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Kidney Failure Prediction in Heart Failure Patients using Neural Network

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A B S T R A C T

Kidney failure, which is associated with bad clinical outcomes, is one of the most common complications of heart failure (HF). Timely prediction of kidney failure can help doctors intervene early to avoid catastrophic consequences. In this paper, we proposed a multi-task deep and wide neural network (MT-DWNN) for predicting fatal complications during hospitalization. These studies have found that worsening kidney function is significantly associated with adverse outcomes in patients with heart failure. The immediate symptom of heart failure is insufficient blood ejection from the heart. Insufficient blood supply can cause diseases in other organs, such as kidney. Many previous researches have reached the same conclusion that kidney failure has a great adverse impact the prognosis of patients with HF. With a focus on the prediction of kidney failure, this paper is aimed at the main task of predicting the occurrence of kidney failure during hospitalization.

Keywords: Kidney failure, Heart Failure, Artificial Neural Network, MT-DWNN, Healthcare prediction

1. Introduction

Heart failure is a disease with high mortality rate and high medical costs. According to the guidelines of European Society of Cardiology (ESC), there are about 26 million adults living with heart failure worldwide. The 5-year survival rate of HF is even worse than that of several kinds of cancer HF was responsible for an estimated health expenditure of around $31 billion in the United States, which is equivalent to more than 10% of the total health expenditure for cardiovascular diseases. The immediate symptom of heart failure is insufficient blood ejection from the heart. Insufficient blood supply can cause diseases in other organs, such as kidney.

1.1 Motivation

Studies have found that worsening kidney function is significantly associated with adverse outcomes in patients with heart failure. Patients with kidney failure suffer higher risk of mortality. The hospital mortality rate of HF patients with kidney failure is 22.72%, compared to that of all the HF patient being 6.30%. Timely prediction of the kidney failure can help medical staff intervene early to avoid catastrophic consequences

1.2 Aim and Objective(s) of the work

Project aim

The aim of this project is to apply deep learning to predict complication of HF patients.

Project objectives

- Proposing a novel deep and wide neural network architecture.
- Adding auxiliary task to improve the prediction performance.
- Validating the proposed model on a real-world dataset.

2. Literature Survey

2.1 Heart Failure Outcomes Prediction

In the past few decades, many works have been dedicated to outcomes prediction of HF patients using machine learning (ML) algorithms. Guidi et al. presented a clinical decision support system (CDSS) for the analysis of heart failure (HF) patients, it is used to assess the severity of heart failure, predict heart failure type, and a management interface that compares different patients' follow-ups. Random forests achieved the best performance compared to neural networks (NN), support vector machines, fuzzy rules, classification and regression trees. Masetic and Subasi compared a number of ML algorithms (decision trees, k-nearest neighbors, support vector machines, artificial neural networks, random forests) to the task of detecting heart failure from electrocardiograms, and RF gives the best performance. Rahimi et al. reviewed the literature for death and hospitalization risk prediction models in patients with HF. Miao et al. proposed an improved random survival forest to predeict inhospital mortality. Acharya et al. proposed a deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals. Nirschl et al. developed a CNN classifier to detect HF from hematoxylin and eosin (H&E) stained whole-slide images.

The researchers also conducted several other comprehensive studies focused on applying machine learning to all aspects of heart failure management. However, most of these works focused on mortality or readmission prediction, with few focusing on complications of heart failure. Wosiak et al. proposed a multilabel classification technique for comorbidities identification, which is a general model for all kinds of diseases. Xiang et al. proposed a multi-task framework to jointly predict the risk of several related diseases, and the method was tested in patients with congestive heart failure and chronic obstructive pulmonary disease.

2.2 Deep Learning and its Application in Healthcare

Deep learning (DL) is one of the most advanced machine learning models. In recent years, DL has significantly outperformed traditional machine learning techniques in image recognition, speech recognition, and natural language processing. DL is also used to solve many medical problems. Miotto et al. proposed an unsupervised representation of patient from the EHRs (Electronic Health Records), named Deep Patient, which is a three-layer stacked denoising autoencoders. Cheng et al. represented the EHRs for every patient as a temporal matrix with time on one dimension and event on the other dimension. Then they built a four-layer convolutional neural network model to extract phenotypes and perform chronic diseases prediction. Choi et al. used a recurrent neural network model for early detection of the onset of heart failure.

3. Methodology

3.1 Multitask Neural Networks

With a focus on the prediction of kidney failure, this project is aimed at the main task of predicting the occurrence of kidney failure during hospitalization. Although the prediction of only one complication is included, prediction of mortality and intubation have been adopted as auxiliary tasks (AT) to improve the performance, as they are the most commonly used outcomes of HF (heart failure) patient in hospitals. The architecture of multi-task networks is shown in Figure 3.1. The input layer and all hidden layers are shared layers, while the output layers are specific layers for different tasks. For multi-task neural networks, the whole network is trained simultaneously. As we know, the training procedure is supervised learning, so multi-task training leads to more supervision, which leads to more general representation of the data. Generally speaking, multi-task mechanism results in better performance and improves generalization ability.

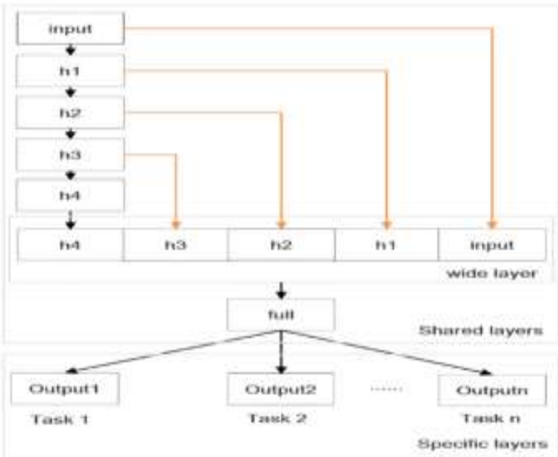

Figure 3.1 Overall architecture of MT-DWNN

3.2 Multitask DWNN and its Implementation Details

In this paper, to build a model for kidney failure prediction, the DWNN was modified for multi-task learning.

The input layer, hidden layers, the wide layer, and the fully connected layer of DWNN are all shared layers. Specifically, the input layer includes 89 neurons, each corresponding to 1 feature. The 4 hidden layers are with dense connections, and each layer includes 512 neurons. Each hidden layer is composed of dense connections, batch normalization, 'relu' activation, and dropouts. The dropout rate was set to 0.65. In the wide layer, the input layer and all the hidden layers are concatenated together and fed into the fully connected layers. The fully connected layer including 1024 neurons with the dropout rate of 0.65, but the activation is changed to 'sigmoid'.

The output layer of DWNN is changed to 3 independent softmax layers, corresponding to one main prediction task: kidney failure, and 2 auxiliary tasks: morality and intubation. For example, for the kidney failure task, the result should be positive if the patient was diagnosed with kidney failure during hospitalization. Conversely, the result should be negative if the patient was not diagnosed with kidney failure during the hospitalization.

The network is trained on Adam, an efficient stochastic gradient-based optimizer. The batch size is set to 1024.

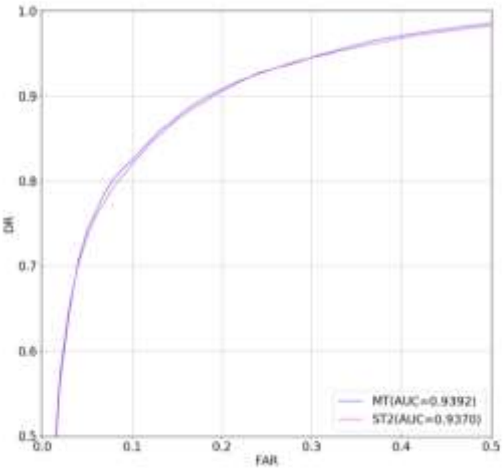

Figure 3.2 Kidney failure prediction performance of MT-DWNN and ST-DWNN

Figure 3.2 shows the AUC for various widths of MT-DWNN with a fixed dropout rate of 0.65. As shown in the table, DenseDNN with 512 neurons per hidden layer perform the best. The median AUC is 0.9455. Figure 3 shows the AUC of MT-DWNN with a fixed width of 512 and different dropout ratios. We can see that the MT-DWNN with a dropout rate of 0.65 exhibits the highest AUC of 0.9457.

3.3 Measurements

Dropout rate.

To measure the performance of the proposed method for complications prediction, sensitivity (Sen), specificity (Spec), Detection Rate (DR), False Alarm Rate (FAR) and accuracy (Acc) are calculated, which are defined as:

$$Sen = TP/(TP + FN), \quad (1)$$

$$Spec = TN/(TN + FP), \quad (2)$$

$$DR = Sen, \quad (3)$$

$$FAR = 1 - Spec, \quad (4)$$

$$Acc = (TP + TN)/(TP + FN + TN + FP), \quad (5)$$

where TP (True Positive) is the number of positive samples recognized as positive. FN (False Negative) is the number of positive samples recognized as negative; TN (True Negative) is the number of negative samples that are recognized as negative; FP (False Positive) is the number of negative samples that are recognized as positive. In general, a good detection method will minimize the FAR while maximize all the other 4 performance metrics.

4. Applications

4.1 Applications of MT-DWNN

1. **Speech Recognition:** Speech recognition relies heavily on artificial neural networks (ANNs). Earlier speech recognition models used statistical models such as Hidden Markov Models. With the introduction of deep learning, several forms of neural networks have become the only way to acquire a precise classification.
2. **Handwritten Character Recognition:** ANNs are used to recognize handwritten characters. Handwritten characters can be in the form of letters or digits, and neural networks have been trained to recognize them.

3. **Signature Classification:** We employ artificial neural networks to recognize signatures and categorize them according to the person's class when developing these authentication systems. Furthermore, neural networks can determine whether or not a signature is genuine.

4. **Medical:** It can be used to detect cancer cells and analyze MRI pictures in order to provide detailed results.

4.2 Advantages & Disadvantages

Advantages

- ANN can handle multiple tasks simultaneously
- The loss of one or more neurons influences the performance of Artificial Neural Networks
- We can train ANN's that these networks learn from past experience events and make decisions
- ANN models can produce output even with inadequate data.
- ANN's have fault tolerance

Disadvantages

- It requires lot of computational power
- ANN models are hard to explain
- Training the model requires lot of data
- Data preparation requires careful attention
- Optimization can be challenging

5. Conclusion

In this paper, we proposed a multi-task deep and wide neural network to predict kidney failure in HF patients. It provides a basis for clinicians to timely individualize the risk of the kidney function worsening in patients with HF so as to intervene early to avoid catastrophic consequences. The main task is to predict the occurrence of kidney failure during hospitalization. The multi-task learning mechanism and the DWNN network architecture improve the performance for kidney failure prediction. Moreover, it is also found that the auxiliary task tends to obtain improved performance if it is more relevant to the main task. Future work will include incorporating more information in EHR into our framework and improving the architecture of the DNN, aiming to further improve the prediction performance.

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