01457

Predicting mortality and length of stay outcomes for individual patients receiving antibiotics using a recurrent neural network

11. Other

11d. Digital health and infection (incl AI, data mining, informatics)

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Background Numerous clinical decision support systems (CDSS) utilising machine learning and electronic health record (EHR) data have been developed to assist with infection management, but their uptake has been limited in part due to acceptance and behavioural issues. By predicting ‘hard’ outcome measures including mortality and length of stay (LOS), we aim to provide standard endpoint information to healthcare professionals to explore how this may influence clinical decision making.

Methods Patient data were extracted from the MIMIC-IV database and filtered to those who received antibiotics in the Intensive Care Unit (ICU). Input features including lab test results and clinical parameters were selected based on prevalence and critical care consultant advice. Features were normalised, aggregated by day and missing values highlighted or forward filled. Data was split into training, validation and testing sets for model development and evaluation. PyTorch was used to create a many-to-many long short-term memory (LSTM) recurrent neural network (RNN, Figure 1) with a custom dataset class to address class imbalance and extract labels and features. The Adam optimiser was used with binary cross entropy loss for classification, mean squared error loss for regression and Ray Tune for hyperparameter optimisation.

Results In total 18,988 patients, associated with 22,845 unique ICU stays, were included across datasets. A RNN architecture was chosen to account for the temporal nature of EHR data. Following training, predictions were made for each day in a unique stay, within the unseen test set. The model achieved an area under the receiver operating characteristic of 0.78 for mortality classification (accuracy of 0.75,

precision of 0.47, recall of 0.57 and F1 score of 0.51), and a root mean square error of 3.67 for LOS prediction.

Conclusions Results present a promising first step towards predicting the 'hard' outcome measures mortality and LOS for patients receiving antibiotics through temporal neural networks and routinely collected EHR data. However, they also highlight the inherent challenge of estimating LOS, while the confusion matrix (Figure 2) shows difficulties associated with discerning false positives and false negatives from true negatives in mortality classification. Future research will discern the ability of such a tool to influence antimicrobial decision making.

Many-to-many LSTM-RNN model architecture

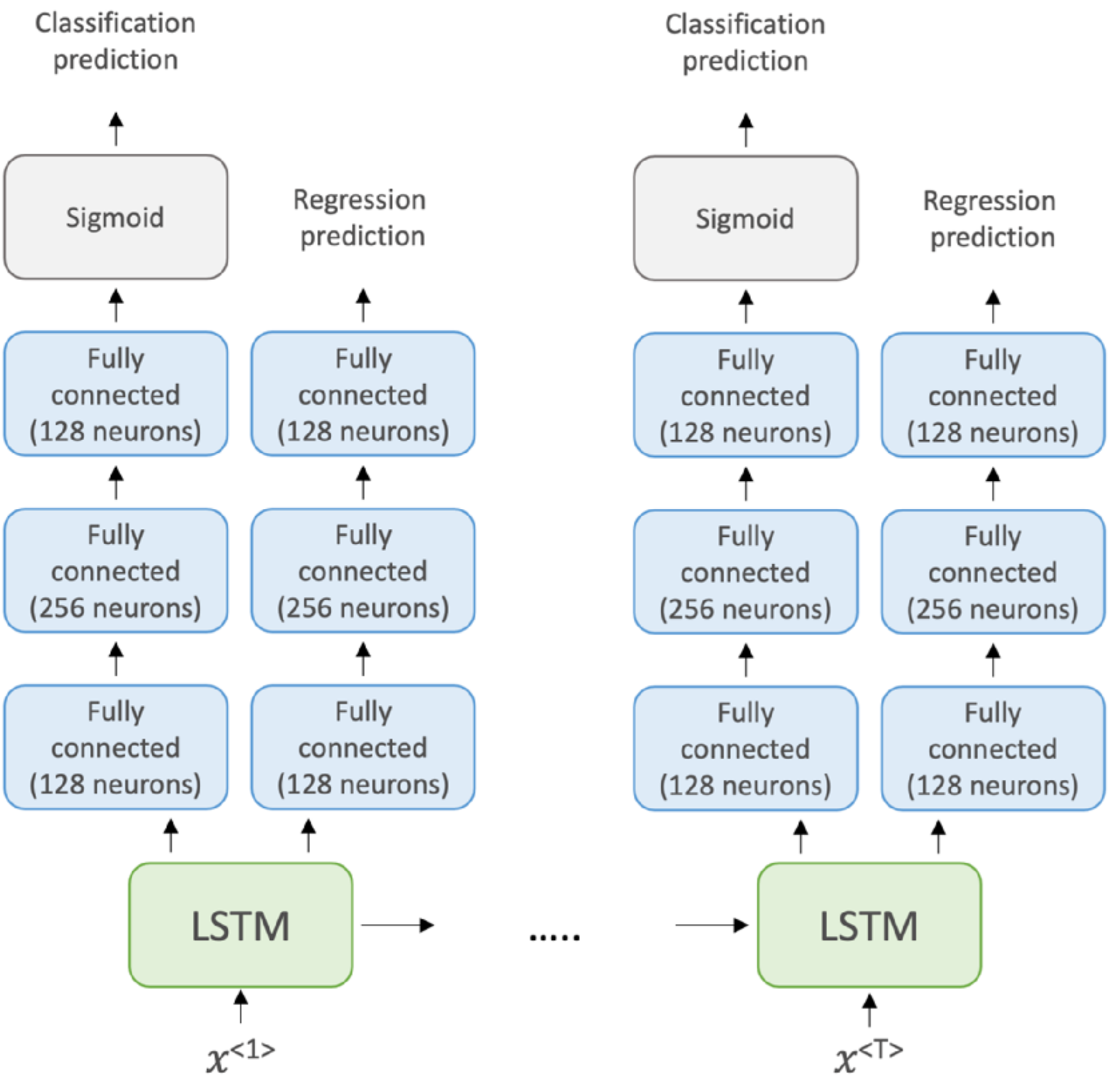

Figure 1: Many-to-many LSTM-RNN model architecture. Time series input is passed into the LSTM modules, fully connected layers using the Rectified Linear Unit (ReLu) activation function then link the LSTM modules to outputs predictions. For mortality classification a Sigmoid function is used to obtain a probability of death, with 0.5 used as the threshold for binary transformation (0,1).

Confusion matrix results for mortality prediction

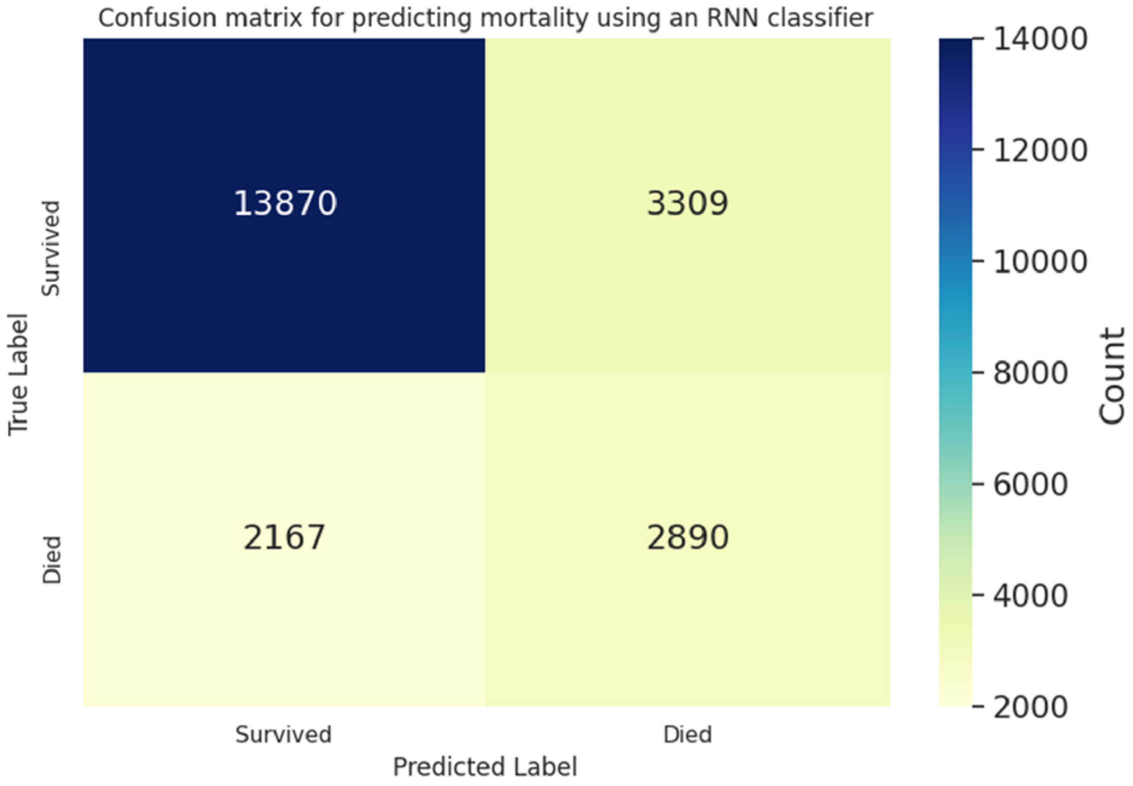

Figure 2: Confusion matrix displaying the binary death prediction results of the many-to-many LSTM-RNN classifier on the unseen test set.

Keyword 1
Artificial intelligence (AI)
Keyword 2
Clinical decision support systems (CDSS)
Keyword 3
Outcome prediction

Conflicts of interest

Do you have any conflicts of interest to declare?
I have no potential conflict of interest to report

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