Hospital Readmission Prediction Of ICU Patients Using Deep Learning Algorithms

by

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Introduction

- A Hospital readmission is an episode when a patient who had been discharged from a hospital is admitted again within a specified time interval.
- Previously baseline classification models were used to estimate the Hospital Readmission Rates. Then Deep Neural Network (DNN) came into picture. A Deep Neural Network (DNN) is an Artificial Neural Network with multiple hidden layers between the input and output layers. Similar to shallow ANNs, DNNs can model complex non-linear relationships. It has been widely used in fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation and bio-informatics where they produced results comparable to and in some cases superior to human experts.

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.

Key related research

Author (Year)	Paper Name	Comments
Ghassemi et al. (2014)	A data-driven approach to optimized medication dosing: a focus on heparin	An approach is developed that help clinicians determine the optimal initial dose of a drug to safely and quickly reach a therapeutic aPTT window.
Pirracchio et al.(2015)	Mortality prediction in intensive care units with the Super ICU Learner Algorithm (SICULA): a population-based study.	A super learner algorithm is used for predicting hospital mortality in patients.
Liang and Hu (2015)	Recurrent convolutional neural network for object recognition	Combination of convolution and recurrent neural network model is used for object detection.

Review of key related research

Author (Year)	Paper Name	Comments
Che et al.(2016)	Interpretable deep models for icu outcome prediction	Interpretable mimic learning is introduced that uses gradient boosting trees to learn interpretable models.
Jhonson et al. (2016)	MIMIC-III, a freely accessible critical care database	Medical Information Mart for Intensive Care (MIMIC-III) consists of data about patients admitted to various critical care units in a large hospital.
Hanson et al.	Improving protein disorder prediction by deep bidirectional long short-term memory recurrent neural networks	Long short term memory rnn in both directions is used to predict disordered proteins.

Review of key related research

Author (Year)	Paper Name	Comments
Greff et al.(2017)	LSTM: A search space odyssey	Overcomes the vanishing gradient problem of traditional RNN.
Franco et al. (2017)	Impact of prealbumin on mortality and hospital readmission in patients with acute heart failure	Statistical Analysis is used to find the mortality and readmission rates.
Reddy and Delen (2018)	Predicting hospital readmission for lupus patients: An RNN-LSTM-based deep-learning methodology	Utilizes deep learning methods to predict rehospitalization within 30 days by extracting the temporal relationships in the longitudinal EHR clinical data.

Research Gaps

In literature survey we find the following research gaps. These are points that we will be focused on in this thesis.

- The results obtained in these techniques can be improved using novel classification algorithms. Most of the researchers have used existing machine learning algorithms and it is expected that deep learning techniques will surpass the conventional techniques.
- These previous works were not able to model high dimensional nonlinear relations as good as RNN.
- Descriptive statistics were being used in earlier methods. However, these statistics like mean, median mode are always under the risk of loosing some vital information.
- Deep learning algorithms are still under shadow for variety of healthcare applications.

Extended Literature Survey

Author (Year)	Paper Name	Comments
Yang and Hossein Gandomi (2012)	Bat algorithm: a novel approach for global engineering optimization	Introduce a new natureinspired optimization algorithm, for solving engineering optimization tasks.
Mirjalili et al. (2014)	Grey Wolf Optimizer	Algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature.

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

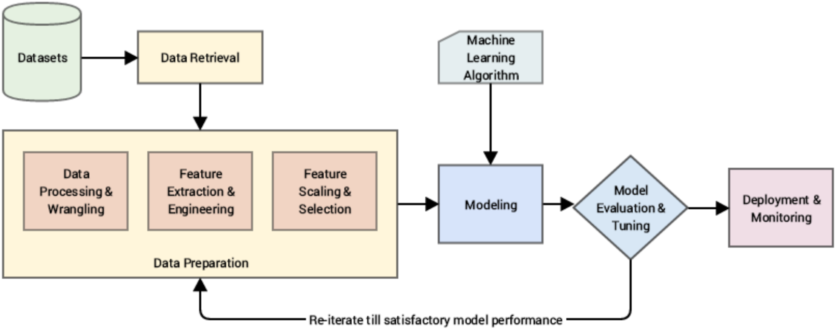

Figure: Flow Diagram

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.

- 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.

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.

Expected research outcome

- Compare the performance of various deep learning models on MIMIC-III dataset based on accuracy and area under roc curve.
- Compare the results of deep learning models with baseline models to point the advantages of deep learning in field of health-care applications.
- Results obtained from proposed model will be comparable with state-of-art literature.

- 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.

Methods	Area Under ROC Curve	Accuracy
Long Short Term Memory	0.88	79.84%
Long Short Term Memory Auto-Encoders	0.73	70.00%
Convolution Long Short Term Memory	0.75	70.98%
Long Short Term Memory with Bat Algorithm	0.75	70.42%
Long Short Term Memory with Grey Wolf optimizer Algorithm	0.85	81.57%

Table: Comparison among different Models implemented so far

Preliminary Testing and Results Obtained

Comparison among different deep learning models

Methods	Area Under ROC Curve	Accuracy
Convolution Long Short Term Memory Auto-Encoders	0.87	80.32%
Bi-Directional Long Short Term Memory	0.85	77.99%

Table: Comparison among different Models implemented so far

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 Baseline Models

Preliminary Testing and Results Obtained

Receiver Operating Characteristic Curves

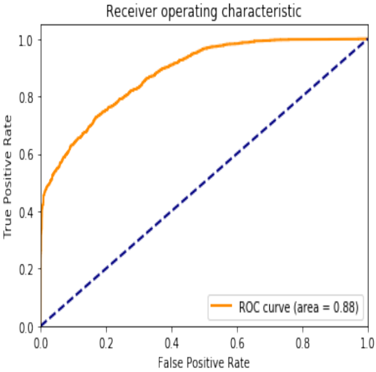

Figure: Receiver Operating Characteristic Curve Long Short Term Memory.

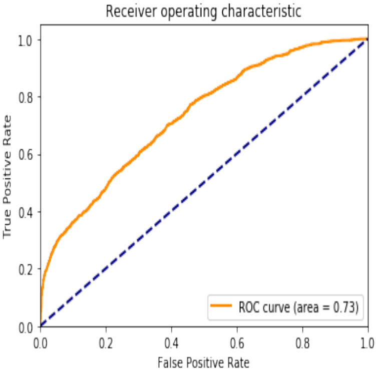

Figure: Receiver Operating Characteristic Curve Long Short Term Memory Auto Encoders.

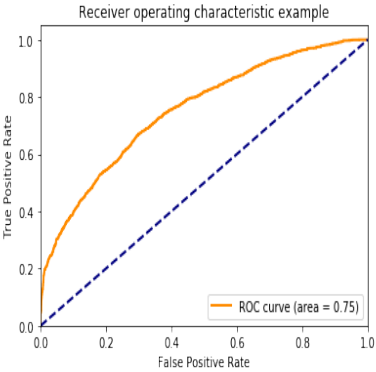

Figure: Receiver Operating Characteristic Curve Convolution Long Short Term Memory.

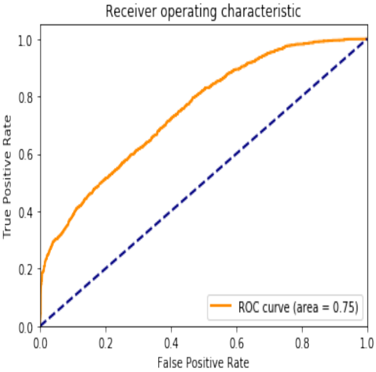

Figure: Receiver Operating Characteristic Curve Long Short Term Memory with Bat Algorithm.

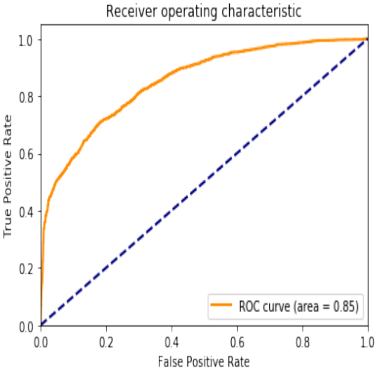

Figure: Receiver Operating Characteristic Curve Long Short Term Memory with Grey Wolf Optimizer Algorithm.

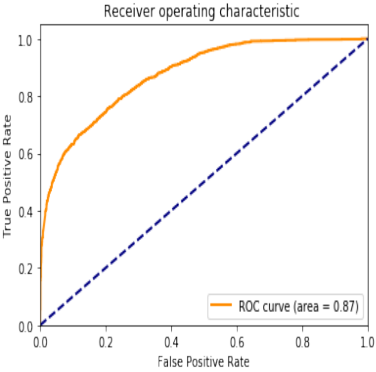

Figure: Receiver Operating Characteristic Curve Convolution Long Short Term Memory Auto Encoders.

Preliminary Testing and Results Obtained

Receiver Operating Characteristic Curves

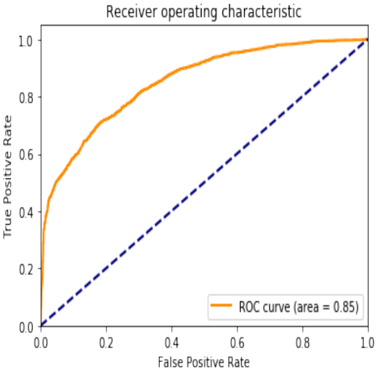

Figure: Receiver Operating Characteristic Curve Bi-Directional Long Short Term Memory.

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