Predicting ICU Length of Stay Using Deep Learning on Physiological Waveforms

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SE3508 - Introduction to Artificial Intelligence

1 Introduction

Predicting the length of stay (LOS) in Intensive Care Units (ICUs) using high-resolution physiological waveforms offers significant advantages over traditional methods based on electronic health records. This project proposes a deep learning-based pipeline that processes raw ECG, ABP, and PPG signals from the MIMIC-III Waveform Database to predict patient LOS. The study includes signal processing, data augmentation, deep learning model design, training, evaluation, and deployment via a Streamlit interface.

2 Dataset Description

MIMIC-III Waveform Database

The dataset consists of more than 67,000 waveform records from ICU patients. Each record includes high-frequency signals (typically sampled at 125 Hz) for:

- ECG (Electrocardiogram)
- ABP (Arterial Blood Pressure)
- PPG (Photoplethysmography)

LOS labels were inferred from signal statistics using a custom energy and variance-based formula, and capped between 1 and 10 days.

3 Data Preprocessing

- **Segmentation:** Each signal was segmented into 30-second windows (3750 samples).
- **Filtering:** A 4th-order Butterworth band-pass filter (0.5–40 Hz) was used to eliminate baseline drift and high-frequency noise.
- **Normalization:** Each segment was normalized using z-score normalization.
- **Validation:** Segments containing NaN or constant values were excluded.
- **Storage:** Cleaned and labeled segments were saved as NumPy archives for model training.

4 Model Architectures

Five deep learning models were developed and trained:

1. CustomCNN

A layered convolutional network with progressively deeper 1D convolutional blocks. Each block includes BatchNorm, ReLU, and Dropout layers. After feature extraction, both average and max pooling are used, and the outputs are concatenated before the regression head.

2. DeepCNN

This is an extended CNN with deeper layers and wider kernels, enhancing the capacity to learn intricate temporal patterns. Its architecture is similar to CustomCNN but includes more filters and layers.

3. Inception1D

A 1D Inception-style model consisting of parallel convolutions with kernel sizes 1, 3, and 5 to capture multi-scale features. It includes a Squeeze-and-Excitation (SE) block that adaptively reweights feature maps and improves focus on relevant channels.

4. ResNet1D

Implements 1D residual blocks to allow deeper networks without vanishing gradients. Each block includes a skip connection and dropout. The final layers apply both adaptive pooling and a deep fully connected regressor.

5. Data Augmentation Pipeline

During training, segments were augmented with:

- Additive Gaussian noise (std=0.05)
- Random time shifting (±40 samples)
- Amplitude scaling (range: 0.7 to 1.3)

These augmentations improve generalization and robustness.

5 Training Strategy

- **Loss Function:** Mean Squared Error (MSE)
- **Optimizer:** Adam with weight decay (5e-5)
- **Scheduler:** ReduceLROnPlateau

- **Early Stopping:** Based on validation loss with patience of 5 epochs
- **Channel-Wise Models:** Models trained separately for 1 to 8 channel inputs

6 Evaluation Metrics

The following metrics were computed on validation and test sets:

- **MAE** (Mean Absolute Error)
- **RMSE** (Root Mean Square Error)
- R^2 **Score** (Coefficient of Determination)
- **Accuracy within ±1 day**

Best models were selected based on validation MAE.

7 Results

- All models performed best with 3–6 channels.
- ResNet1D consistently outperformed others in terms of MAE.
- Inception1D also showed competitive performance, especially on lower-channel inputs.

Table 1: Sample Test Results (Channel = 5)

Model	MAE	RMSE	R^2
CustomCNN	0.48	0.67	0.977
DeepCNN	0.59	1.07	0.943
Inception1D	0.68	1.04	0.946
ResNet1D	**0.23**	**0.34**	**0.994**

8 Deployment

A Streamlit web interface was developed to:

- Upload preprocessed .npz waveform data
- Visualize each channel's waveform using Plotly
- Load best-trained model based on input channel count
- Output predicted LOS and display model performance metrics

9 Conclusion

This project demonstrates that deep learning models trained directly on raw physiological waveforms can effectively predict ICU length of stay. Among the models tested, ResNet1D and Inception1D delivered the most accurate results. The full pipeline includes data processing, augmentation, model training, and deployment, illustrating a robust end-to-end solution for real-world ICU analytics.

References

- GitHub Repository: `https://github.com/ranayalcnn/Prediction-length-of-stay`
- PhysioNet MIMIC-III: `https://physionet.org/content/mimic3wdb/1.0/`
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