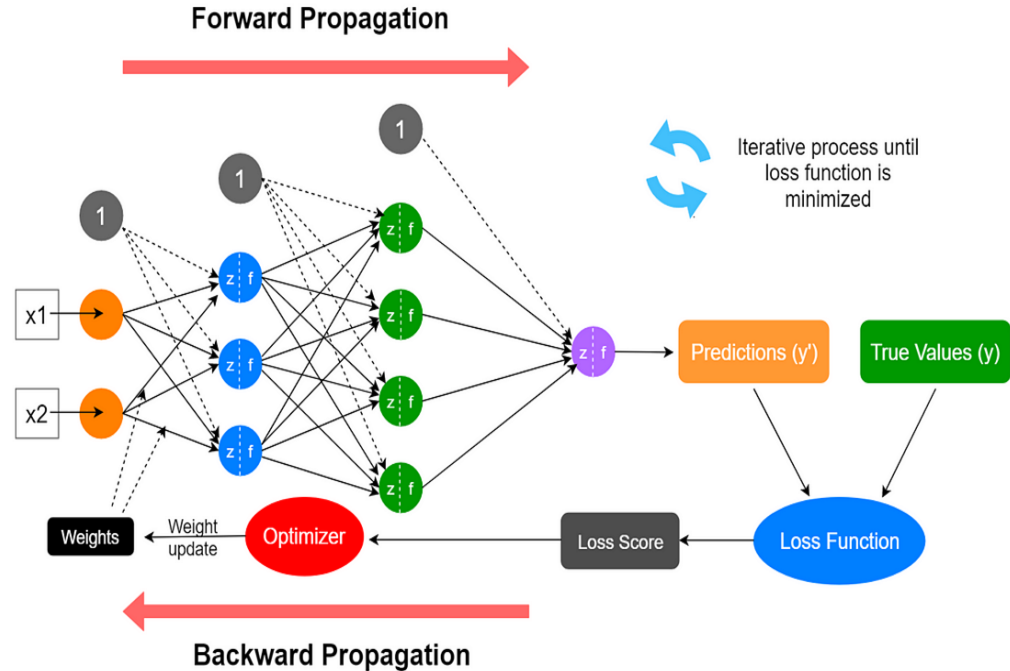


- Neural Networks (NNs) are layered structures of interconnected neurons: an input layer, hidden layers and output layer.

- NNs handle complex data like medical images and health records, aiding in diagnosis, risk prediction, and personalized treatment.

-Traditional neural networks lack memory, struggle with time-dependent patterns, and risk overfitting with sliding windows. Static structures can't adapt to dynamic changes.

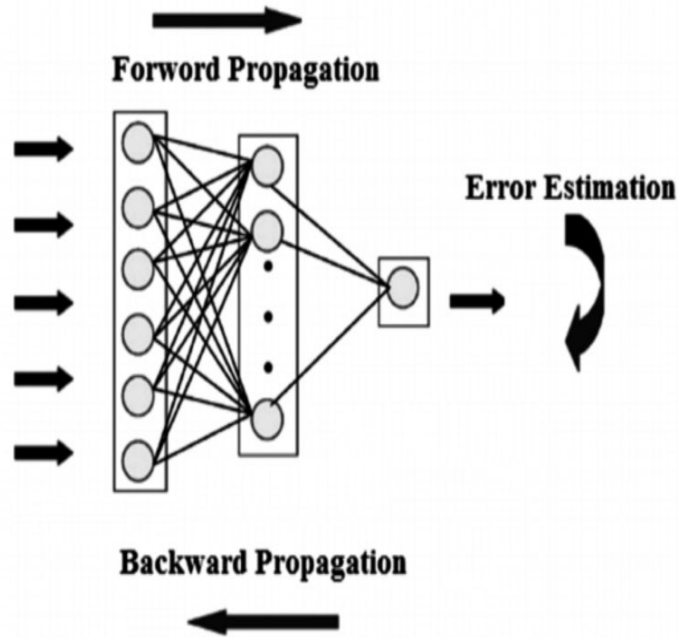
## Understanding Neural Networks (NNs)





## Recurrent Neural network in Time series data

- Input Layer
- Hidden Layer
- Output Layer



### Variants of RNNs:

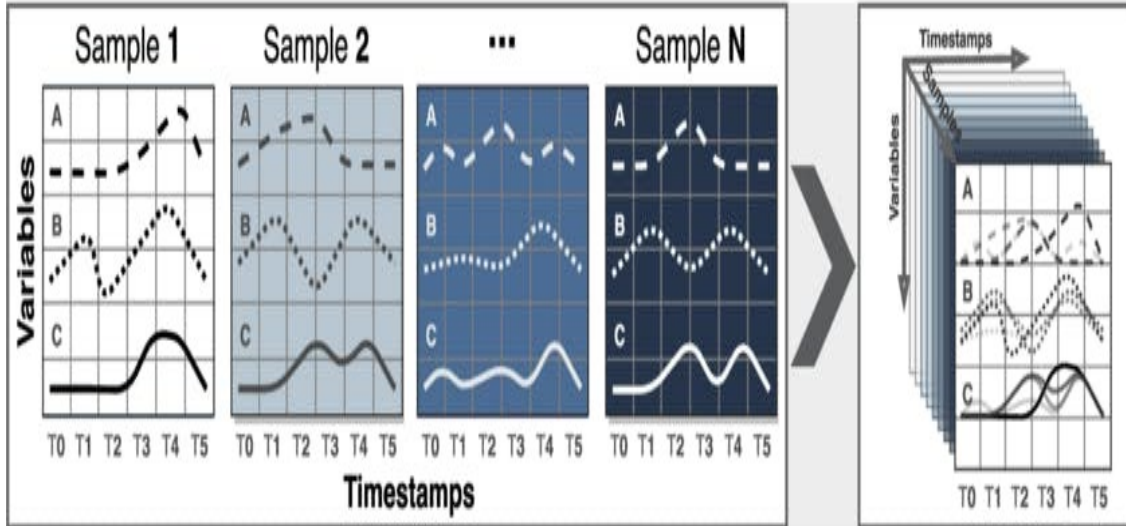
GRU (Gated Recurrent Unit): A simpler version of RNNs, GRUs help process sequences quickly by using fewer steps to "decide" what to remember, making them faster for real-time tasks.

LSTM (Long Short-Term Memory): A more advanced RNN that's better at remembering important details over long sequences, useful for tasks like understanding health trends or speech patterns over time.

## Recurrent Neural network in Time series data

Multivariate Time-Series

Multiple Multivariate Time-Series



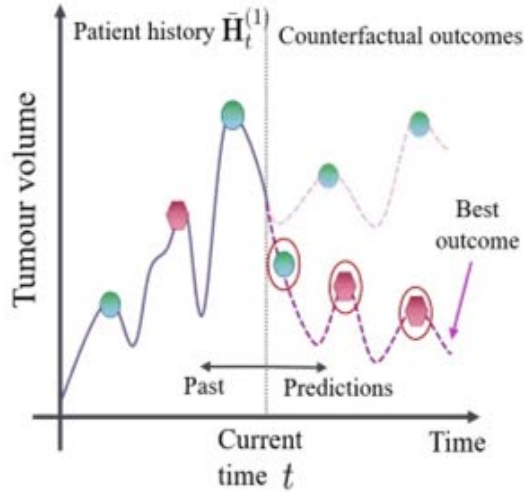
- RNNs retain memory, ideal for detecting patterns in sequential data.
- They handle temporal dependencies, suited for prediction, anomaly detection, and sequence classification.
- RNNs work with variable-length sequences, enabling real-time, dynamic predictions.
- Advanced variants like LSTMs and GRUs improve long-term dependency handling for extended sequences.

## Practical application of RNNs in Time series data analysis

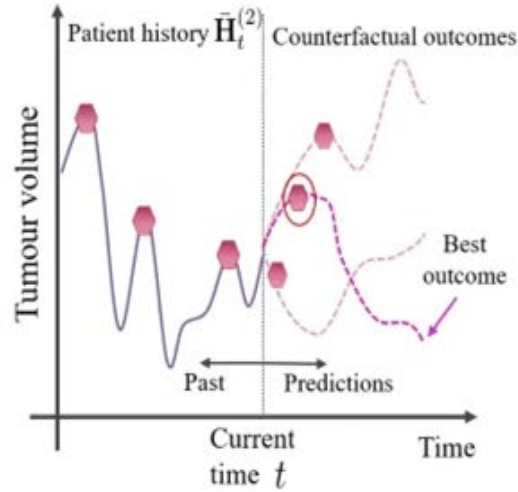
- **Vital Sign Monitoring**
- **Sepsis Risk Prediction**
- **Chronic Disease Management**
- **Patient Deterioration Alerts**
- **Heart Disease Detection**
- **Diabetes Management**

## Applications

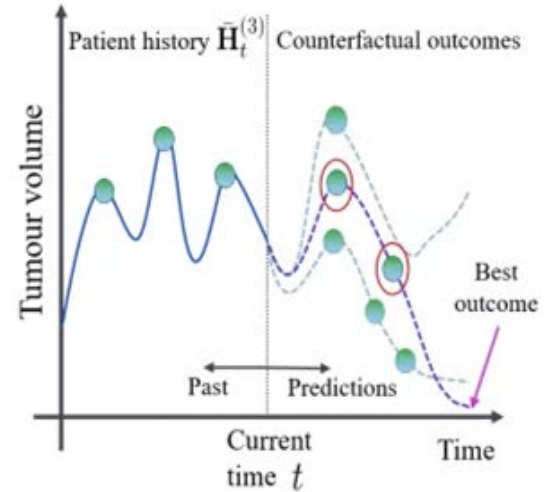
● Chemotherapy      ● Radiotherapy



(a) Decide treatment plan



(b) Decide optimal time of treatment



(c) Decide when to stop treatment

# METHODS

## AI Model Training and Validation

### Data Prep



Cleaned Dataset  
Normalized Values  
Data Split (Train, Val,  
Test)

### Model Training



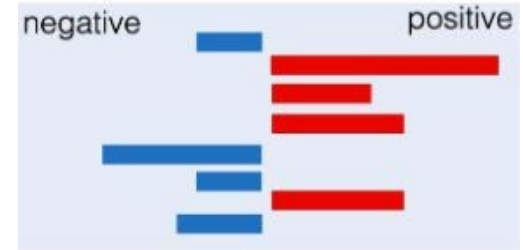
Trained Model  
Performance Metrics  
Validation Results

### Model Evaluation



Evaluation Report  
Performance Metrics  
Generalization  
Assessment

### Deployment & Monitoring



Deployed Model  
Monitoring Dashboard  
Retraining Plan

## Key Techniques in AI Healthcare Models and how it differs from traditional machine learning methods:

### Feature Engineering

Identifies and enhances critical data features to improve AI's ability to interpret complex healthcare information.

### Regularization Techniques

Strategies like dropout help prevent overfitting, making models more adaptable and reliable on new patient data.

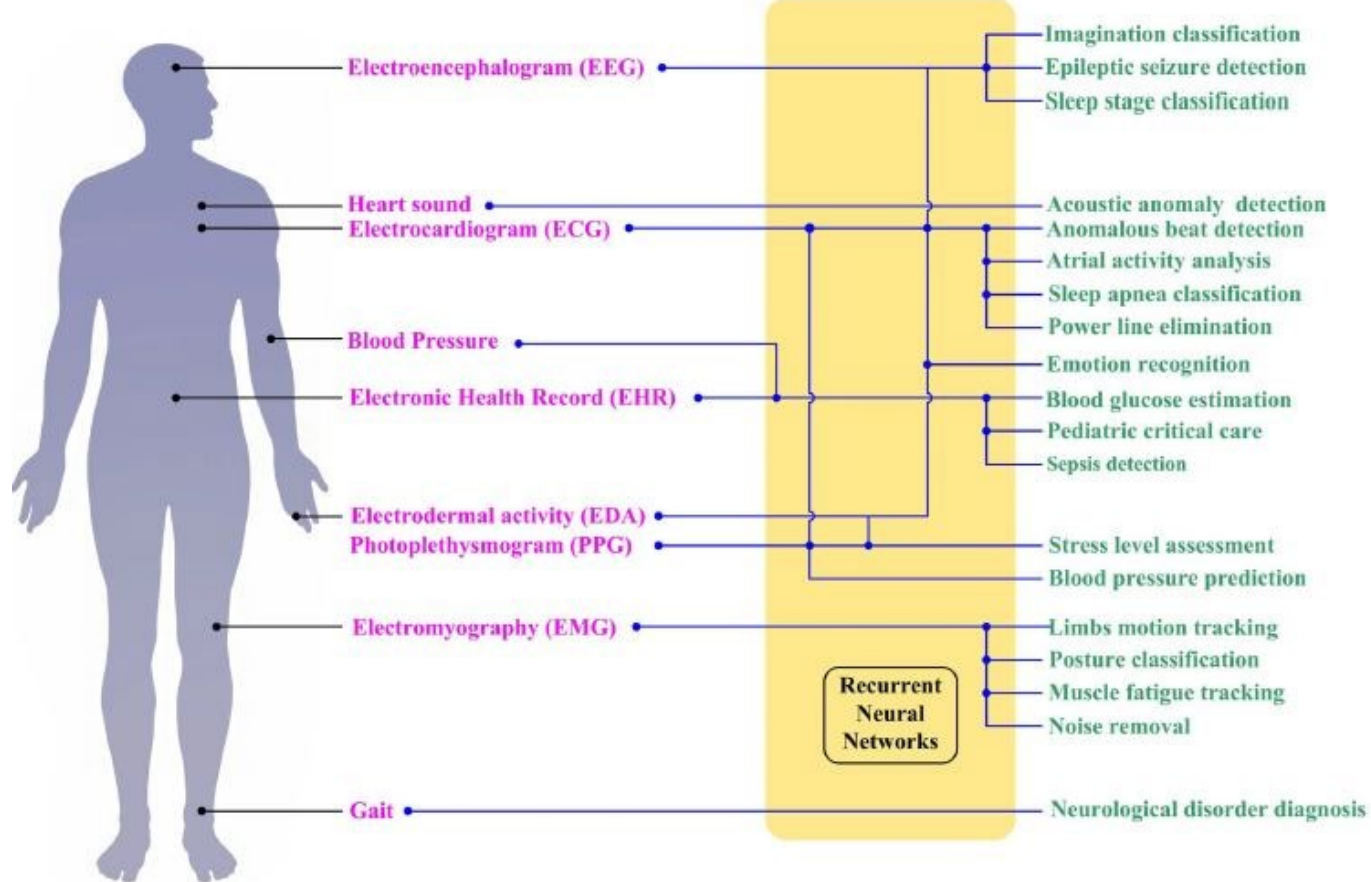
### Attention Mechanisms

Directs the model's focus to important data points, boosting interpretability—especially useful in imaging to highlight potential problem areas.

### Data Augmentation

Expands training data through transformations (e.g., rotations, scaling), increasing model robustness in applications like imaging.

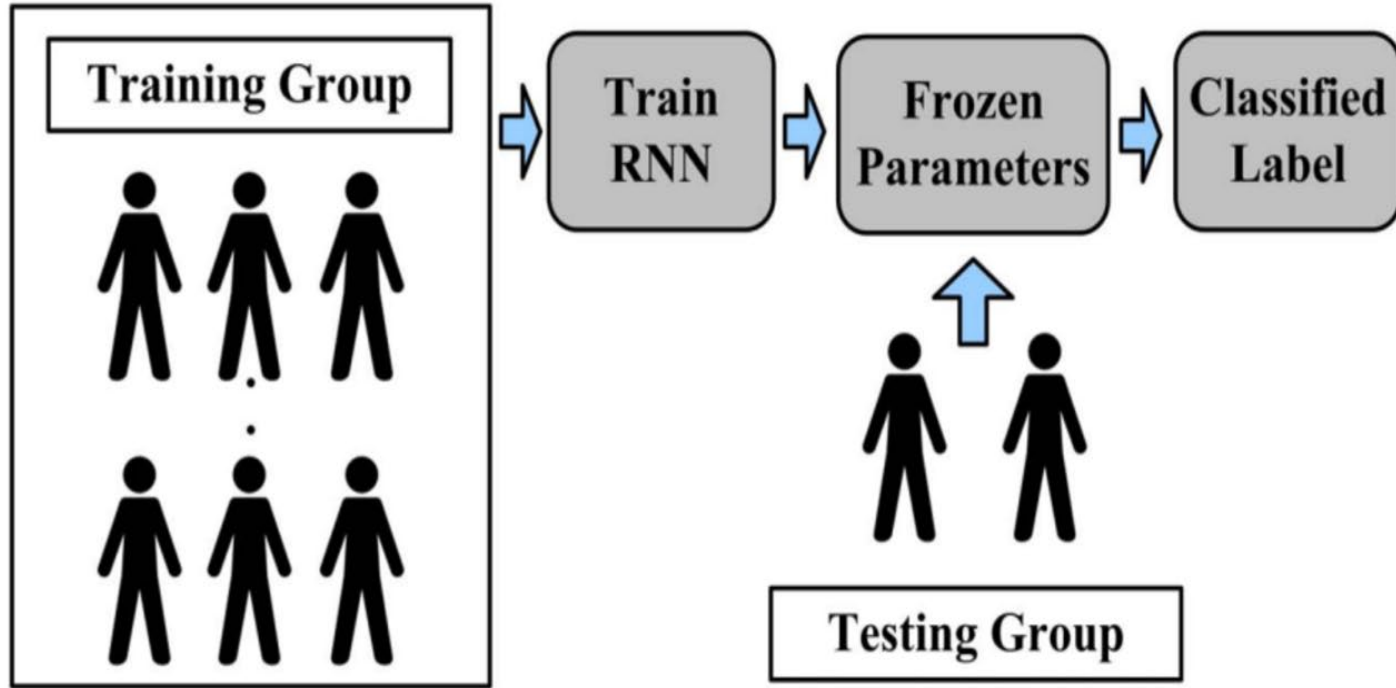
# Methods: How RNN can be used in Healthcare



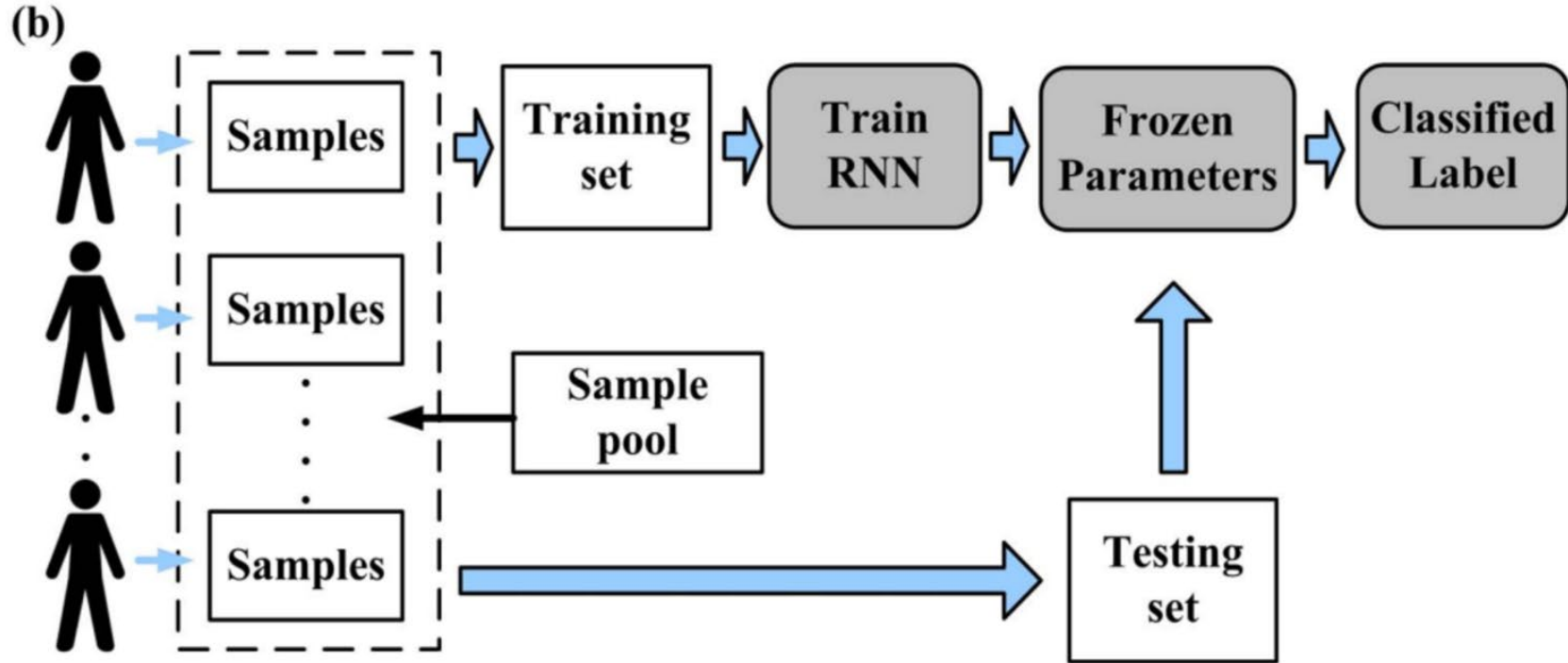


# Methods: Training RNN in Healthcare

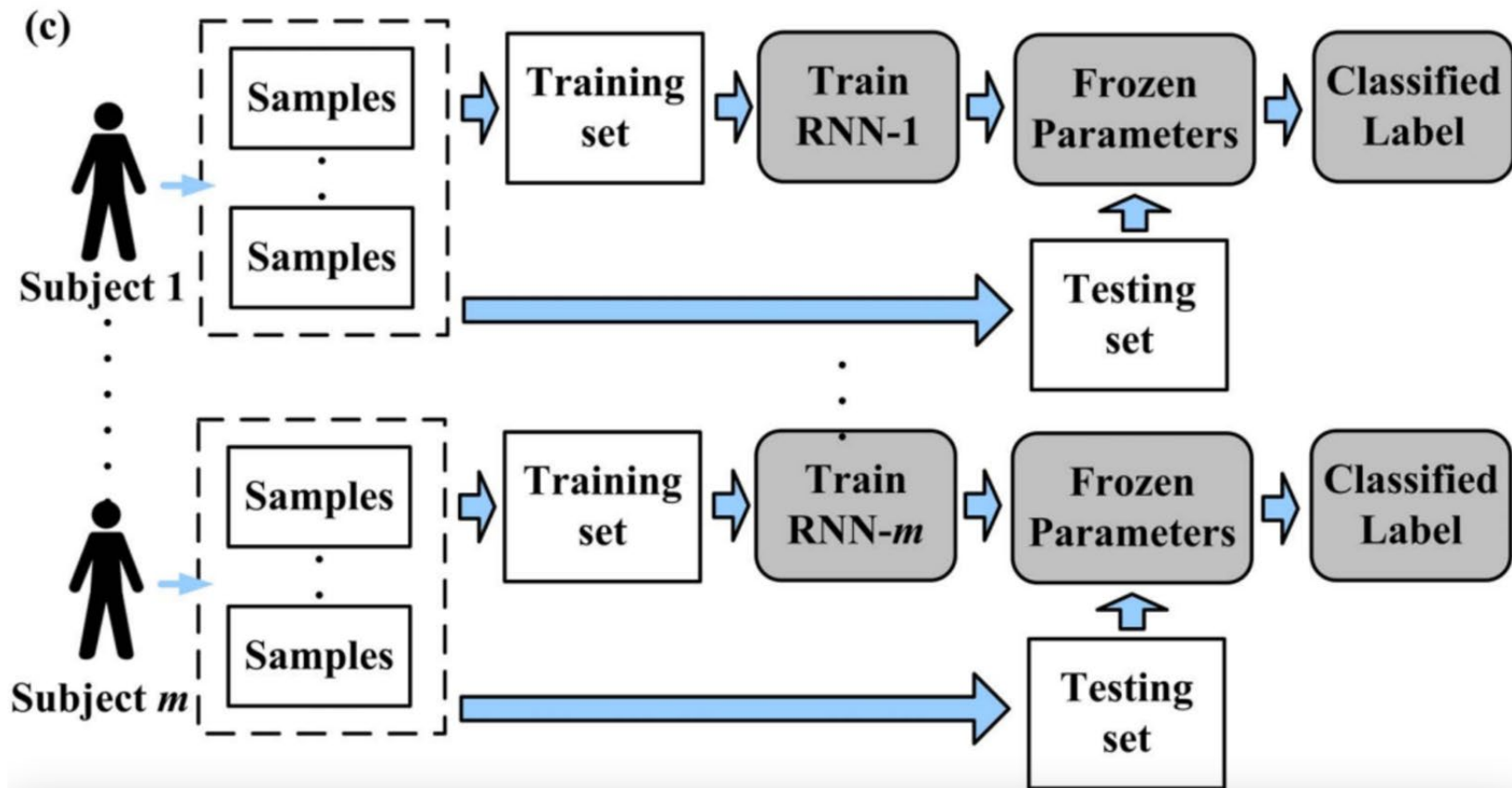
(a)



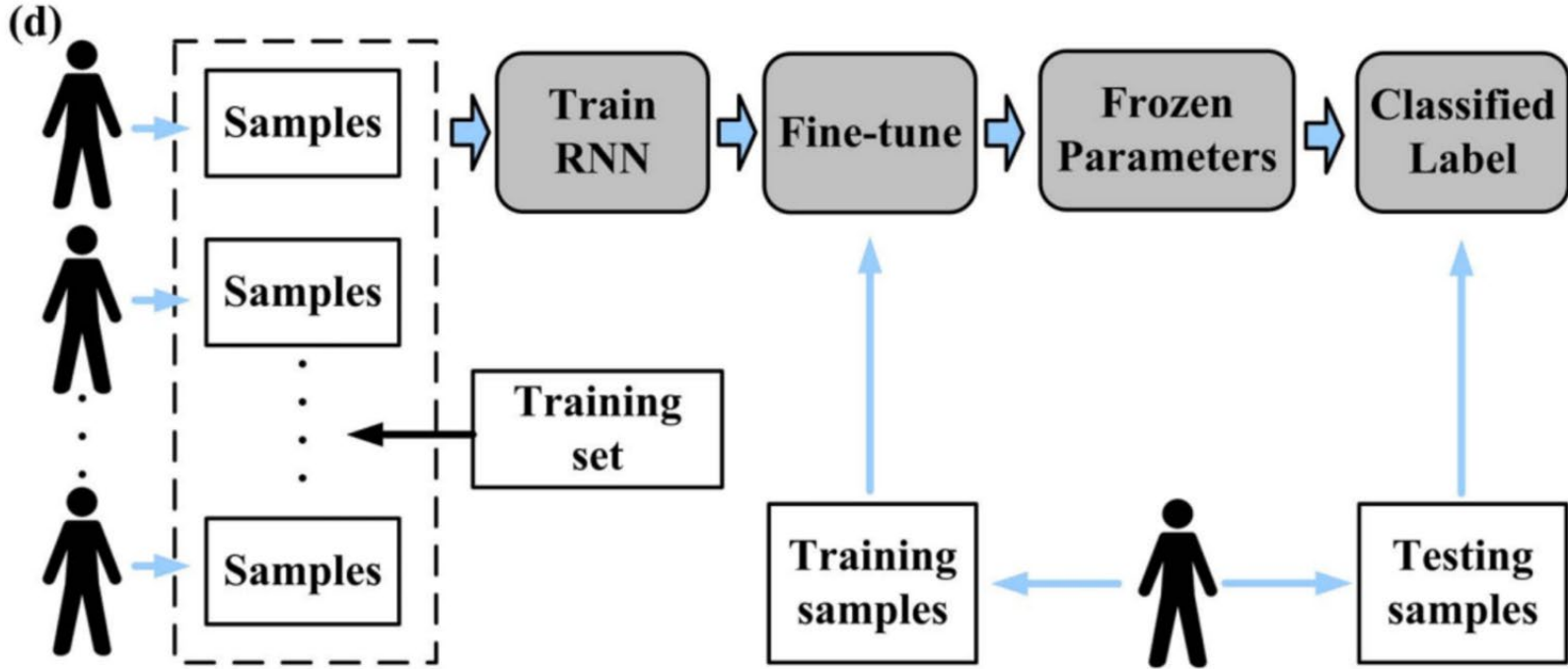
# Methods: Training RNN in Healthcare



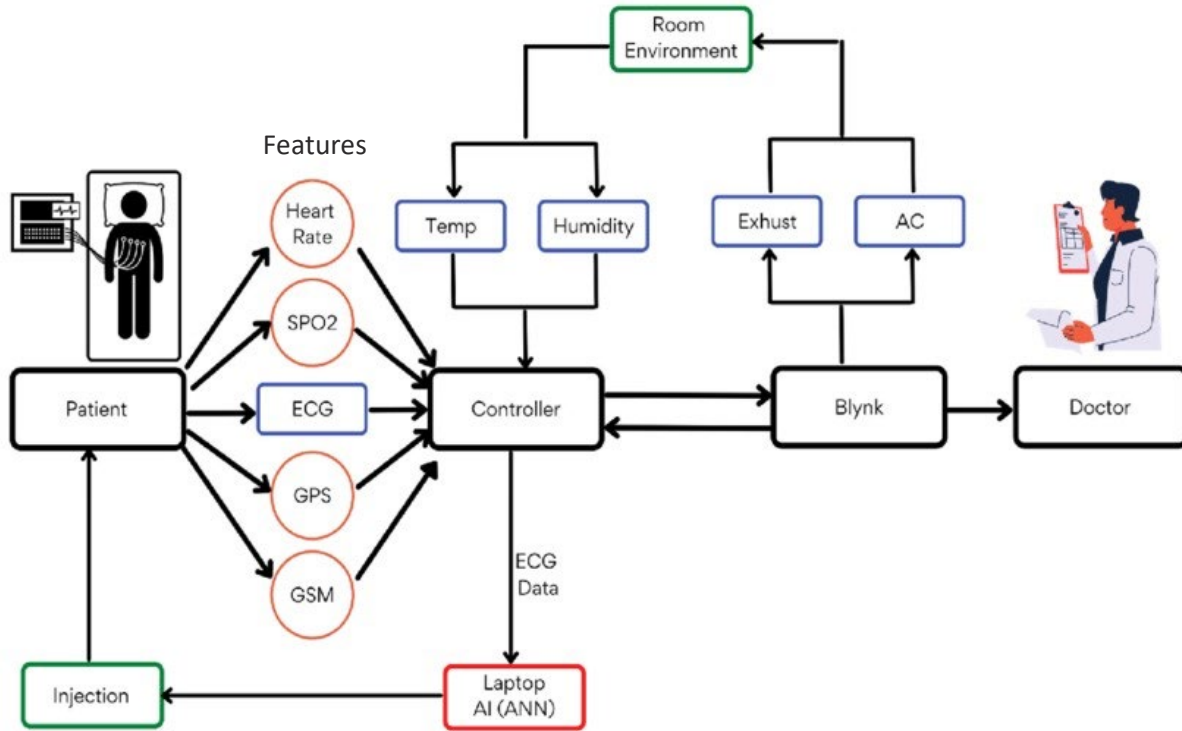
# Methods: Training RNN in Healthcare



# Methods: Training RNN in Healthcare



# Methods: Using RNN in Healthcare



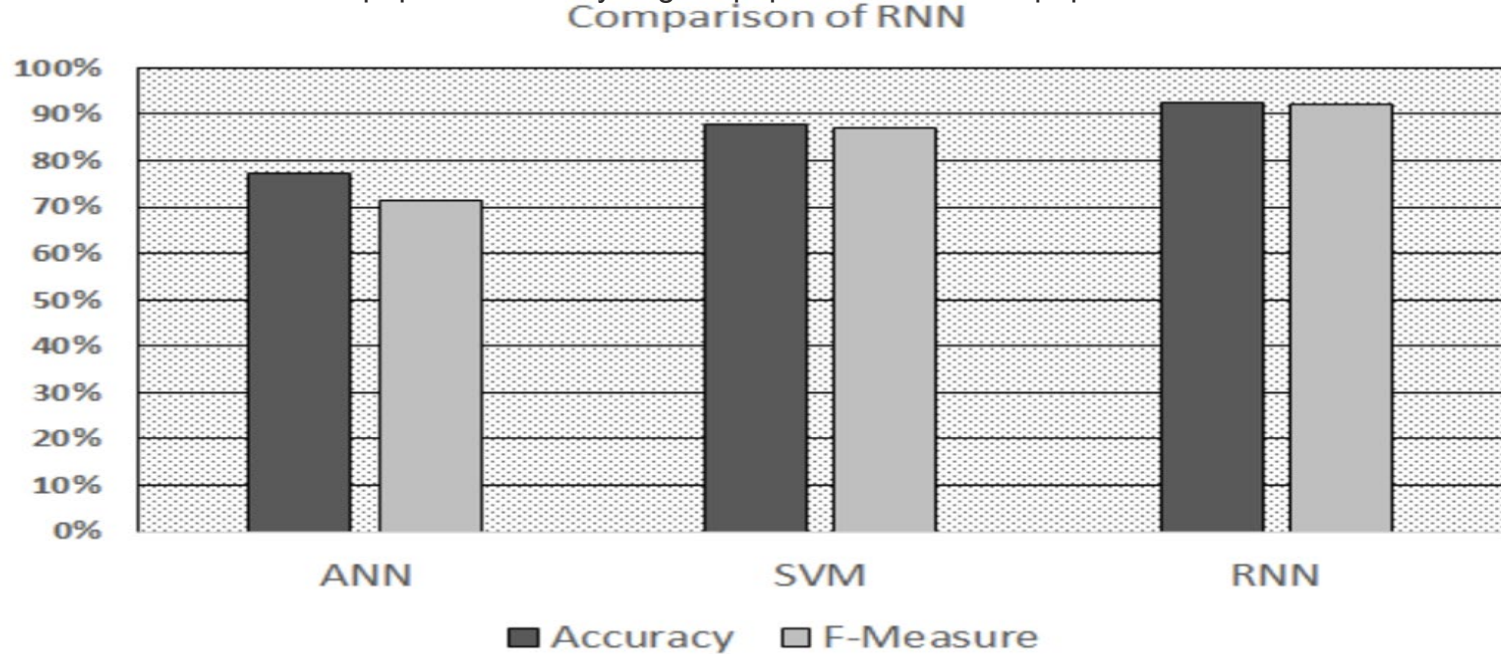
- Patient Monitoring: Tracks vitals (heart rate, SpO2, ECG) and room conditions (temperature, humidity).
- Data Processing: Controller processes data; RNN on laptop analyzes it.
- Alerts & Communication: Sends real-time updates to doctor via Blynk for timely intervention.

**Using time series data to train RNN can design personalized treatment plans**

# FINDINGS & RESULTS

# Results: Using RNN in Healthcare

These results are based the cited papers below. My original paper is an overview paper.

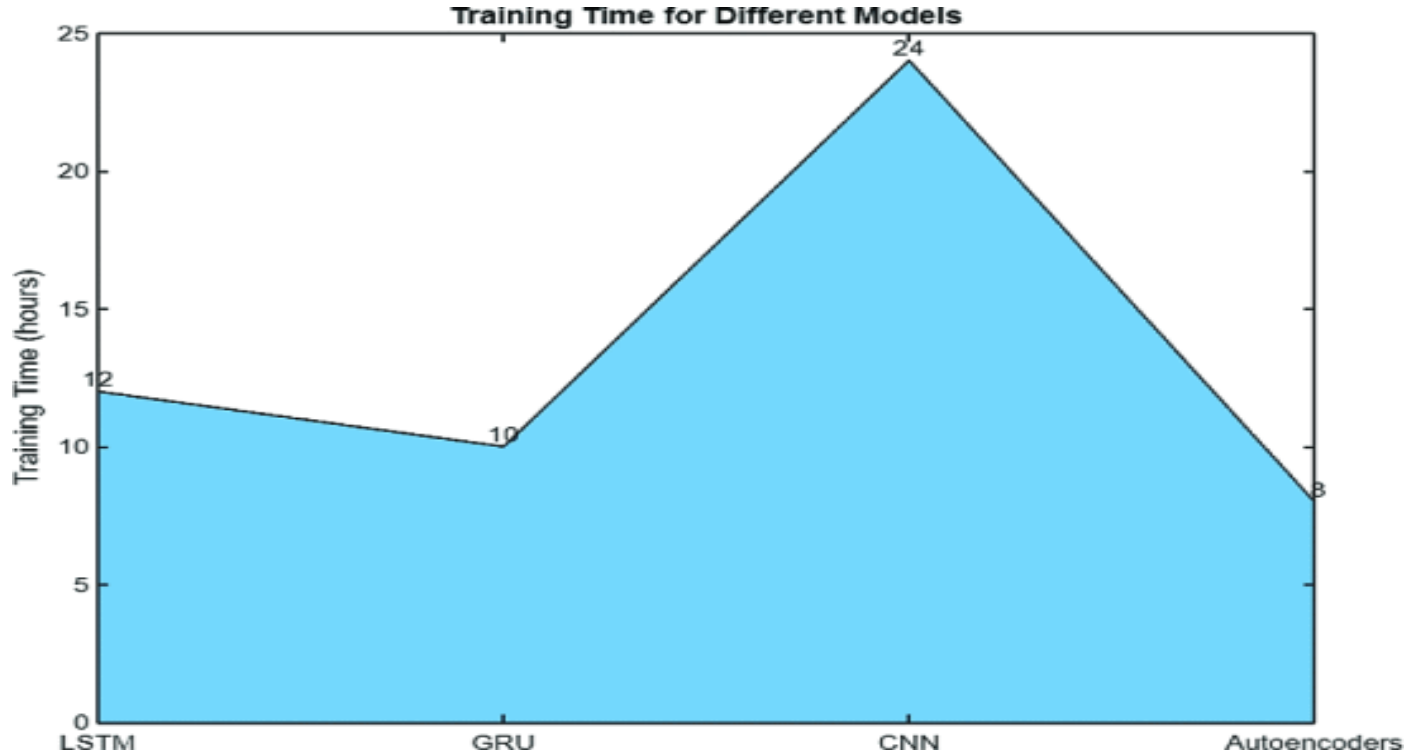


**Fig. 3.2 Comparison of RNN with ANN and SVM.**

**RNN model outperforms the other two models Artificial Neural Network & Support Vector Machine, achieving a higher precision of 98.03% compared to 96.04% and 95.77% for ANN and SVM, respectively.**

# Results: Using RNN in Healthcare

These results are based the cited papers below. My original paper is an overview paper.



**RNNs take less time to be trained as well making them more efficient.**



## Key Findings

- RNNs, including LSTMs and GRUs, are used in 84% of healthcare studies for time series predictions, analyzing sequential data like patient vitals.
- GRUs outperform LSTMs by 1% AUC—a metric measuring model accuracy in distinguishing between risk categories, where 1.0 is perfect and 0.5 is random guessing.
- Bidirectional RNNs further enhance performance in predicting outcomes like hospital readmissions, mortality rates, and length-of-stay, aiding better healthcare decisions.
- GRUs' feature-specific decay patterns reduced Mean Squared Error (MSE) by 5%, enhancing accuracy in predicting long-term disease progression such as Alzheimer's.
- Incorporating time intervals into models for heart failure predictions increased the Area Under the Curve (AUC) by 3%, highlighting the importance of time-sensitive data analysis.

## Key Findings

- RNNs have demonstrated a performance improvement of up to 15% over traditional methods in predicting patient mortality rates.
- GRUs in diabetes management have reduced false positive rates by 20%, allowing for better monitoring and intervention strategies.
- Early warning systems using RNNs have significantly improved survival rates for sepsis patients by facilitating timely interventions.

# ETHICAL CONSIDERATIONS

# Ethical Considerations in AI Healthcare

## Data Bias in AI Models

- AI models trained on non-representative data can perpetuate existing biases.
- Bias in training datasets can lead to unequal healthcare outcomes across demographics.
- Examples of bias have been observed in diagnostic tools that perform poorly on underrepresented populations.

## Model Transpare ncy and Interpreta bility

- Many AI systems operate as 'black boxes', obscuring decision-making processes.
- Lack of transparency can erode trust among healthcare providers and patients.
- Explainable AI (XAI) aims to clarify AI decisions, enhancing clinician confidence in AI recommendations.

# CONCLUSION

## Conclusion

### AI in Healthcare:

- Impact
- Challenges

### Future Direction:

- Hybrid Models
- Explainable AI
- Data Diversity

# Questions?



## Acknowledgments

I would like to express my gratitude to everyone in Computer Science faculty for being very supportive and kind throughout the process, especially Dr. Elena, Dr. Nic and Dr. Wenkai for their invaluable insights and guidance throughout the research process.

I would also like to thank my friends, especially Linnea for being so awesome and helpful. At last but not the least, I would like to thank my boyfriend, Eshwar for “forcing” me not to quit.



# References

- K.B. Johnson et al. 2021. Precision Medicine, AI, and the Future of Personalized Health Care. *Clinical and Translational Science* 14, 1 (2021), 86–93. <https://doi.org/10.1111/cts.12884> PMID: PMC7877825.
- Mohammad Amin Morid et al. 2023. Time Series Prediction Using Deep Learning Methods in Healthcare. *ACM Transactions on Management Information Systems* 14, 1, Article 2 (2023), 29 pages. <https://doi.org/10.1145/3531326>.
- S. Mao and E. Sejdić, "A Review of Recurrent Neural Network-Based Methods in Computational Physiology," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 10, pp. 6983-7003, Oct. 2023, doi: 10.1109/TNNLS.2022.3145365.
- Kelly, B.S., Mathur, P., Plesniar, J. et al. Using deep learning–derived image features in radiologic time series to make personalised predictions: proof of concept in colonic transit data. *Eur Radiol* 33, 8376–8386 (2023). <https://doi.org/10.1007/s00330-023-09769>
- Zhu Y, Bi D, Saunders M, Ji Y. Prediction of chronic kidney disease progression using recurrent neural network and electronic health records. *Sci Rep.* 2023 Dec 13;13(1):22091. doi: 10.1038/s41598-023-49271-2. PMID: 38086905; PMCID: PMC10716428.

**Thank you**

