Hospital Readmission Prediction Of ICU Patients Using Deep Learning Algorithms

by

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Motivation

- For Medicare patients, hospitalizations can be stressful, even more so when they result in subsequent readmissions. A number of studies show that hospitals can engage in several activities to lower their rate of readmissions, such as clarifying patient discharge instructions, coordinating with post-acute care providers etc.
- The purpose of this thesis is to use deep neural networks which can work effectively to predict the result that can be utilized to avoid unnecessary hospital readmissions.

Objectives

The primary objective of this thesis is:

- To develop Deep Neural Network(DNN) models for Healthcare application i.e Hospital Readmission.
- To predict hospital readmission of patients using deep neural networks.
- To compare results between Deep Learning Models and with exiting algorithms.

Novelty of the proposal

- With this thesis, the aim is to use deep learning algorithms to overcome the drawbacks of conventional machine learning algorithms.
- The thesis aims to use nature inspired algorithms for feature extraction.
- The thesis also aims to use hybrid model (Convolution Recurrent Neural Network) which can further increase the accuracy of the proposed model.

Methodology

Flow Diagram

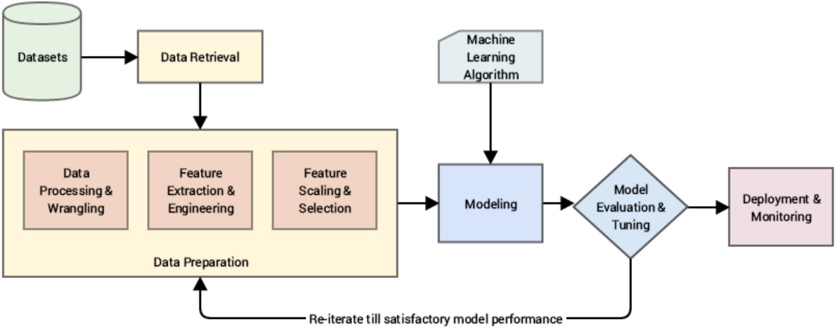

Figure: Flow Diagram

Medical Information Mart for Intensive Care (MIMIC-III)[4] consists of data about patients admitted to various critical care units in a large hospital. A large number of different parameters are present in MIMIC III database. These parameters include information such as vital signs, medications, laboratory measurements, observations, fluid balance, procedure codes, diagnostic codes, imaging reports, hospital length of stay, survival data, and others. The database consists of information of around 58,576 distinct patients who were admitted to various critical care units of the hospital between 2001 and 2012. The data comprises of patients aged 16 years or above only.

Methodology Contd..

Dataset Preprocessing

- Since the dataset is very large, we only consider data of those patients who were readmitted again which gives the details of 7,534 patients. The data set is divided into two classes:-
  - Patients readmitted in 30 days.
  - Patients readmitted after 30 days.
- MIMIC-III dataset contains missing values in some of the features.
  - If feature contains large number of missing values then the feature is removed.
  - If feature contains fewer missing values than mean is used to fill the missing values.

- Normalization is used to remove the biases among the features. It brings the data on a standard scale. It standardizes the range of independent features or variables of data, called feature scaling. Min Max Normalization technique is used.

$$v' = (v - min_A)/(max_A - min_A) \tag{1}$$

where A can be vector.

Features are selected through Nature Inspired Algorithms:

- **Bat Algorithm** is an optimization algorithm inspired by the echolocation behavior of microbats. Bats uses echolocation to sense distance, and they also distinguish between food/prey and other background barriers.
- **Grey Wolf Optimizer** (GWO) Algorithm inspired by grey wolves. The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves are employed for simulating the leadership hierarchy such as alpha, beta, delta, and omega. Also, the three main steps of hunting, searching for prey, encircling prey, and attacking victim, are implemented.

Methodology Contd..

Features are extracted through Convolution Neural Networks: **Convolutional Neural Network** is an effective machine learning technique from the deeplearning and it is similar to ordinary Neural Networks. Convolutional neural network is a network with convolutional layers. Convolutional neural network is consists of three steps of neural layers to build its architectures: Convolutional, Pooling, and Fully-Connected.

- **Recurrent Neural Network** (RNN) are used to capture the temporal dependency in the time series data. We are usually provided with a series of observations $x_1...x_T$ and we train a classifier to generate hypotheses ŷ.
- **Long Short Term Memory** networks usually just called LSTMs are a special kind of RNN, capable of learning long-term dependencies. Remembering information for long periods of time is practically their default behavior.
- **Bidirectional Recurrent Neural Networks** also called BRNN is just like RNN but it trains simultaneously on both sides of the time series data. This model gives the better result in both regression and classification problem.

- **Auto Encoders** are an unsupervised learning method, although technically, they are trained using supervised learning methods, referred to as self-supervised. They are typically trained as part of a broader model that attempts to recreate the input.
For a given dataset of sequences, an encoder-decoder LSTM is configured to read the input sequence, encode it, decode it, and recreate it. The performance of the model is evaluated based on the modelâĂŹs ability to recreate the input sequence.

- The entire dataset was split using stratified sampling and 10% of the dataset was used as a validation set.
- The rest 80% of the dataset was used for training purpose and was tested on 10% of the dataset.
- The LSTM model was trained with 30 epochs using Adam optimizer. LSTM layer uses 100 memory cell with no dropout and 25 memory cell with 20% dropout and these architectures are found after validation performance. Also train this model with Bat Algorithm.
- CLSTM model was trained with 30 epochs and the batch size of 1000. First, the convolution layer was used with 45 filters of size 5×5. Then the LSTM layer that uses 100 memory cell with 20% dropout. Also train this model with Grey Wolf Optimizer Algorithm.

Table: Comparison among different Deep Learning Models

Methods	Area Under ROC Curve	Accuracy
Long Short Term Memory	0.88	81.71%
Long Short Term Memory Auto-Encoders	0.73	75.00%
Convolution Long Short Term Memory	0.87	85.63%
Long Short Term Memory with Bat Algorithm	0.75	77.58%
Long Short Term Memory with Grey Wolf optimizer Algorithm	0.85	87.48%

Table: Comparison among different Deep Learning Models

Methods	Area Under ROC Curve	Accuracy
Convolution Long Short Term Memory Auto-Encoders	0.87	82.41%
Bi-Directional Long Short Term Memory	0.85	83.42%

Table: Comparison with Baseline Models

Methods	Area Under ROC Curve	Accuracy
Logistic Regression	0.54	58.09%
Support Vector Machines	0.54	59.37%
Decision Tree	0.52	55.68%
Random Forest	0.53	60.49%

Table: Comparison with State of Art Models

Paper	Methods	Comparison Factor	Value
Predicting Hospital Length of Stay Using Neural Networks on MIMIC III Data	Neural Network	Accuracy	80%
Predicting ICU Readmission with Machine Learning Using EHR Data	Gradient Boosting	AUC	0.76
Prediction of ICU Readmissions Using Data at Patient Discharge	XGBoost	AUC	0.75

Table: Comparison with State of Art Models

Paper	Methods	Comparison Factor	Value
Prediction of early unplanned ICU readmission in a UK tertiary care hospital: a cross-sectional ml approach	Ensemble Transfer Learning Algorithm	AUC	0.71
Predictive modeling in urgent care: a comparative studyof machine learning approaches	LSTM	AUC	0.58
Analysis and Prediction of Unplanned ICU Readmission using RNN with LSTM.	CLSTM	AUC	0.791

Results

Receiver Operating Characteristic Curves

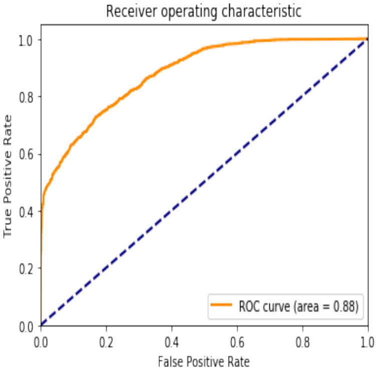

Figure: Receiver Operating Characteristic Curve Long Short Term Memory.

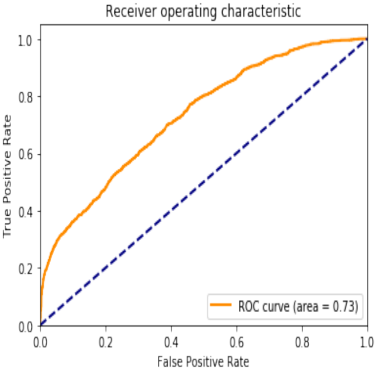

Figure: Receiver Operating Characteristic Curve Long Short Term Memory Auto Encoders.

Results

Receiver Operating Characteristic Curves

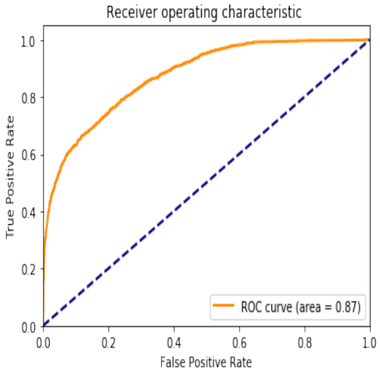

Figure: Receiver Operating Characteristic Curve Convolution Long Short Term Memory.

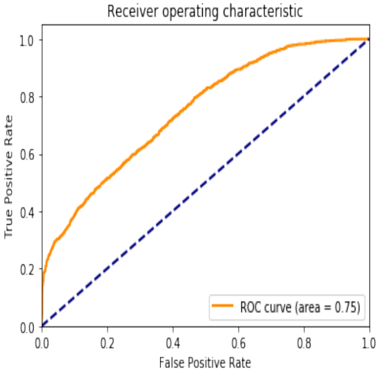

Figure: Receiver Operating Characteristic Curve Long Short Term Memory with Bat Algorithm.

Receiver Operating Characteristic Curves

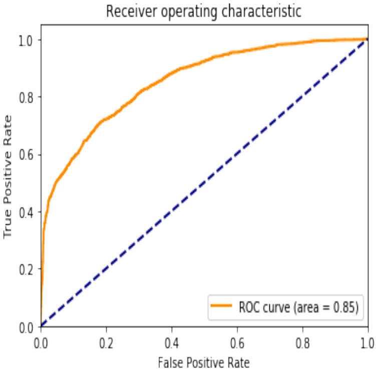

Figure: Receiver Operating Characteristic Curve Long Short Term Memory with Grey Wolf Optimizer Algorithm.

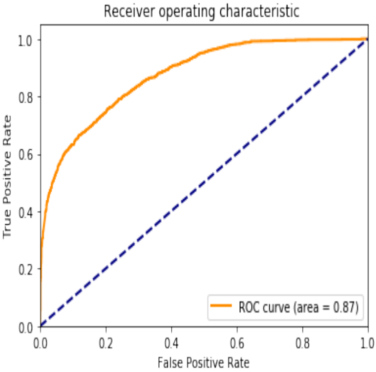

Figure: Receiver Operating Characteristic Curve Convolution Long Short Term Memory Auto Encoders.

Receiver Operating Characteristic Curves

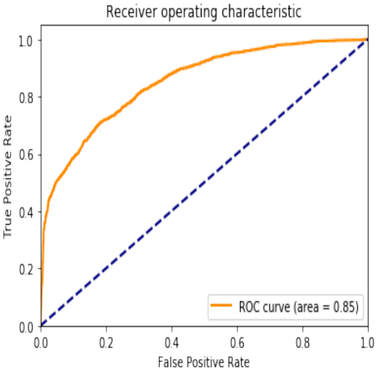

Figure: Receiver Operating Characteristic Curve Bi-Directional Long Short Term Memory.

Results

Model Loss Curves

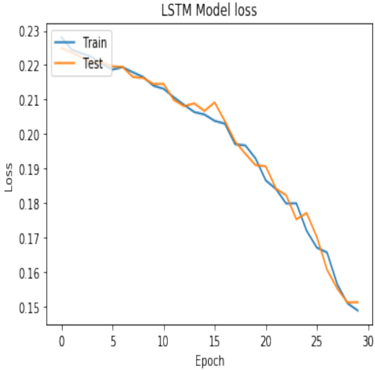

Figure: Loss Curve:LSTM.

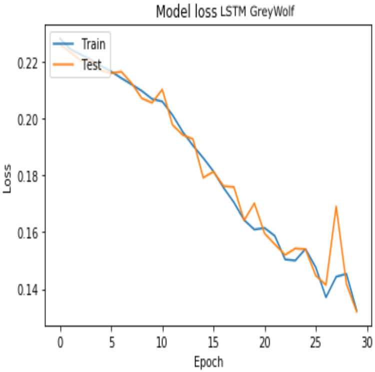

Figure: Loss Curve: LSTM Grey Wolf.

Results

Model Loss Curves

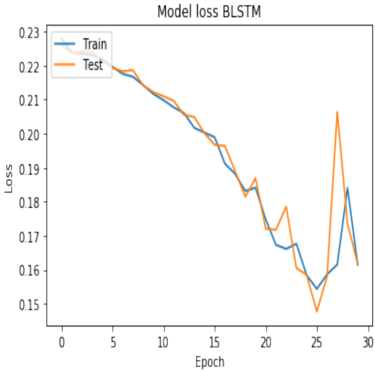

Figure: Loss Curve: Bidirectional LSTM.

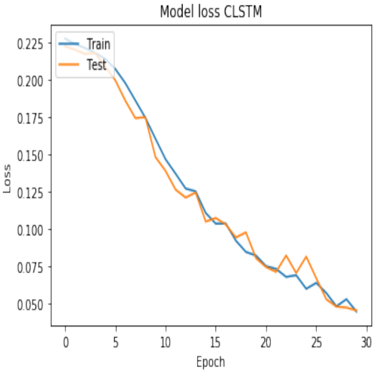

Figure: Loss Curve: Convolution LSTM.

Conclusion

Health Care Readmissions is extremely difficult task for both patients and hospitals. In our thesis, we design a robust algorithm to determine the amount of patients readmitted to a hospital. We measured the performance of different deep learning models with and without Nature-inspired algorithms to predict readmission probability and concluded that Long Short Term Memory with grey wolf optimizer performed better than the remaining ML algorithms in the accuracy value. We also establish that the result of the combination of LSTM and Convolution layer was remarkable on this dataset. This architecture can be used in current's health system to aim at high possibility patients, decrease the degree of readmission, and provide excellent health care.

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