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A Deep Learning Model Incorporating Dynamic Delta Changes for Prediction of Continuous Kidney Replacement Therapy Filter Lifespan

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Objectives : Continuous kidney replacement therapy (CKRT) is widely used in critically ill patients, but premature filter failure frequently interrupts treatment and increases resource utilization. We aimed to develop and externally validate a deep learning model incorporating dynamic delta changes from baseline parameters to improve prediction of CKRT filter failure.
Methods : We retrospectively analyzed 4,849 CKRT filter sessions from patients treated with the PrismaFlex system (Baxter Healthcare, Deerfield, IL, USA) at Severance Hospital between 2021 and 2024. Additionally, patients who underwent CKRT at Yongin Severance Hospital in 2025 were collected for external validation. Machine log data were extracted at 5-minute intervals to obtain operational parameters including weight, flow rates (dialysate, effluent, pre- and post-replacement, and patient fluid removal), and circuit pressures. Summary statistics were calculated for each interval, and deviations from the initial 5-minute mean were used to quantify dynamic changes from baseline (delta variables). The primary outcome was premature filter failure requiring exchange within 30, 60, or 120 minutes, while successful survival was defined as circuit patency until scheduled exchange at 48 hours. The model combined Gated Recurrent Unit (GRU)–based temporal encoding with Causal Self-Attention mechanisms.
Results : Among 4,849 CKRT filter sessions, 657 were replaced as scheduled (47–48 hours) and 4,192 were replaced early (<47 hours). The mean filter runtime was 25.59 ± 13.88 hours. In 5-fold cross-validation, the model achieved AUCs of 0.926, 0.925, and 0.926 for predicting filter events within 30, 60, and 120 minutes, respectively. Using optimal thresholds, accuracies were 0.913, 0.901, and 0.918 with negative predictive values (0.984–0.996). External validation using 170 CKRT sessions demonstrated AUCs of 0.783, 0.772, and 0.759, with similar performance after excluding effluent-related variables.
Conclusions : A deep learning model incorporating dynamic delta changes predicted imminent CKRT filter failure and may serve as a real-time decision-support tool for optimizing circuit management.

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Table 1. Predictive performance of the deep learning model for predicting premature CKRT filter failure at different prediction windows.

Prediction window	AUC (Internal)	AUC (External)	Cut-off	Accuracy	Sensitivity	Specificity	PPV	NPV
30 minutes	0.926	0.783	0.014	0.913	0.804	0.915	0.144	0.996
60 minutes	0.925	0.772	0.023	0.901	0.815	0.904	0.232	0.993
120 minutes	0.926	0.759	0.060	0.918	0.798	0.927	0.443	0.984

Model performance is presented as the area under the receiver operating characteristic curve (AUC) from five-fold cross-validation and external validation, along with optimal probability cut-off thresholds, accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV).