A Multi-task Machine Learning Approach for Comorbid Patient Prioritization

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Abstract*—With the advent of Internet of Things, remote patient monitoring and diagnosis is becoming the more advanced and accessible feature in healthcare industry regardless of age and disorder. With the increase in patient population, remotely prioritizing and diagnosing patients becomes a major problem. Research has been conducted to address this issue. However, many models fail to support the condition of comorbidity. In this paper, we developed a multi-task machine learning model that supports remote patient prioritization based on disease severity. This model not only considers patients diagnosed with a single disease, but also acknowledges comorbidity of a patient to calculate their severity utilizing physiological data. Classifying a comorbid patient based on their disease(s) severity is a challenging task. We achieve this by exploiting the commonalities and differences between the diseases using multi-task machine learning. Based on the correlation between diseases, we classify the patient into appropriate severity level. In addition to this, our model also supports continuous patient monitoring based on their severity levels, which is made possible by implementing in Apache Spark. Apache Spark also serves as a real-time streaming processor suitable for remote patient monitoring and diagnosis.

Keywords*—*Body sensors, remote monitoring, remote diagnosis, multi-task learning, comorbidity, disease severity, patient prioritization, Apache Spark, continuous monitoring

I. INTRODUCTION

Low-cost and increasing miniaturization of microelectronics makes intelligent wireless sensor networks more significant and enables this technology for a wide range of applications. It integrates seamlessly with little to no user interaction and awareness. In healthcare, this technology could likely reduce the number of hospital admissions. Using remote diagnosis, many health issues can be addressed before the condition becomes serious.

Patients can be prioritized in many ways and for different purposes. Many models have been developed to prioritize patients, where most of them were aimed to reduce healthcare costs [1]. However, according to [2], prioritizing patients based on severity should be given utmost importance. Comorbidity is generally defined as the co-occurrence of two or more disorders. A study shows that one in four Americans younger than 65 years have multiple chronic conditions [3]. The extent of comorbidity gradually increases with age as almost three out of four Americans 65 years or older have comorbidity [4][3]. By 2050, the population aged 65 and over is projected to be 83.7 million [5], which aggravates the problem of comorbidity. This complicates the process of remote monitoring and diagnosing, as it is very difficult to prioritize patients based on their severity if they have multiple disorders. There are few models which address this problem of comorbid patient prioritization. Nonetheless, some of them focus on mortality rate of a patient with respect to each disease [6] and some models calculate a severity score of patient based on number of comorbid disorders and medications used, even though they are unrelated diseases [7][8].

In this paper, we use multi-task machine learning technique [9] to derive the severity of a patient suffering from pneumonia and pulmonary embolism (PE), by finding the correlation between those two diseases. This model constitutes of two neural networks, one for each disease, where the hidden layer is shared by the networks to learn from each other. As they share the learning process, we calculate the relationship between them. We implemented this model in Apache Spark which supports real-time patient monitoring. We also propose a continuous patient monitoring system, which makes this machine learning model appropriate for calculating patient severity in real-time considering the changes in data from time to time.

In the next section, we discuss the related work in this area. In section III, we describe our framework and preliminary mechanism for disease severity prediction. Disease relatedness and comorbid disease severity are mainly presented in section IV. Finally, we discuss the efficiency of disease relatedness and conclude this paper in section V.

II. RELATED WORK

Data transmission is one of the important factors to be considered during remote monitoring of patients. Increased transmission rate helps to improve bandwidth utilization and reduces power consumption of hand-held personal devices. Abidoye et al. in [10], introduced priority scheduling and a data compression technique to increase transmission rate. The priority scheduling here, depends on high/low data transmission rates and high/low latency traffic. In [11], Ramesh et al. developed a risk based scheduling algorithm as a component of a Decision Support System that can support data collection and processing from multiple wearable wireless sensors. This algorithm schedules data on basis of cardiac diseases in increasing order of their disease severity and waiting time in the queue.

Manirabona et al. in [12], proposed a scheduling strategy named Priority-Weighted Round Robin (PWRR). It is a two stage algorithm where emergency cases flow through the first stage and in the second stage patients are sorted using a

Weighted Round Robin algorithm based on their waiting time. Sarkar et al. designed an integer programming model [13], which will be used to formulate the shift patterns of the nurse scheduling problem. Fuzzy sets are used for priority classification, where highest priority patients are always assigned to highest graded nurse.
Barua et al. proposed an efficient secure data transmission scheme in [14]. In order to provide priority scheduling, this scheme aims to minimize waiting time by classifying the incoming traffic as real-time and non-real-time data, where real-time data is given priority over non-real-time data. On the other hand, a secure key is shared among all sensors in a Wireless Body Area Network to minimize any additional memory and processing power requirements. A Multi-task learning framework is proposed in [15], where it predicts the risk of multiple diseases with the same set of symptom groups. Many models prioritize patients based on waiting time rather than disease severity. Though this work [11] considers disease severity for patient prioritization, this model lacks in handling the patients with comorbidity. In [15], this model even though considers comorbidity, it aims to predict the disease(s) rather than its severity. Also, it does not involve in any physiological sensor data, making it unsuitable for remote monitoring and diagnosis.

III. Disease Severity Predictor

A. Framework

Our framework mainly consists of five phases (see figure 1); Data collection, Data management, Multi-task learning, Comorbid disease severity, Continuous patient monitoring.

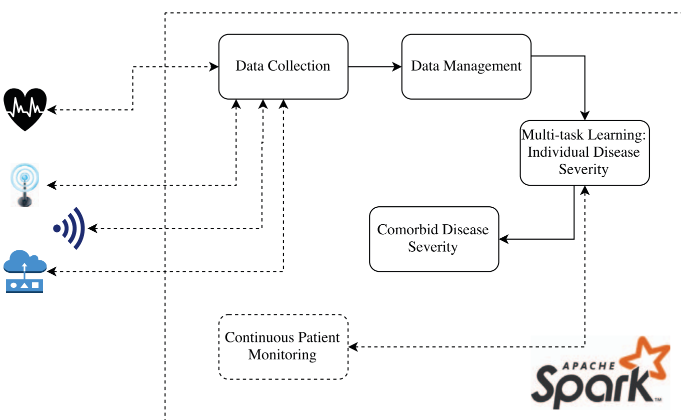

Fig. 1. Framework for Remote Patient Monitoring & Diagnosing

Data Collection: We design this model with an assumption that the patient had already registered with the healthcare provider and diagnosed with some disease(s). In this phase, physiological data is collected from different body sensors and transmitted over the Internet to a healthcare server.

Data Management: As there will be several kinds of sensors for different body organs and diseases, the data format will be different for each such device. So, we categorize the incoming data based on the diseases we are focused on. Since the patient is registered with the healthcare provider, it already has the basic information of the patient like demographics. The server extracts this basic information of respective patient from the healthcare database to generate an input for our machine learning model.

Our main contributions of this paper are the multi-task machine learning model for disease severity prediction and derivation of comorbid severity index, which are discussed in detail in further sections.

B. Multi-task Learning: Individual Disease Severity

Multi-task learning (MTL) improves generalization performance, where the primary task of the network helps remaining (related) tasks to use the domain-specific information contained in the training signals. This is possible when the tasks are trained in parallel while using the shared information. This knowledge-transfer enhances the learning speed, accuracy and intelligibility of tasks [9]. Figure 2 shows a simple structure of a MTL neural network.
In this paper, we repeatedly use the terms ”pneumonia task” and ”PE task” to refer the tasks of finding severity of a patient for those diseases. Initially we calculate the severities of a patient individually for each disease using standard severity indexes used for pneumonia and PE. So, finding the severity of a patient for each disease is considered a separate task in our MTL model, where pneumonia task is treated as the primary task. We classify severities as; Low risk (1), Moderate risk (2), High risk (3) and Emergency (4). This applies to every condition in the model, including comorbid severity (discussed later). This implies that the output of each task in our MTL model ranges from 1 to 4. Figure 3 shows our MTL neural network. We use back propagation algorithm for our MTL neural network, where sigmoid function serves as the activation function. Out of many error minimizing techniques, we use sum-of-squares errors, which works best for ranking in a MTL network.

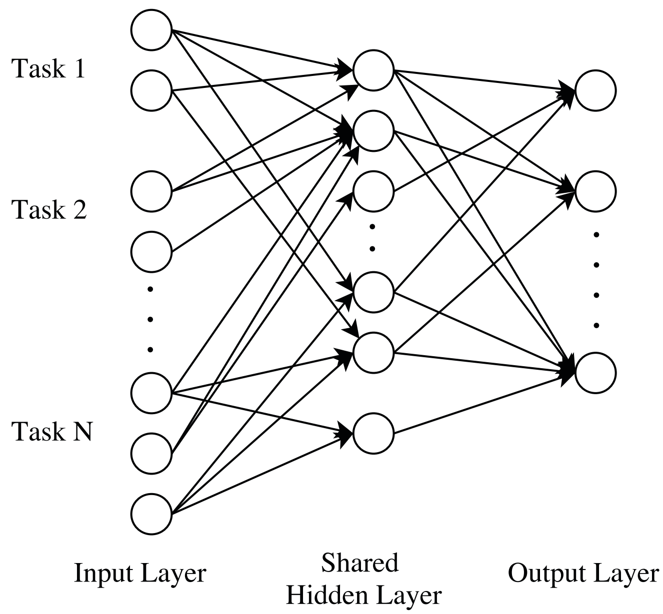

Fig. 2. Simple Multi-task Neural Network

Based on [16][17], the total number of features necessary to determine the severities of pneumonia and PE are 13 and 8 respectively. However, information shared between these

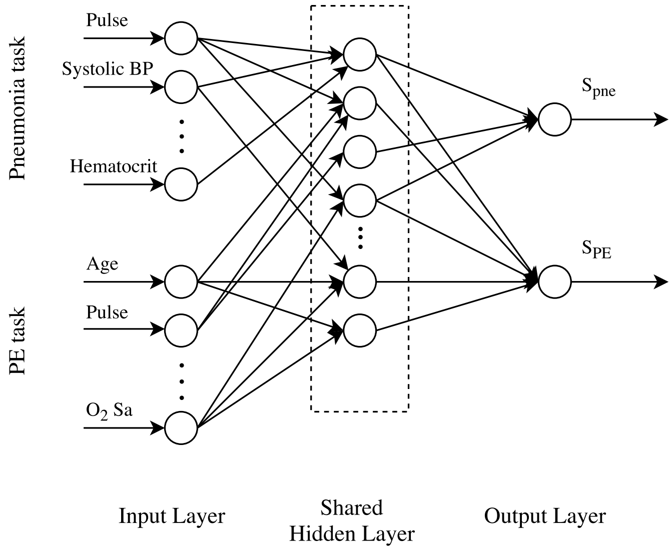

Fig. 3. Proposed Multi-task Neural Network

two tasks will be based on the common features. ”Gender”, ”Age”, ”Pulse”, ”Respiratory rate”, ”Systolic blood pressure” and ”Temperature” are the common features of pneumonia and PE. We use 66% and 34% of the dataset (containing only pneumonia and PE) for training and testing the network to determine the individual severities of the diseases.

C. Dataset

We use Medical Information Mart for Intensive Care (MIMIC-III) data [18], to design our disease severity predictor model. Using this data, we also derive comorbid severity of a patient. MIMIC-III data consists of de-identified health related data associated with over 40,000 patients collected between 2001 and 2012 who stayed in critical care units. It is a large dataset with several details of patients including demographics, vital sign measurements, medications, caregiver notes etc., since we intend to use our model for remote diagnosis, we only utilize physiological data from this dataset. We use the physiological data of 1736 and 89 patients suffering from pneumonia and pulmonary embolism respectively.

IV. Comorbid Severity Derivation

A. Disease Relatedness

As mentioned earlier, we exploit the commonalities and differences from our MTL network to determine the relatedness between pneumonia and pulmonary embolism. According to the concept of multi-task learning[9], multiple tasks can be trained well when the tasks are related. In order to find the relation between diseases and determine the patient comorbid severity, we consider their trained weights to find the relation. We derive the comorbid severity by calculating the angle between weight vectors of pneumonia and pulmonary embolism obtained after the individual training of pneumonia task and PE task respectively. These weight vectors can also be obtained using single-task learning of pneumonia and pulmonary individually, but the importance of multi-task learning can be observed here. With a limit on iteration count and error rate, the single-task learning may not yield appropriate weights that determine the exact relation between any two tasks. While in multi-task learning, as the tasks learn from each other the weights are adjusted or sometimes initiated based on the knowledge of primary task and sum of errors. We determine the angle between these two weight vectors using the cosine formula (see equation 1). The value of cosine angle between these two vectors always ranges from 0 to 1. We consider this value as disease relatedness, where any value close to 1 indicates that the tasks are closely related, and they are not if it is near to 0.

$$\begin{aligned} |u-v|^2 &= |u|^2 + |v|^2 - 2|u||v|\cos\theta \\ \cos\theta &= \frac{u.v}{|u|.|v|} \end{aligned} \tag{1}$$

Individual Severities (S_{pne} , S_{PE})	**Relatedness threshold (R_{T})**	**Comorbid Severity**
If $max(S_{\text{pne}}, S_{\text{PE}}) = 4$	$R_{\text{T}} = N/A$	$S_{\text{final}} = 4$
If $\lvert S_{\text{pne}} - S_{\text{PE}} \rvert = 0$	$R_{\text{T}} = 0.5$	$S_{\text{final}} = max(S_{\text{pne}}, S_{\text{PE}}) + 1$
If $\lvert S_{\text{pne}} - S_{\text{PE}} \rvert = 1$	$R_{\text{T}} = 0.6$	$S_{\text{final}} = max(S_{\text{pne}}, S_{\text{PE}}) + 1$
If $\lvert S_{\text{pne}} - S_{\text{PE}} \rvert = 2$	$R_{\text{T}} = 0.7$	$S_{\text{final}} = max(S_{\text{pne}}, S_{\text{PE}}) + 1$

TABLE I. Comorbid Severity Derivation

B. Comorbid Severity Index

Comorbid severity index is the final severity estimation level of a patient with comorbidity. There may be no difference in severity if the diseases are not closely related and also the opposite is true [19][20]. Based on this notion and individual severities of the patient for each disease, we derive the Comorbid Severity Index. If any one of the individual disease severity is 4 (i.e. Emergency), the final comorbid severity is assigned as 4 irrespective of the relatedness between the diseases. With a relatedness threshold of 0.5, if the individual severities are same and relatedness is more than 0.5, the final comorbid severity is assigned one level up to that of individual severity. It is not feasible to promote the final severity level (comorbid) if the individual severities of multiple diseases vary too much and have less relatedness. So, as the difference between the individual severities increases the final comorbid severity is promoted a level with simultaneous increase in the relatedness threshold. Table I shows the detailed derivation of comorbid severity.

C. Continuous Patient Monitoring

Our model supports continuous patient monitoring with the help of Apache Spark real-time data streaming and processing. Each severity class is assigned a particular frequency by a domain expert. This frequency minimizes as the severity level decreases. After the patients are categorized based on their final comorbid severity and according to the frequency set for their respective severity class, each patient is monitored continuously from time to time for any change in their condition (whether still in the queue or recently diagnosed). This helps to determine the condition of a patient at each interval. If the condition of patient worsens or by any chance improves, severity classification of that particular patient is changed accordingly.

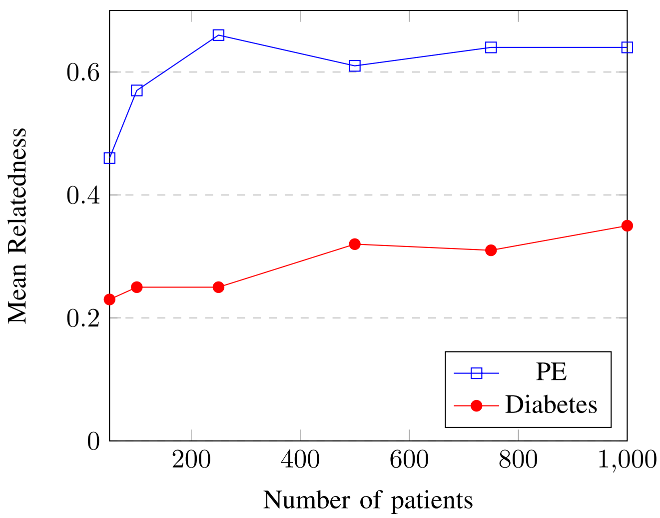

Fig. 4. Relatedness with Pneumonia: Comparison

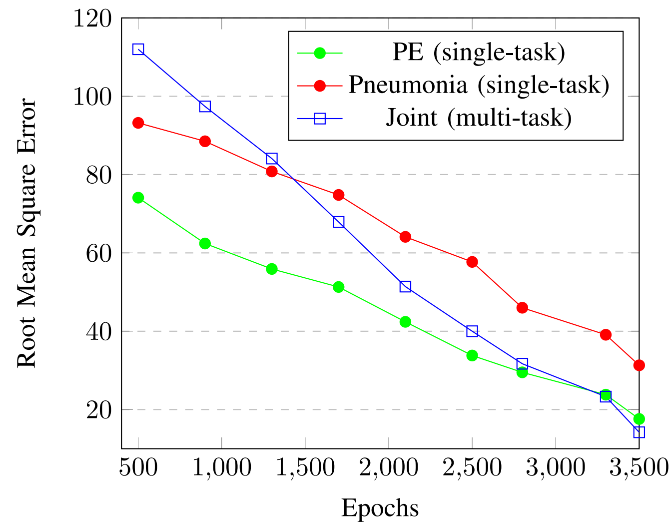

Fig. 5. Training Error Single-task vs Multi-task

V. Discussion and Conclusion

Our model mainly depends on the disease relatedness measure as it helps us to determine the relation between diseases. We consider another disease, Diabetes mellitus (DM) from the dataset, which is not closely related to our primary task, pneumonia. This helps to test the efficiency of disease relatedness. Figure 4 shows the mean relatedness of PE with pneumonia and DM with pneumonia for different samples of randomly selected patients. The possible reason for low relatedness between DM and pneumonia could be due to very few common features (3 including demographics) and the difference in ”Glucose” measurement for the individual patient severity classification for each disease.

As we discussed earlier, the advantage of multi-task learning over single task learning is, it helps the related tasks to learn quickly and efficiently. In order to test our model, we check the error rate of single task learning (severity estimation) individually for pneumonia and PE compared to multi-task learning. In figure 5, we can observe that even though initially the multi-task learning has slightly high error rate compared to single-task learning of both diseases, as the epochs increases the rate of error correction is high in multi-task learning and finally produces a better error rate leading to convergence quickly as compared to single task learning. We can also understand that the adjustment of weights in multi-task learning can be more accurate or near to accuracy quickly and efficiently when the tasks are related.

Multi-task machine learning has been used for different purposes in literature, while severity estimation for comorbid patients was proposed in many different ways which are not conducive to remote patient monitoring and diagnosis. In this paper, we proposed a multi-task learning approach to prioritize patients based on their comorbid severity for multiple diseases. We used the physiological data from MIMIC-III dataset, which serves as the sensor data in our model. We also proposed the idea of continuous patient monitoring in a remote scenario.
This work can be further extended to support patients with more than two diseases by observing the correlation between numerous tasks in MTL. Also, there could be other forms of input such as scan reports, x-rays, etc., where data is extracted from them. This is more advantageous in a scenario where body sensors produce graphical outputs.

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