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A hemodialysis mortality prediction model based on active contrastive learning

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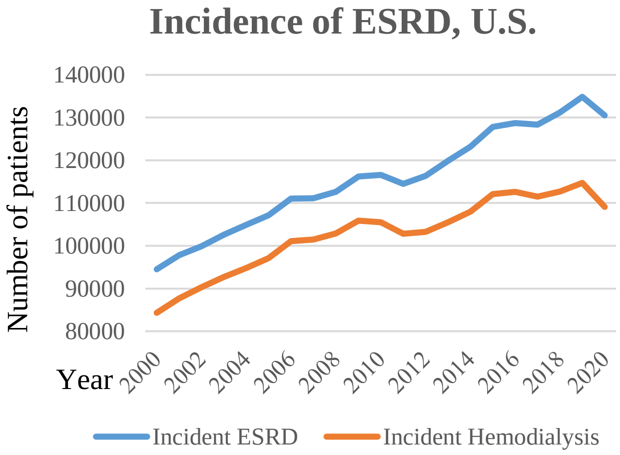
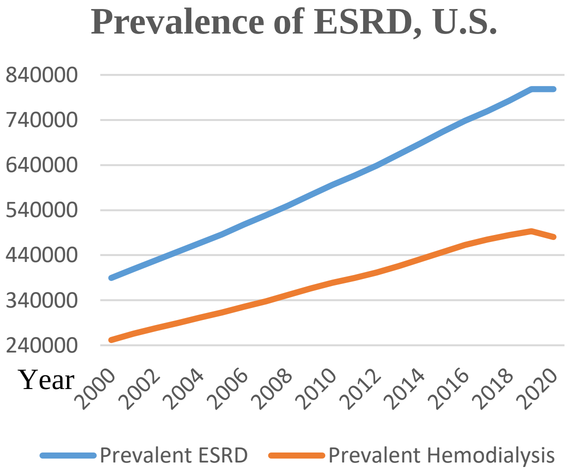
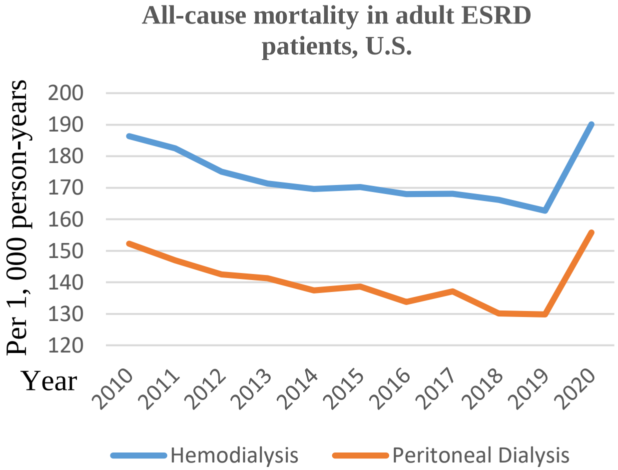
1. Introduction

- Hemodialysis (HD) is the main treatment for end-stage renal disease with high mortality and heavy economic burdens.



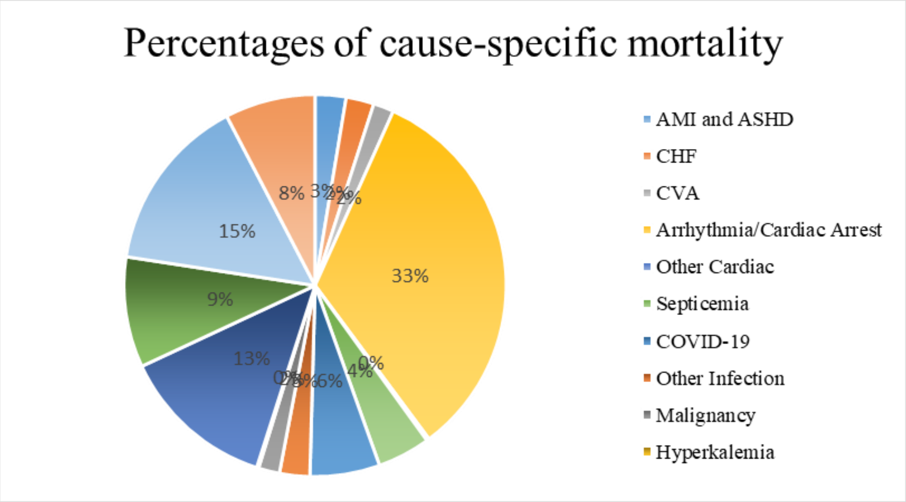




Data from USRDS Annual Data Report: 2022

1. Introduction

- Controlling the mortality and identifying risk factors of patients undergoing maintenance HD are of great clinical significance.



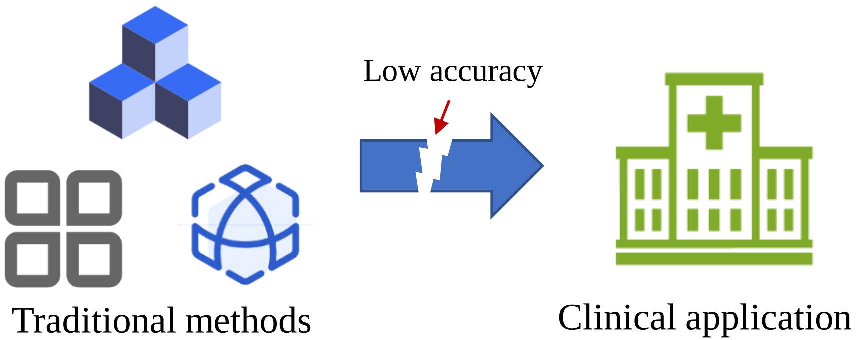
Mortality in patients with ESRD receiving hemodialysis

cause-specific mortality	**Percentages**
AMI and ASHD	2.6%
CHF	2.4%
CVA	1.7%
Arrhythmia/Cardiac Arrest	33.1%
Other Cardiac	0.2%
Septicemia	4.5%
COVID-19	5.9%
Other Infection	2.6%
Malignancy	1.8%
Hyperkalemia	0.2%
Withdrawal	13.1%
All Other Causes	9.4%
Unknown Causes	14.9%
Missing	7.7%

Data from USRDS Annual Data Report: 2022

1. Introduction

- This study aimed to develop and validate a more accurate and generalized AI model for predicting first-year mortality in patients undergoing maintenance HD.



More accurate and generalized AI model !

Traditional methods are not generalizable or accurate enough.

2. Methods - Study population

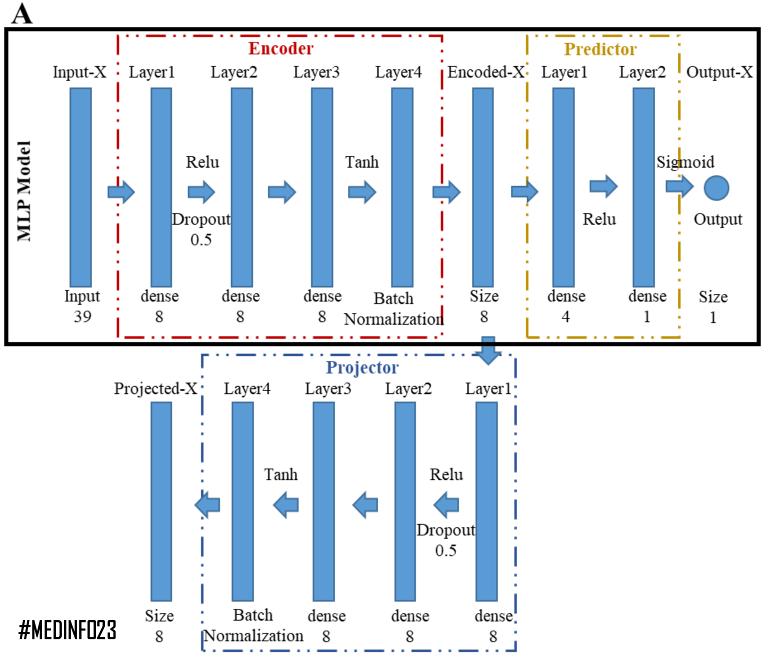
Data Source	EHR system of the First Affiliated Hospital of Zhejiang University (FAHZJU), PRC
Time	Patients received HD treatment between January 1, 2000, and August 20, 2016
Cutoff time of observation	20-Aug-17
Exclusion criterion	*According to the definition of maintenance HD, patients who died within 3 months after starting dialysis were excluded.

Features	**Count**
Demographic information	9
Diagnoses	9
Laboratory test results	12
Drugs	9
Total	39

Ultimately, we included 1,229 ESRD patients (survival: 1193; death: 36) on maintenance HD.

2. Methods - Model architectures

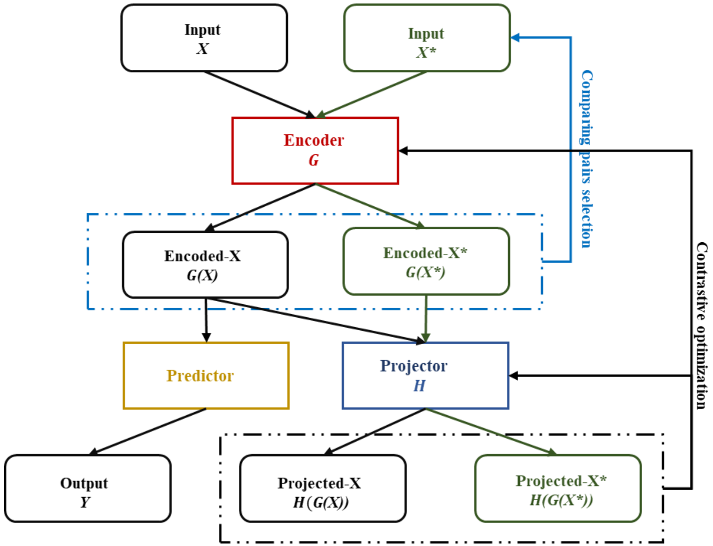
ACL model architecture (A) and flowchart (B)



- The MLP model consists of an Encoder and a Predictor.
- The ACL model consists of MLP model and a Projector.

2. Methods - Training and evaluation

B Training flowchart (B)



- Training
  - First stage – Train MLP model with cross-entropy loss
  - Second stage – Actively selected the most representative comparing sample pairs, the ones with the largest, smallest and random distances. And calculated a contrastive loss to optimize the Encoder and the Projector.
- Evaluation
  - 5-fold cross validation (80% for training, 20% for validation)
  - verified F1-score and AUROC across MLP model, ACL model, SVM and RF

3. Results

In total, we verified F1-score and AUROC across MLP model, ACL model, SVM and RF by 5-fold cross validation (80% for training, 20% for validation). The comparing results is shown in Table1. We used the t-SNE algorithm to visualize the distribution of features of Input layer, Encoded-X layer and Projected-X layer across training dataset and validation dataset in Figure 2.

Table 1. Model performance across the 5 folds

Model	F1-score [95% CI]	AUROC [95% CI]
SVM	0.667 [0.667-0.667]	0.561 [0.522-0.600]
RF	0.702 [0.663-0.741]	0.736 [0.680-0.792]
MLP	0.797 [0.752-0.843]	0.830 [0.794-0.866]
ACL	0.816 [0.777-0.855]	0.851 [0.819-0.883]

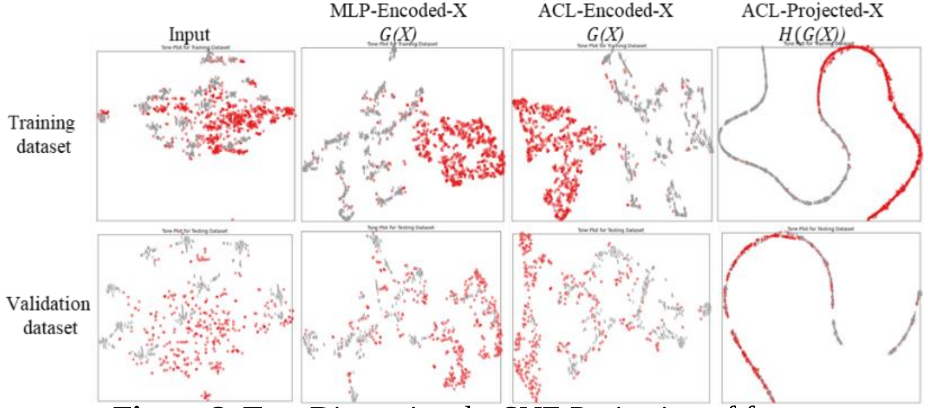


Figure 2. Two-Dimensional t-SNE Projection of features at different layers in ACL model. (Red: Survival, Grey: Death)

4. Discussion and conclusions

- The ACL model proposed in this study outperformed other models in predicting first-year mortality.
- The two-stage protocol of ACL can steadily improve the performance of the MLP model. This study has important clinical implications for other studies.
- This work is generalizable to analyses of cross-sectional EHR data, while this two-stage approach can be applied to other diseases as well.

5. Acknowledgements and references

Acknowledgements

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THE END

THANKS