PATIENT DETERIORATION PREDICTIVE MODEL USING LONG SHORT-TERM MEMORY RECURRENT NEURAL NETWORK WITH GENETIC ALGORITHM OPTIMIZATION

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DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time. Not to forget my beloved wife Dr. Mayyada and my lovely kids Doha, Ibrahim, Salma, and Shatha who stand with me from the first step with all their power. It is also dedicated to my great brothers Mohammad, Abdel Latif, Hamza, and Ghaith as well as my little sister who do not avoid (or delay) to provide any kind of help.

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ABSTRACT

The clinical investigation found that early recognition and intervention are crucial for preventing clinical deterioration in patients in Intensive Care units (ICUs) as well as in general wards. Deterioration of patients is predictable and can be avoided if early risk factors are recognized and developed in the clinical setting. Existing patient deterioration prediction methods generally have some disadvantages such as limited to specific patient groups or diseases that lead to lack of generalization, low prediction performance, and less optimized model parameter setting. This thesis proposes a patient deterioration predictive model based on Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) with Genetic Algorithm (GA) optimization. The LSTM-RNN predictive model able to accept multiple input and data types in both static and dynamic parameters to predict patient deterioration, in terms of mortality and sudden transfer of patients from general wards to ICU with good accuracy. Another main strength of this predictive model is the input dataset is based on minute-by-minute time-series data obtained from open-source MIMIC-III research database for both model training and testing, hence also contribute to good prediction performance. To identify the baseline reference model with optimal performance, the setting of LSTM-RNN predictive model is explored using heuristically approach in terms of number of hidden layers, number of neurons in the first hidden layer, number of epochs, feature selection approach, as well as the impact of data cleaning in data pre-processing. On the other hand, the GA acts as an optimization model to further enhance the prediction performance of the baseline reference LSTM-RNN predictive model by exploration and identification of the optimum parameter settings, which include observation window size, prediction window size, and number of neurons in the first hidden layer. In this study, the proposed predictive model is benchmarked with other related work in terms of various prediction model, data sequence type, patient's age involved, number and types of features, dataset splitting ratios, prediction and observation window size and data source. For standard benchmarking result comparison, the selected performance metrics includes accuracy, area under receiver operating curve (AUROC), and test loss. The benchmarking results show that the proposed model outperforms other related models in general as it is capable to predict patient deterioration up to six hours before the onset with minimum prediction accuracy above 0.80 as recommended in the clinical setting. In specific, the best optimum LSTM-RNN predictive model after GA optimization able to achieve AUROC of 0.933, prediction accuracy of 0.921, test loss of 0.435, longer prediction window of 4.77 hours while reducing the observation window from 24 hours to 9.6 hours (60%) at the same time. The proposed patient deterioration prediction model based on LSTM-RNN, and GA will be very useful to clinical team as they have more sufficient time window to take prompt medical action before the onset of deterioration. As a result, this will help to reduce the mortality rate of patients or sudden transfer of patients from general wards to ICU.

ABSTRAK

Penyelidikan klinikal mendapati bahawa pengecaman dan intervensi awal adalah sangat penting untuk mencegah kemerosotan klinikal pada pesakit di Unit Rawatan Rapi (ICU) dan juga di wad umum. Kemerosotan pesakit dapat diramal dan dielakkan sekiranya faktor risiko awal dikesan dan dikembangkan dalam penetapan klinikal. Kaedah ramalan kemerosotan pesakit yang sedia ada secara umumnya mempunyai beberapa kelemahan tertentu seperti terhad kepada kumpulan pesakit atau penyakit tertentu yang menyebabkan kekurangan generalisasi, prestasi ramalan yang rendah, dan tetapan parameter model yang kurang dioptimumkan. Tesis ini mencadangkan sebuah model ramalan kemerosotan pesakit berdasarkan Rangkaian Neural Berulang Ingatan Jangka-Pendek Panjang (LSTM-RNN) dengan pengoptimuman Algoritma Genetik (GA). Model ramalan LSTM-RNN ini dapat menerima pelbagai input dan jenis data dalam kedua-dua parameter statik dan dinamik untuk meramalkan kemerosotan pesakit, dari segi mortaliti dan pemindahan pesakit dari wad umum ke ICU secara tiba-tiba dengan ketepatan yang baik. Satu lagi kekuatan utama model ramalan ini adalah set data inputnya adalah berdasarkan data siri masa minit-demi-minit yang diperolehi dari pangkalan data penyelidikan sumber terbuka MIMIC-III untuk latihan dan ujian model, oleh itu juga menyumbang kepada prestasi ramalan yang baik. Untuk mengidentifikasikan model rujukan asas dengan prestasi yang optimum, penetapan model ramalan LSTM-RNN adalah dieksplorasi dengan menggunakan pendekatan heuristik dari segi jumlah lapisan tersembunyi, bilangan neuron pada lapisan tersembunyi pertama, bilangan zaman, pendekatan pemilihan ciri, serta impak pembersihan data dalam pra-pemprosesan data. Dari sudut lain, GA bertindak sebagai model pengoptimuman untuk meningkatkan lagi prestasi ramalan pada model ramalan LSTM-RNN rujukan asas dengan penerokaan dan pengenalpastian tetapan parameter yang optimum, di mana meliputi ukuran tetingkap pemerhatian, ukuran tetingkap ramalan, dan jumlah neuron pada lapisan tersembunyi pertama. Dalam kajian ini, model ramalan yang dicadangkan adalah dibandingkan dengan karya lain yang berkaitan dari segi model ramalan yang pelbagai jenia, jenis urutan data, usia pesakit yang terlibat, bilangan dan jenis ciri, nisbah pemisahan set data, ukuran tetingkap ramalan dan tetingkap pemerhatian serta sumber data. Untuk perbandingan keputusan yang standard, metrik prestasi yang dipilih merangkumi ketepatan, kawasan di bawah keluk operasi penerima (AUROC), dan kehilangan ujian. Hasil perbandingan menunjukkan bahawa model yang dicadangkan mengatasi model-model lain pada umumnya kerana ia mampu meramalkan kemerosotan pesakit sehingga enam jam sebelum permulaan dengan ketepatan ramalan minimum yang melebihi 0.80 seperti yang disarankan dalam tetapan klinikal. Secara khusus, model ramalan LSTM-RNN optimum yang terbaik setelah pengoptimuman GA dapat mencapai AUROC 0.933, ketepatan ramalan 0.921, kehilangan ujian 0.435, tetingkap ramalan yang lebih panjang selama 4.77 jam sambil mengurangkan tetingkap pemerhatian dari 24 jam kepada 9.6 jam (60%) pada masa yang sama. Model ramalan kemerosotan pesakit ini yang dicadangkan berdasarkan LSTM-RNN dan GA akan sangat berguna kepada pasukan klinikal kerana mereka mempunyai masa yang lebih mencukupi untuk mengambil tindakan perubatan yang cepat sebelum permulaan kemerosotan. Justeru itu, ini akan membantu mengurangkan kadar mortaliti pesakit atau pemindahan pesakit secara tiba-tiba dari wad umum ke ICU.

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LIST OF ABBREVIATIONS

AD	-	Alzheimer's Disease
ADNI	-	Alzheimer's Disease Neuroimaging Initiative
AHA	-	American Health Association
AKI	-	Acute Kidney Injury
ANN	-	Artificial Neural Network
APACHE	-	Acute Physical and Chronic Health Evaluation
aPTT	-	Activated Partial Thromboplastin Time
AUC	-	Area Under the Curve
AUROC	-	Area Under the Receiver Operating Curve
AVPU	-	Alert, Voice, Pain, and Unresponsive
BiLSTM	-	Bidirectional Long Short-Term Memory
BN	-	Bayes Net
BP	-	Blood Pressure
BRNN	-	Bidirectional Recurrent Neural Network
BUN	-	Blood Urea Nitrogen
CAC	-	Coronary Artery Calcium
Ca^+	-	Calcium ion
CCHS	-	Christiana Care Health System
CCU	-	Coronary Care unit
CDSS	-	Clinical Decision Support System
CHMM	-	Coupled Hidden Markov Model
CITI	-	Collaborative Institutional Training Initiative
CNMF	-	Constrained Non-negative Matrix Factorisation
CNN	-	Convolutional Neural Network
CPT	-	Current Procedural Terminology
CRI	-	Cardiorespiratory Insufficiency
CSRU	-	Cardiac Surgery Recovery Unit
CT	-	Computed Tomography
DEAP	-	Distributed Evolutionary Algorithms in Python
Dl	-	Decilitre

DiasBP	-	Diastolic Blood Pressure
Dim	-	Dimension
DOB	-	Date of Birth
DRG	-	Diagnoses Related Group
ED	-	Emergency Department
EHR	-	Electronic Health Record
ELM	-	Extreme Learning Machine
EM	-	Expectation Minimization
EMS	-	Emergency Medical service
EWS	-	Early Warning Score
FC	-	Fully Connected
FFNN	-	Feed-Forward Neural Network
FOC	-	Free of Charge
GA	-	Genetic Algorithm
GB	-	Gradient Boosting
GB	-	Giga Bytes
GCS	-	Glasgow Coma Scale
GHz	-	Giga Hertz
GMM	-	Gaussian Mixture Model
GPU	-	Graphical Processing unit
GRNN	-	General Regression Neural Network
GRU	-	Gated Recurrent Unit
GUI	-	Graphical User Interface
HADM	-	Hospital Admission
HDP	-	Hierarchical Dirichlet Processes
HE	-	Hypotensive Episodes
HER	-	Electronic Health Record
HIPAA	-	Health Insurance Portability and Accountability Act
HIS	-	Hospital Information System
HMM	-	Hidden Markov Model
HR	-	Heart Rate
HRV	-	Heart Rate Variability
ICD	-	International Classification of Diseases

ICU	-	Intensive Care Unit
ID	-	Identifier
IMCU	-	Intermediate Care Unit
INR	-	International Normalized Ratio
K^+	-	Potassium
KB	-	Kilo Byte
kNN	-	k-Nearest Neighbour
LDCT	-	Low Dose Computed Tomography
LOOCV	-	Leave-One-Out Cross Validation
LOS	-	Length of Stay
LSTM	-	Long Short-Term Memory
MAD	-	Mean Absolute Difference
MCI	-	Mild Cognitive Impairment
MDRP	-	Multi Modal Disease Risk Prediction
MeanBP	-	Mean Blood Pressure
MEWS	-	Modified Early Warning System
Mg	-	Milli gram
MICU	-	Medical Intensive Care Unit
MIMIC	-	Medica Information Mart for Intensive Care
MLP	-	Multilayer Perceptron
MMDL	-	Multi Modal Deep Learning
MOGA	-	Multi Objective Genetic Algorithm
MVCC	-	Multi-Version Concurrency Thromboplastin
Na^+	-	Sodium
NaN	-	Not a Number
NB	-	Naïve Bayes
NBP	-	Non-Invasive Blood Pressure
NC	-	Normal Control
NEWS	-	National Early Warning Scoring
NP	-	Non-deterministic Polynomial
OW	-	Observation Window
PCA	-	Principle Component Analysis
PDPA	-	Probability Distribution Patterns Analysis

PHI	-	Protected Health Information
PICU	-	Paediatric Intensive Care Unit
pMCI	-	Progressive state Mild Cognitive Impairment
PPV	-	Positive Predictive Value
PSM	-	Patient Similarity Metric
PT	-	Prothrombin Time
PTT	-	Partial Thromboplastin Time
PW	-	Predictive Window
RDS	-	Real-Time Data Sensing
RF	-	Random Forest
RLR	-	Regularized Logistic Regression
RNN	-	Recurrent Neural Network
ROC	-	Receiver Operating Curve
RR	-	Respiratory Rate
RRV	-	Respiratory Rate Variability
SANMF	-	Subgraph Augmented Non-Negative Matrix Factorization
SAPS	-	Simplified Acute Physiology Score
SAX	-	Symbolic Aggregate Approximation
sCr	-	Serum Creatinine
SICU	-	Surgical Intensive Care Unit
sMCI	-	Stable state Mild Cognitive Impairment
SPO_2	-	Saturation of Oxygen in the Blood
SQL	-	Structured Query Language
SVM	-	Support Vector Machine
SysBP	-	Systolic Blood Pressure
Temp	-	Temperature
TN	-	True Negative
TP	-	True Positive
TSC	-	Tissue Sodium Concentration
TSICU	-	Trauma/Surgical Intensive Care Unit
T3	-	Triiodothyronine
T4	-	Thyroxine
T-data	-	Text Data

T&T	-	Track and Trigger
UDRP	-	Unimodal Disease Risk Prediction
ViSiBiD	-	Vital Sign Big Data
VT	-	Ventricular Tachycardia
WEKA	-	Waikato Environment for Knowledge Analysis
WFDB	-	Waveform Database

LIST OF SYMBOLS

C_t	-	Cell State at time t
t	-	Time
h_t	-	Hidden Representation at time t
i	-	Input gate
f	-	Forget gate
o	-	Output gate
p_i	-	Probability
b	-	Bias vector
$tanh$	-	hyperbolic tangent
x_t	-	new event
b_f	-	forget bias
h_{t-1}	-	output of the previous cell
a_t	-	input activation
U_a	-	input activation update
W_a	-	input activation weight
b_a	-	input activation bias
i_t	-	Input
U_i	-	input update
W_i	-	W_i input weight
b_i	-	input bias
o_t	-	output gate
W_o	-	output weight
U_o	-	output update
b_o	-	output bias
Δt	-	output difference as computed by any subsequent layers
Δh_t	-	output difference as computed by the next time step
δC_t	-	change in the output
δh_t	-	change in the state
δa_t	-	change in the activation input

δi_t	-	change in the input gate
δf_t	-	change in the forget gate
C_{t-1}	-	previous state
Δo_t	-	change in the output gate
δx_t	-	change in the new event
Δh_{t-1}	-	change in the output difference as computed by the next time step LSTM
$\delta gates_t$	-	change in gate values at time t
δW	-	change in weight
δU	-	change in update
δb	-	change in bias
κ	-	selective pressure
$R(i)$	-	rank of individual i
m	-	number of individuals
Pm	-	probability that one gene has been modified for a binary
s	-	a given binary
S	-	Space
N	-	Length of gene
$indpb$	-	individual input probability
z_{fi}	-	forecast value
z_{oi}	-	observed value

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CHAPTER 1

INTRODUCTION

This chapter discusses the study background to illustrate the research motivation, followed by the problem statement, the research objectives and its associated scopes, as well as research significance.

1.1 Background of the Study

Identifying of patients who have a high deterioration risk is vital so that treatment decisions, quality assurance, and resource use management can be guided to reduce mortality rate. Patients who are admitted to ICUs and survive hospitalization have a high mortality rate in the six months after discharge (Wunsch *et al.*, 2010). A lot of these post-discharge deaths are within patients transferred to other acute-care hospitals (Vasilevskis *et al.*, 2009) or long-term acute care facilities (Hall *et al.*, 2012). Unidentified deteriorations could delay the ICU transfer of patients, which would necessitate resuscitation in as much as 67% of cases or eventually result in deaths (Wellner *et al.*, 2017). A report by the American Health Association (AHA) in 2015 showed that about 209,000 in-hospital cardiac arrests occur annually in the United States of America (USA) (Kolte *et al.*, 2015). There are approximately 2,300 annual cases of cardiac arrests in Swedish hospitals as reported by the Swedish Resuscitation Council, which oversees 95% of Swedish hospitals (Spångfors *et al.*, 2016). It was also found by the 2010 USA government investigation that 44% of adverse events could have been clearly or likely prevented (Levinson and General, 2010). Some researchers in New Zealand (Davis *et al.*, 2003), the United Kingdom (UK) (Vincent *et al.*, 2001), and Canada (Baker *et al.*, 2004) used deterioration as defined by the result of health care management instead of the underlying disease process in the assessment of more than 25,000 patient records, from which 8% - 17% of admissions were related to unfavourable events, preventable deteriorations made thought to be around 37% - 51%, and 7% - 19% ended in disability or death.

To this end, several studies have put forward different definitions of deterioration that are dependent on the various causes and the involved critical procedure. For instance, some studies (Churpek *et al.*, 2013; Churpek *et al.*, 2014a; Hu *et al.*, 2016b; Smith *et al.*, 2013) defined the deterioration as the patient being transferred to an ICU or experiencing a cardiac arrest, while there are other researchers related the term to patients who are admitted, transferred to another specialised hospital for emergency surgical treatment, or died after revisiting the emergency department (ED) (Mochizuki *et al.*, 2017). There is also a research demonstrated that deterioration is primarily connected with organ dysfunctions like liver failure, kidney injury, respiratory failure, ICU admission, or death at a hospital (Quinten *et al.*, 2018). Further, deterioration have also been defined by several studies to be a patient's sudden transfer from the general ward to an ICU with positive pressure ventilation, vasopressors, fluid resuscitation, or any immediate procedure that may be conducted between 2 hours pre or 12 hours post transfer (Bonafide *et al.*, 2014; Wellner *et al.*, 2017). (Henriksen *et al.*, 2014) has also defined the deterioration as a patient deviating from the specified normal range in the 2 - 24 hours interval after hospital admission. Nevertheless, in the present, the physiological importance of deterioration is appreciated and the exact definition of it is still vague among the scientific community (Zheng and Shi, 2018).

Deterioration of patients in can be avoided by utilizing technologies that detect deterioration in a timely manner, by logging several data types in health informatics systems, and processing the data by utilizing software analysis models with accurate performance (Bonnici *et al.*, 2013; Findlay *et al.*, 2012; Stewart, 2009; Stewart 2011). There are many excellent data-driven learning models could be implemented in clinical decision support system by the implementation of electronic health records (EHRs), Markov models (Santamaria Ariza *et al.*, 2020) and dynamic Bayesian network (Abebe and Tesfamariam, 2020) to study disease development through modelling the temporal characteristics of EHRs. Moreover, preventing the occurrence of patients' deterioration in an adequate time window turns into a need in medicinal services communities and biomedical research fields. It is also imperative that hospital care quality is enhanced significantly so that unwanted results are reduced. The notable hypothesis is recent technology can be used so that models that were developed using dynamic variables (e.g., vital signs and/or lab tests) and static variables (e.g., age, gender, and admission type) are utilized to build and strengthen an automated classification algorithm that can predict deterioration accurately.

In this study, the patient deterioration is defined as the patients either suddenly being transferred to ICUs from general wards (i.e., urgent admission type), or ICU patients suddenly dying (Churpek *et al.*, 2013; Churpek *et al.*, 2016; Edelson *et al.*, 2018; Smith *et al.*, 2013). Studies by a few researchers (Goldhill and Sumner, 1998; Lundberg *et al.*, 1998) showed a sudden ICU transfer is related with worse outcomes and increased mortality. The complex patterns in patients' longitudinal data affect the clinical interventions and ICU deaths (Catling and Wolff, 2020). As such, this study intends to forecast these events more reliably prior to their occurrence so suitable pre-emptive action can be taken by the hospital staff.

The Early Warning Score (EWS) systems are currently the common utilized models to improve the early detection of deteriorating patients (Hu *et al.*, 2016b; Kivipuro *et al.*, 2018; Panday *et al.*, 2017; Quinten *et al.*, 2018; Singer *et al.*, 2016). These systems provide early notification or warning to medical teams to take suitable and prompt medical action to save patients’ lives. The design of these systems aims to solve sudden harmful events by combining various measures into an exact score that is quantifiable. The systems normally are integrated with the hospital equipment, such as patient monitor to track when patients reach certain thresholds. For example, "Track and Trigger" (T&T) systems track vital signs based on their periodic measurement and act (triggered) when patient vital sign reaches a specific threshold value. Fletcher et al. (Fletcher and Cuthbertson, 2010) showed that T&T systems are based on an erroneous foundation which derives from huge datasets that are regressed logistically, resulting in the prediction of death by using certain parameters. Some hospitals have asserted that the problem of deteriorating patients can be solved by continuous monitoring via measuring the impact of diseases on patients' daily lives (Edelson *et al.*, 2018;

Newman, 2017; Tilly *et al.*, 1995). However, the long hours continuous monitoring would consume great human resources of medical teams in hospitals.

Identifying deterioration prior to its onset is a huge and challenging issue in modern healthcare. Much research have proposed different predictive models to reliably predict such occurrences. Based on sufficient observation window and prediction window, the crucial techniques used to solve patient deterioration problems are machine learning and deep learning models (Bonnici *et al.*, 2013; Choi *et al.*, 2017; Goodfellow *et al.*, 2016; Shotton and Findlay, 2012; Stewart, 2009; Stewart 2011; Ward *et al.*, 2016b). Machine learning applies computational methods that depend on past experience to predict a task or outcome perfectly (Ward *et al.*, 2016a). In contrast, deep learning constitutes an operation to refine information in multiple stages, where highly purified information is gained after being put through successive filters (Bengio *et al.*, 2017). However, unlike deep learning models, machine learning-based models cannot frequently provide accurate performance and explicit interpretability; as a result, this research aims to propose a generic prediction framework based on deep learning models. Technologies used for deep learning produce approximately 2.5 quintillion bytes of data daily, the volume, velocity, and variety of information enable the "Big Data" analysis (Masud and Al Harahsheh, 2016; Nepal *et al.*, 2015). The highest quality personalised healthcare is provided by big medical data and it is a vital factor in the success of a healthcare industry that has been revolutionised (Cheng *et al.*, 2016; Madsen, 2014). Therefore, this study aims to utilize data from various types of patients so that patient deterioration can be detected in real-time, and the occurrence can be predicted. This study is vitally needed so that its results can be used to save the lives of more patients and in the provision of better healthcare services for people in general.

1.2 Problem Statement

This research takes into consideration of three major research problems of prediction of deterioration for patients. The first problem is the framework of deterioration-based predictive models. The second problem is the shortcoming of current predictive models based on machine learning / deep learning. The third issue is the optimization problem for prediction model.

The first outstanding issue in the framework is the impractical workflow (i.e., sequence of processes) embedded in a predictive model. One example of an unrealistic approach is using laboratory tests as the only variables in the patient deterioration prediction (AlNuaimi *et al.*, 2015; Masud and Al Harahsheh, 2016). Each patient undergoes different medical tests, and a particular patient might need undergo the same tests more than once. Patients are initially placed into different groups according to their demographic profile, and every group is further clustered into groups of patients with similar test profile. After that, every group is utilized to implement a predictive model. However, the results from such models cannot be benchmarked (Masud and Al Harahsheh, 2016). Also, some previous works (Clifton *et al.*, 2011; Hu *et al.*, 2016b) performed studies on hospitals specialized in certain diseases, as well as patients with targeted diseases like cancer and suspected infection or sepsis (Masud and Al Harahsheh, 2016). As a result, a strong influence on the final model causes a high variance in behaviour and performance. This also negatively affects the generalization of the proposed prediction framework based on selected models.

Besides, certain proposed deterioration prediction framework is most focusing on in-hospital deterioration outcome evaluation based on specific factor. For example, (Jones *et al.*, 2013) evaluates an in-hospital deterioration in USA focus on medical neglect. This predictive model-based framework takes a long time, uses a design that is retrospective, sometimes considers adverse events caused by pre-hospital treatment, and ignores the fact that sometimes part of the natural dying process involves deterioration. Superior frameworks are required to categorise patient risks in a prospective and stratified approach while they are being admitted, and at the same time updating the approaches to educating and care models in preventing, identifying, and improving care for clinical deterioration.

Another research issue is overcoming the performance issue of existing deterioration predictive models. A few researches (Garla and Brandt, 2012; Seide *et al.*, 2011) have proposed patient deterioration prediction model based on machine learning, but they are inadequate because they only consider the most crucial of feature engineering in machine learning workflow. A number of researches also utilized logistic regression statistical model to build patient deterioration prediction model in ICUs (Churpek *et al.*, 2016). These researches (Churpek *et al.*, 2016; Kate *et al.*, 2016; Mao *et al.*, 2012; Quinten *et al.*, 2018; Spångfors *et al.*, 2016), obtained a minimum Area Under Receiver Operating Curve (AUROC) results of 0.679, 0.68, 0.74, 0.76, and 0.77, respectively. In fact, Machado et al. (Machado and Cortez-Pinto, 2013) illustrated that models with the AUROC value of 0.5 are considered randomly predictive models, whereas models with the AUROC value higher than 0.8 represent good discriminatory models.

There are also previous works (Mao *et al.*, 2012; Ong *et al.*, 2012), proposed support vector machine (SVM) to predict cardiac arrest within the next 72 hours and achieved clinical deterioration with AUROC of 0.781 and 0.775, respectively. Alnuaimi *et al*. (2015) used a decision tree model to predict mortality and obtained an accuracy of 0.77. Ghosh et al. (Ghosh *et al.*, 2017) used coupled hidden Markov models (CHMMs) to predict septic shock and received a likelihood of 0.71. As a result, it can be observed that most of the obtained AUROC values are less than recommended 0.8 and hence conventional machine learning predictive models suffer from inaccurate performance.

Current models are also subject to robustness due to data uncertainty problems like missing data, null values, and irregular sampling clinical measurements. Quantitative research regards missing data as the norm, but the effects of missing data in quantitative studies are occasionally severe, resulting in biased parameter estimates, loss of information, and an inferior findings' generalisability (Dong and Peng, 2013; PANDA). To compensate the problem of missing data, a few researchers (Mochizuki *et al.*, 2017) limited their analyses to patients with full data (i.e., no missing data is associated with any selected variable), which results in an approach that is not applicable in the real world. A few current models (Wellner *et al.*, 2017) made no effort to account for missing values. Thus, the undertaking of this work is proposing a predictive patient deterioration model that adopt superior techniques for raw data pre-processing to evolve data uncertainty issues.

Moreover, it is necessary to determine an optimal interval of time-series windows involved in predictive models. Past researchers mainly took parameter values and settings that were defined by other studies to use in their work. However, the parameters of predictive models need to be adjusted for various applications and databases to enhance their discrimination capability (Rashedi *et al.*, 2013). Previous works (Caballero Barajas and Akella, 2015; Celi *et al.*, 2012; Ghassemi *et al.*, 2014; Ghassemi *et al.*, 2015; Hoogendoorn *et al.*, 2016; Hug and Szolovits, 2009; Johnson *et al.*, 2017a; Joshi and Szolovits, 2012; Knaus *et al.*, 1981; Le Gall *et al.*, 1993; Lee and Maslove, 2017; Lee *et al.*, 2015; Lehman *et al.*, 2012; Pirracchio, 2016; Potes *et al.*, 2017; Ripoll *et al.*, 2014; Vincent *et al.*, 1996) involved a 24-hour observation window, whereas others (Che *et al.*, 2018; Deng *et al.*, 2009; Harutyunyan *et al.*, 2017; Joshi *et al.*, 2016) involved a 48-hour observation window to achieve acceptable prediction performance; hence increasing the volume of data. The long duration of observation window will have great demand in data storage and compute intensive operations. Thus, this study aims to solve the research problem of decreasing the window of observation from 24 hours to only 4 hours (i.e., an 83% reduction) while still maintaining an acceptable accuracy rate in its prediction.

Further, this issue also facing challenge due to inability of automatic techniques to tune several models at the same time without conducting a grid search or using the trial and error approach (Yuan *et al.*, 2018). In predictive models, it is well known that bias will be larger for smaller observation windows. This issue can be mitigated if the observation window is sufficiently long. It is important to carry out the optimization and monitoring of individual units as well as the whole process, which can largely improve the structure of predictive models of deterioration of patients. As a result, it is necessary to build an optimization algorithm that can automatically tune several important parameters and settings at the same time, such as observation window, prediction window, and the number of units in hidden layers (either separately or in combination) to maximize the prediction performance. Towards this end, the optimization problem will be solved using a modified genetic algorithm (GA). Furthermore, implementing the proposed models using advanced hardware to overcome challenges of gain (i.e., execution time), estimation time, and testing processing time is a necessity in proposing predictive models.

1.3 Objective

Based on the research problems, this study aims to develop a generic and robust patient deterioration prediction framework targeted for ICU patients. The detail objectives are as stated below:

(a) To develop an accurate predictive model that can accept multiple input and data types using Long Short-Term Memory (LSTM).

(b) To design an automated optimization approach using the Genetic Algorithm (GA) for identifying optimum parameters for accurate prediction of patient deterioration.

1.4 Scope of Work

To fulfil the aforementioned research aims and objectives, this study has limited its research scope as shown in Figure 1.1. The prediction model is developed based on long-short term memory - recurrent neural network (LSTM-RNN) deep learning algorithm, to predict the patient deterioration in terms of patients either suddenly being transferred to ICUs from general wards, or ICU patients suddenly dying. The input of LSTM-RNN predictive model consists of two categories of data, which are static data and dynamic data obtained from Medical Information Mart for Intensive Care (MIMIC-III) version 1.4 “restricted access” database based on inclusion criteria of patient age more than 15 years old, first admission, and patients who have stayed more than 5 hours in ICU. Referring to figure 1.1, the static data consists of age, gender, and types of admission, whereas the dynamic data consists of seven vital signs, eight laboratory measurements, and Glasgow Come Scale (GCS) in the form of minute-by-minute time trends where each patient's selected parameter of interest is updated in every minute. The impact of data pre-processing technique and different feature selection approach to prediction performance is studied and compared. The baseline reference model is developed using heuristic approach to identify optimal parameter setting in terms of number of hidden layers, number of epochs, and number of neurons in the 1st hidden layer.

On the other hand, the optimization model is designed based on Genetic Algorithm (GA) to further optimize the performance of the developed LSRM-RNN baseline reference model. It is conducted by auto exploration of different configuration setting in terms of observation window size, prediction window size and number of neurons in the first hidden layer through performance trade-off analysis. The performance metrics used for predictive performance evaluation and comparison includes accuracy, AUROC, and testing loss. For performance comparison, this work also develop other two different predictive models based on logistic regression (LR) and Support Vector Machine (SVM) using standard libraries provided in PostgreSQL and Jupyter Notebook. This research employs comprehensive benchmarking experiments with related previous works based on prediction task, sequence type, ages involved, number of features, splitting ratios, observation window, data source, performance metrics, and hardware features. All the modelling and performance analysis are executed in a virtual Graphical Processing Unit (GPU) provided by Google Collaboratory as well as a conventional Central Processing Unit (CPU).

1.5 Significance of the Study

The implementation of the proposed deep learning approach is expected to result in a new model that possesses reliable accuracy to predict patient deterioration. It is expected that the proposed model will assist in building a prediction model based on "Big Data" which has enhanced prediction accuracy. The clinical state of patients will be identified using this model via present and past data that comprise several parameters and measurements (i.e., periodic data). The interaction between various parameters is currently ignored by the existing prediction models. This study contributes by revealing previously unknown relationships between many variables (predictors) which could result in useful diagnostic or prognostic insights. The study also proposed the required clinical intervention to alleviate the effect of these events.

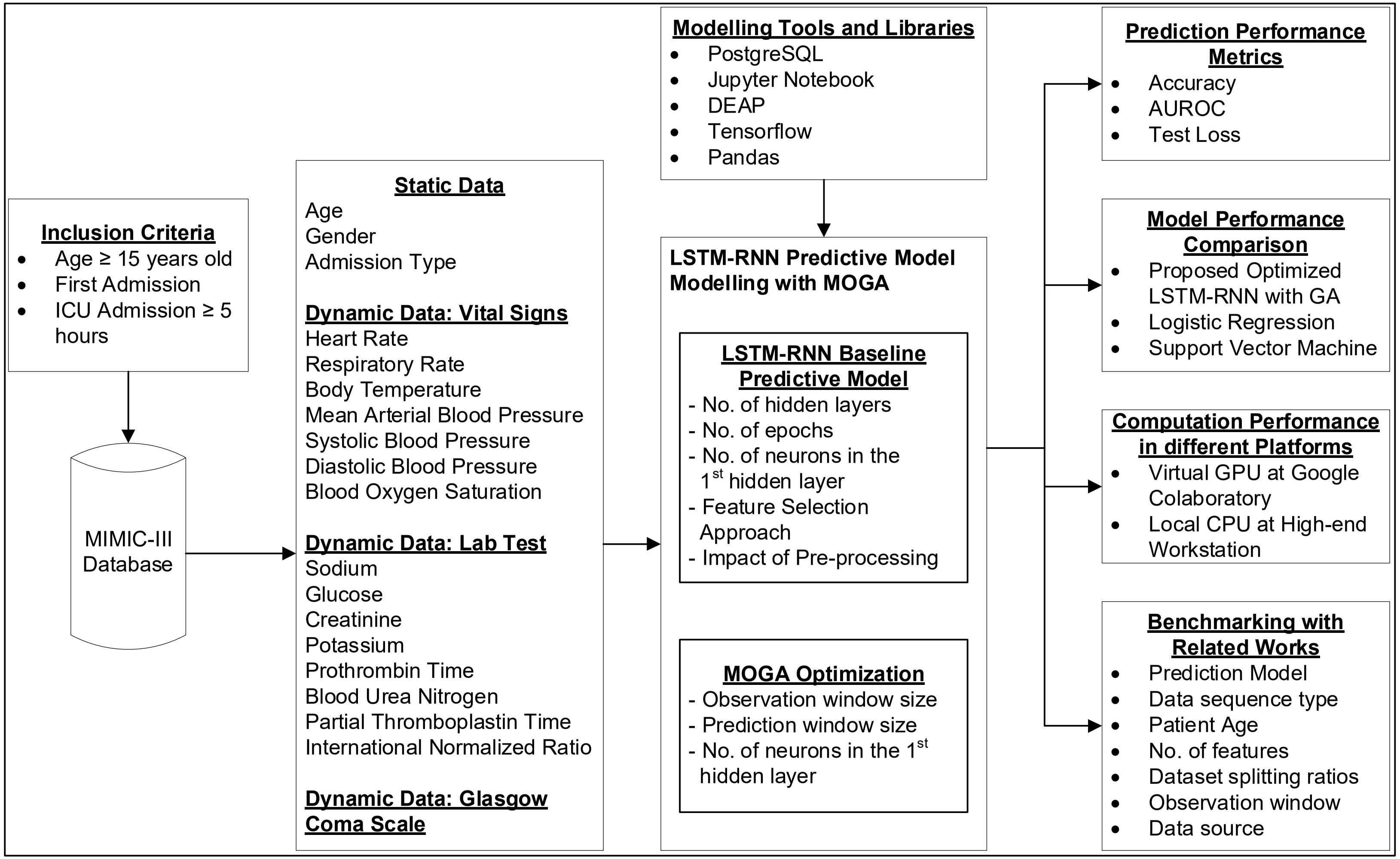

Figure 1.1 Scope of the proposed patient deterioration prediction framework for ICU patients

Moreover, this research uses definitions of deterioration, where its endpoint measure will be either mortality or sudden transfer to ICUs, which is used by researchers to obtain a better classification of patients.

In this study, the proposed predictive model is implemented using the state-of-the-art GPU virtual machine provided by Google Colaboratory. Moreover, the study uses a minute-by-minute time-series approach. This approach enables the proposed model to obtain highly accurate results. The deep learning predictive model's ability to identify patterns in multivariate time-series of different clinical measurements is empirically evaluated by this research. To overcome the impractical workflow of predictive models that use one form of data, this study utilizes the individual and combined effectiveness of different types of variables (i.e., vital signs, laboratory measurements, GCS, and demographic data). Previous works face the problem of generalization due to data from hospitals specialized in certain diseases, or patients with certain diseases. In this study, data extracted from an open source that can be easily benchmarked and generalizing the results achieved.

Current predictive models suffer from weakness in performance due to using machine learning models that require feature engineering. However, this research proposes an LSTM-RNN deep learning model that does not require feature engineering. Existing predictive models use conventional hardware suffers from challenges in gain, estimation time and testing processing time. This work proposes an advanced hardware that overcome challenges in gain, estimation time via using a virtual GPU. The ad-hoc frameworks proposed by previous studies can be improved by the generic prediction framework proposed in this research, which will result in predictions of higher accuracy. The proposed predictive model could reduce the required observation window for the prediction task while improving the performance. In fact, the proposed significant small size of observation window could obtain higher results which outperformed all previous works that utilize different sizes of observation window (i.e., 48 hours and 24 hours). The proposed predictive model achieved accurate performances when using a prediction window with sizes longer than 1 hour.

The proposed optimization algorithm based on GA could improve the accuracy obtained by the predictive model. It also could increase the prediction window. It also reduced the observation window by 60% compared to the size of observation windows used by most of the studies used in the literature to predict the deterioration of patients (i.e., 24 hours). In addition, the proposed optimization algorithm could reduce test loss. The study identifies the most important medical lab tests without using any informed domain knowledge. Some current predictive models implement the structure of the models via trial and error, whereas this study propose an optimization model based on GA to determine the size of the observation window, prediction window, and number of units in the hidden layer.

1.6 Thesis Organization

The rest of the thesis is organised as described below. A comprehensive literature review of works related to this study is presented in Chapter 2. The methodology for proposing a generic prediction framework is discussed in Chapter 3. It also discusses the detail of different layers that form the generic prediction framework. Moreover, modelling software libraries and tools is demonstrated in this chapter. It also illustrates the performance metrics and framework verification strategy. Chapter 4 covers the details for the modelling and algorithmic development in the proposed predictive model based on LSTM-RNN performed in this thesis. It also includes the findings of performing the research methodology to obtain the dataset and the results of performing feature selection. A description of different sizes of observation window and prediction window is also included. Chapter 5 illustrates the test works that confirm the usefulness and dissect the presentation of the proposed modified optimization model based on multi objective GA. Chapter 6 presents the experimental works that verify the functionality and analyse the performance of the proposed predictive algorithm based on LSTM-RNN and the proposed optimized algorithm based on GA described in Chapters 4 and 5, respectively. It also includes the benchmarked results of performance against the related previous works. Chapter 7 shows the future works, contributions, and conclusions of this research.

REFERENCES

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., et al. (2016). 'Tensorflow: A system for large-scale machine learning'. *The 12th Symposium on Operating Systems Design and Implementation* (16), 265-283.

Abebe, Y., and Tesfamariam, S. (2020). Storm sewer pipe renewal planning 'Considering deterioration, climate change, and urbanization: a dynamic Bayesian network and GIS framework'. *Sustainable and Resilient Infrastructure*, 1-16.

Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., Adam, M., Gertych, A., et al. (2017). 'A deep convolutional neural network model to classify heartbeats'. *Computers in Biology and Medicine, 89*, 389-396.

Aczon, M., Ledbetter, D., Ho, L., Gunny, A., Flynn, A., Williams, J., et al. (2017). 'Dynamic mortality risk predictions in pediatric critical care using recurrent neural networks'. *arXiv preprint arXiv:1701.06675*.

Adnan, J., Daud, N. N., Mokhtar, A., Hashim, F., Ahmad, S., Rashidi, A., et al. (2017). 'Multilayer perceptron based activation function on heart abnormality activity'. *Journal of Fundamental and Applied Sciences, 9*(3S), 417-432.

Aeeni, S. (2019). 'Development of an Open-source Multi-objective Optimization Toolbox'.

Afshar, A., Perros, I., Park, H., Defilippi, C., Yan, X., Stewart, W., et al. (2020). 'TASTE: Temporal and static tensor factorization for phenotyping electronic health records'. *The Proceedings of the ACM Conference on Health, Inference, and Learning*, 193-203.

Ageeva, P., Matyukhina, M., and Pochutina, N. (2020). 'Results and prospects of selection of green manure varieties of narrow-leaved lupine at the All-Russian Research Institute of Lupine'. *Cyberleninka*(2 (34)), 59-63.

Akbari, M., Asadi, P., Besharati-Givi, M., and Khodabandehlouie, G. (2014). 'Artificial neural network and optimization'. *Advances in Friction-Stir Welding and Processing. Woodhead Publishing*, 543-599.

Al-Ali, A., Muhsin, B., and O'reilly, M. (2018). 'System for determining confidence in respiratory rate measurements': *Google Patents*.

Aladin, A. I., Whelton, S. P., Al-Mallah, M. H., Blaha, M. J., Keteyian, S. J., Juraschek, S. P., et al. (2014). 'Relation of resting heart rate to risk for all-cause mortality by gender after considering exercise capacity (the Henry Ford exercise testing project)'. *The American Journal of Cardiology, 114*(11), 1701-1706.

Alam, N., Hobbelink, E. L., van Tienhoven, A.-J., van de Ven, P. M., Jansma, E. P., and Nanayakkara, P. W. (2014). 'The impact of the use of the Early Warning Score (EWS) on patient outcomes: a systematic review'. *Resuscitation, 85*(5), 587-594.

AlNuaimi, N., Masud, M. M., and Mohammed, F. (2015). 'ICU patient deterioration prediction: A data-mining approach'. *arXiv preprint arXiv:1511.06910*.

Amarappa, S., and Sathyanarayana, S. (2014). 'Data classification using Support vector Machine (SVM), a simplified approach'. *Int. J. Electron. Comput. Sci. Eng, 3*, 435-445.

Andrade, N., Faria, F. A., and Cappabianco, F. A. M. (2018). 'A practical review on medical image registration: from rigid to deep learning based approaches'. *The 2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, 463-470.

Ardakani, A., Ji, Z., Smithson, S. C., Meyer, B. H., and Gross, W. J. (2018). 'Learning recurrent binary/ternary weights'. *arXiv preprint arXiv:1809.11086*.

Atrey, K., Sharma, Y., Bodhey, N. K., and Singh, B. K. (2019). 'Breast Cancer Prediction Using Dominance-based Feature Filtering Approach: A Comparative Investigation in Machine Learning Archetype'. *Brazilian Archives of Biology and Technology, 62*.

Bachler, M., Niederwanger, C., Hell, T., Höfer, J., Gerstmeyr, D., Schenk, B., et al. (2019). 'Influence of factor XII deficiency on activated partial thromboplastin time (aPTT) in critically ill patients'. *Journal of Thrombosis and Thrombolysis, 48*(3), 466-474.

Bäck, T., Fogel, D. B., and Michalewicz, Z. (1997). 'Handbook of evolutionary computation'. *Release, 97*(1), B1.

Baek, Y., and Kim, H. Y. (2018). 'ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module'. *Expert Systems with Applications, 113*, 457-480.

Bahdanau, D., Chorowski, J., Serdyuk, D., Brakel, P., and Bengio, Y. (2016). 'End-to-end attention-based large vocabulary speech recognition'. *The 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 4945-4949.

Baig, M. M., Afifi, S., GholamHosseini, H., and Ullah, E. (2020). 'Deterioration to decision: a comprehensive literature review of rapid response applications for deteriorating patients in acute care settings'. *Health and Technology, 10*(3), 567-573.

Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., et al. (2018). 'Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge'. *arXiv preprint arXiv:1811.02629*.

Baker, G. R., Norton, P. G., Flintoft, V., Blais, R., Brown, A., Cox, J., et al. (2004). 'The Canadian Adverse Events Study: the incidence of adverse events among hospital patients in Canada'. *CMAJ, 170*(11), 1678-1686.

Balendran, C. A., Lövgren, A., Hansson, K. M., Nelander, K., Olsson, M., Johansson, K. J., et al. (2017). 'Prothrombin time is predictive of low plasma prothrombin concentration and clinical outcome in patients with trauma hemorrhage: analyses of prospective observational cohort studies'. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine, 25*(1), 30.

Bangerter, N. K., Tarbox, G. J., Taylor, M. D., and Kaggie, J. D. (2016). 'Quantitative sodium magnetic resonance imaging of cartilage, muscle, and tendon'. *Quantitative Imaging in Medicine and Surgery, 6*(6), 699.

Bashier, A. M., Hussain, A. K. B., Alawadi, F., Alsayyah, F., Alsaeed, M., Rashid, F., et al. (2019). 'Impact of optimum diabetes care on the safety of fasting in Ramadan in adult patients with type 2 diabetes mellitus on insulin therapy'. *Diabetes Research and Clinical Practice, 150*, 301-307.

Basta, M., Lin, H.-M., Pejovic, S., Sarrigiannidis, A., Bixler, E. O., and Vgontzas, A. N. (2008). 'Lack of regular exercise, depression, and degree of apnea are predictors of excessive daytime sleepiness in patients with sleep apnea: sex differences'. *Journal of Clinical Sleep Medicine, 4*(01), 19-25.

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., and Escobar, G. (2014). 'Big data in health care: using analytics to identify and manage high-risk and high-cost patients'. *Health Affairs, 33*(7), 1123-1131.

Beardsall, K., Thomson, L., Guy, C., van Weissenbruch, M. M., Iglesias, I., Muthukumar, P., et al. (2018). 'Protocol of a randomised controlled trial of real-time continuous glucose monitoring in neonatal intensive care 'REACT''. *BMJ Open, 8*(6), e020816.

Bedia, C., Tauler, R., and Jaumot, J. (2018). 'Introduction to the Data Analysis Relevance in the Omic Era'. In *Comprehensive Analytical Chemistry* (Vol. 82, pp. 1-12): Elsevier.

Bedoya, A. D., Clement, M. E., Phelan, M., Steorts, R. C., O'Brien, C., and Goldstein, B. A. (2019). Minimal impact of implemented early warning score and best practice alert for patient deterioration. *Critical care medicine, 47*(1), 49.

Bengio, Y. (2009). 'Learning deep architectures for AI': *Now Publishers Inc*.

Bengio, Y., Goodfellow, I., and Courville, A. (2017). *Deep learning* (Vol. 1): Citeseer.

Bera, S., and Shrivastava, V. K. (2020). 'Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification'. *International Journal of Remote Sensing, 41*(7), 2664-2683.

Berry, C., Brett, M., Stevenson, K., McMurray, J., and Norrie, J. (2008). 'Nature and prognostic importance of abnormal glucose tolerance and diabetes in acute heart failure'. *Heart, 94*(3), 296-304.

Betts, J. G., Desaix, P., Johnson, E., Johnson, J., Korol, O., Kruse, D., et al. (2013). 'OpenStax College & Rice University'. *Anatomy & Physiology*.

Bhutta, M., Arshad, M., Hassan, S., and Henderson, J. (2012). 'knee arthroplasty: trends in litigation in the past 5 years within the UK healthcare model'. *The Orthopaedic Proceedings*, 7-7.

Bodenhofer, U. (2003). 'Genetic algorithms: theory and applications: Lecture notes', *Fuzzy Logic Laboratorium Linz-Hagenberg, Winter*.

Boland, T. A., Lee, V. H., and Bleck, T. P. (2015). 'Stress-induced cardiomyopathy'. *Critical Care Medicine, 43*(3), 686-693.

Bonafide, C. P., Localio, A. R., Song, L., Roberts, K. E., Nadkarni, V. M., Priestley, M., et al. (2014). 'Cost-benefit analysis of a medical emergency team in a children's hospital'. *Pediatrics, 134*(2), 235-241.

Bonnici, T., Tarassenko, L., Clifton, D. A., and Watkinson, P. (2013). 'The digital patient'. *Clinical Medicine, 13*(3), 252.

Bose, S., Johnson, A. E., Moskowitz, A., Celi, L. A., and Raffa, J. D. (2019). 'Impact of intensive care unit discharge delays on patient outcomes: a retrospective cohort study'. *Journal of Intensive Care Medicine, 34*(11-12), 924-929.

Brand, L., Patel, A., Singh, I., and Brand, C. (2018). 'Real Time Mortality Risk Prediction: A Convolutional Neural Network Approach'. *The HEALTHINF*, 463-470.

Braverman, L. E., Ingbar, S. H., and Sterling, K. (1970). 'Conversion of thyroxine (T4) to triiodothyronine (T3) in athyreotic human subjects'. *The Journal of Clinical Investigation, 49*(5), 855-864.

Breuel, T. M. (2015). 'The effects of hyperparameters on SGD training of neural networks'. *arXiv preprint arXiv:1508.02788*.

Brosschot, J. F., and Thayer, J. F. (2003). 'Heart rate response is longer after negative emotions than after positive emotions'. *International Journal of Psychophysiology, 50*(3), 181-187.

Brownlee, J. (2016). 'Deep learning with Python: develop deep learning models on Theano and TensorFlow using Keras': *Machine Learning Mastery*.

Bruce, A., Andersson, M., Arvidsson, B., and Isaksson, B. (1980). 'Body composition. Prediction of normal body potassium, body water and body fat in adults on the basis of body height, body weight and age'. *Scandinavian Journal of Clinical and Laboratory Investigation, 40*(5), 461-473.

Caballero Barajas, K. L., and Akella, R. (2015). 'Dynamically modeling patient's health state from electronic medical records: A time series approach'. *The Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 69-78.

Caldeira, J., and Rosa, A. C. (1997). 'School timetabling using genetic search'. *Practice and Theory of Automated Timetabling, Toronto*.

Calvert, J., Mao, Q., Hoffman, J. L., Jay, M., Desautels, T., Mohamadlou, H., et al. (2016). 'Using electronic health record collected clinical variables to predict medical intensive care unit mortality'. *Annals of Medicine and Surgery, 11*, 52-57.

Capan, M., Ivy, J. S., Rohleder, T., Hickman, J., and Huddleston, J. M. (2015). 'Individualizing and optimizing the use of early warning scores in acute medical care for deteriorating hospitalized patients'. *Resuscitation, 93*, 107-112.

Caragata, R., Wyssusek, K., and Kruger, P. (2016). 'Acute kidney injury following liver transplantation: a systematic review of published predictive models'. *Anaesthesia and Intensive Care, 44*(2), 251-261.

Cardona-Morrell, M., Prgomet, M., Lake, R., Nicholson, M., Harrison, R., Long, J., et al. (2016). 'Vital signs monitoring and nurse–patient interaction: A qualitative observational study of hospital practice'. *International Journal of Nursing Studies, 56*, 9-16.

Carni, D. L., Grimaldi, D., Sciammarella, P. F., Lamonaca, F., and Spagnuolo, V. (2016). 'Setting-up of PPG scaling factors for SpO2% evaluation by smartphone'. *The 2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, 1-5.

Catling, F. J., and Wolff, A. H. (2020). 'Temporal convolutional networks allow early prediction of events in critical care'. *Journal of the American Medical Informatics Association, 27*(3), 355-365.

Celi, L. A., Galvin, S., Davidzon, G., Lee, J., Scott, D., and Mark, R. (2012). 'A database-driven decision support system: customized mortality prediction'. *Journal of Personalized Medicine, 2*(4), 138-148.

Che, Z., Purushotham, S., Cho, K., Sontag, D., and Liu, Y. (2018). 'Recurrent neural networks for multivariate time series with missing values'. *Scientific Reports, 8*(1), 1-12.

Che, Z., Purushotham, S., Khemani, R., and Liu, Y. (2016). 'Interpretable deep models for ICU outcome prediction'. *The AMIA Annual Symposium Proceedings*, 371.

Chen, J. H., and Asch, S. M. (2017). 'Machine learning and prediction in medicine—beyond the peak of inflated expectations'. *The New England Journal of Medicine, 376*(26), 2507.

Chen, L., Ogundele, O., Clermont, G., Hravnak, M., Pinsky, M. R., and Dubrawski, A. W. (2017). 'Dynamic and personalized risk forecast in step-down units. Implications for monitoring paradigms'. *Annals of the American Thoracic Society, 14*(3), 384-391.

Cheng, G., Peddinti, V., Povey, D., Manohar, V., Khudanpur, S., and Yan, Y. (2017). 'An Exploration of Dropout with LSTMs'. *The Interspeech*, 1586-1590.

Cheng, Y., Wang, F., Zhang, P., and Hu, J. (2016). 'Risk prediction with electronic health records: A deep learning approach'. *The Proceedings of the 2016 SIAM International Conference on Data Mining*, 432-440.

Cheong, C. Y., Tan, K. C., and Veeravalli, B. (2007). 'Solving the exam timetabling problem via a multi-objective evolutionary algorithm-a more general approach'. *The 2007 IEEE Symposium on Computational Intelligence in Scheduling*, 165-172.

Chesnokov, Y. V. (2008). 'Complexity and spectral analysis of the heart rate variability dynamics for distant prediction of paroxysmal atrial fibrillation with artificial intelligence methods'. *Artificial Intelligence in Medicine, 43*(2), 151-165.

Chhachhiya, D., Sharma, A., and Gupta, M. (2019). 'Designing optimal architecture of recurrent neural network (LSTM) with particle swarm optimization technique specifically for educational dataset'. *International Journal of Information Technology, 11*(1), 159-163.

Chicco, D. (2017). 'Ten quick tips for machine learning in computational biology'. *BioData mining, 10*(1), 35.

Chiroma, H., Abdulkareem, S., Abubakar, A., and Herawan, T. (2017). 'Neural networks optimization through genetic algorithm searches: a review'. *Appl. Math. Inf. Sci, 11*(6), 1543-1564.

Choi, E., Bahadori, M. T., Schuetz, A., Stewart, W. F., and Sun, J. (2016). 'Doctor AI: Predicting clinical events via recurrent neural networks'. *The Machine Learning for Healthcare Conference*, 301-318.

Choi, E., Schuetz, A., Stewart, W. F., and Sun, J. (2017). 'Using recurrent neural network models for early detection of heart failure onset'. *Journal of the American Medical Informatics Association, 24*(2), 361-370.

Choudhury, A., and Greene, C. M. (2018). 'Evaluating patient readmission risk: a predictive analytics approach'. *arXiv preprint arXiv:1812.11028*.

Churpek, M. M., Snyder, A., Twu, N. M., and Edelson, D. P. (2018). 'Accuracy comparisons between manual and automated respiratory rate for detecting clinical deterioration in ward patients'. *Journal of Hospital Medicine, 13*(7), 486.

Churpek, M. M., Yuen, T. C., and Edelson, D. P. (2013). 'Predicting clinical deterioration in the hospital: the impact of outcome selection'. *Resuscitation, 84*(5), 564-568.

Churpek, M. M., Yuen, T. C., Park, S. Y., Gibbons, R., and Edelson, D. P. (2014a). 'Using electronic health record data to develop and validate a prediction model for adverse outcomes on the wards'. *Critical Care Medicine, 42*(4), 841.

Churpek, M. M., Yuen, T. C., Winslow, C., Meltzer, D. O., Kattan, M. W., and Edelson, D. P. (2016). 'Multicenter comparison of machine learning methods and conventional regression for predicting clinical deterioration on the wards'. *Critical Care Medicine, 44*(2), 368.

Churpek, M. M., Yuen, T. C., Winslow, C., Robicsek, A. A., Meltzer, D. O., Gibbons, R. D., et al. (2014b). 'Multicenter development and validation of a risk stratification tool for ward patients'. *American Journal of Respiratory and Critical Care Medicine, 190*(6), 649-655.

Clifton, L., Clifton, D. A., Watkinson, P. J., and Tarassenko, L. (2011). 'Identification of patient deterioration in vital-sign data using one-class support vector machines'. *The 2011 federated conference on computer science and information systems (FedCSIS)*, 125-131.

Contreras, G., Garces, G., Quartin, A. A., Cely, C., LaGatta, M. A., Barreto, G. A., et al. (2002). 'An epidemiologic study of early renal replacement therapy after orthotopic liver transplantation'. *Journal of the American Society of Nephrology, 13*(1), 228-233.

Cooijmans, T., Ballas, N., Laurent, C., Gülçehre, Ç., and Courville, A. (2016). 'Recurrent batch normalization'. *arXiv preprint arXiv:1603.09025*.

Cook, S., and Hess, O. M. (2010). 'Resting heart rate and cardiovascular events: time for a new crusade?' *European Heart Journal, 31*(5), 517.

Costin, H., Rotariu, C., and Păsărică, A. (2013). 'Atrial fibrillation onset prediction using variability of ECG signals'. *The 2013 8th International symposium on advanced topics in electrical engineering (ATEE)*, 1-4.

Crandall, J. P., Mather, K., Rajpathak, S. N., Goldberg, R. B., Watson, K., Foo, S., et al. (2017). 'Statin use and risk of developing diabetes: results from the Diabetes Prevention Program'. *BMJ Open Diabetes Research and Care, 5*(1), e000438.

Cretikos, M. A., Bellomo, R., Hillman, K., Chen, J., Finfer, S., and Flabouris, A. (2008). 'Respiratory rate: the neglected vital sign'. *Medical Journal of Australia, 188*(11), 657-659.

Crockett, A., Heberlein, E. C., Glasscock, L., Covington-Kolb, S., Shea, K., and Khan, I. A. (2017). 'Investing in CenteringPregnancy™ group prenatal care reduces newborn hospitalization costs'. *Women's Health Issues, 27*(1), 60-66.

Crump, C., Saxena, S., Wilson, B., Farrell, P., Rafiq, A., and Silvers, C. T. (2009). 'Using bayesian networks and rule-based trending to predict patient status in the intensive care unit'. *The AMIA Annual Symposium Proceedings*, 124.

Dagliati, A., Marini, S., Sacchi, L., Cogni, G., Teliti, M., Tibollo, V., et al. (2018). 'Machine learning methods to predict diabetes complications'. *Journal of Diabetes Science and Technology, 12*(2), 295-302.

Dahl, D., Wojtal, G. G., Breslow, M. J., Huguez, D., Stone, D., and Korpi, G. (2012). 'The high cost of low-acuity ICU outliers'. *Journal of Healthcare Management, 57*(6), 421-433.

Dai, Y., Wang, C., Dong, J., and Sun, C. (2019). 'Visual relationship detection based on bidirectional recurrent neural network'. *Multimedia Tools and Applications*, 1-17.

Data, I. W. I. B. (2012). 'Bring Big Data to the Enterprise': *IBM*.

Davis, L. (1991). 'Handbook of genetic algorithms'.

Davis, P., Lay-Yee, R., Briant, R., Ali, W., Scott, A., and Schug, S. (2003). 'Adverse events in New Zealand public hospitals II: preventability and clinical context'. *The New Zealand Medical Journal (Online), 116*(1183).

Davis, S. (2019). 'Pain relief for minor aches and pains in the pharmacy'. *SA Pharmacist's Assistant, 19*(1), 6-8.

Deasy, J., Liò, P., and Ercole, A. (2019). 'Dynamic survival prediction in intensive care units from heterogeneous time series without the need for variable selection or pre-processing'. *arXiv preprint arXiv:1909.07214*.

Deitcher, S. R. (2002). 'Interpretation of the international normalised ratio in patients with liver disease'. *The Lancet, 359*(9300), 47-48.

Deliberato, R. O., Ko, S., Komorowski, M., Armengol de La Hoz, M., Frushicheva, M. P., Raffa, J. D., et al. (2018). 'Severity of illness scores may misclassify critically ill obese patients'. *Critical Care Medicine, 46*(3), 394-400.

Deliberato, R. O., Neto, A. S., Komorowski, M., Stone, D. J., Ko, S. Q., Bulgarelli, L., et al. (2019). 'An evaluation of the influence of body mass index on severity scoring'. *Critical Care Medicine, 47*(2), 247.

Dempsey, J. A., and Wagner, P. D. (1999). 'Exercise-induced arterial hypoxemia'. *Journal of Applied Physiology, 87*(6), 1997-2006.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. (2009). 'Imagenet: A large-scale hierarchical image database'. *The 2009 IEEE conference on computer vision and pattern recognition*, 248-255.

Devi, S., and Saravanan, M. (2018). 'An innovative modular device and wireless control system enabling thermal and pressure sensors using FPGA on real-time fault diagnostics of steam turbine functional deterioration'. *Mechanical Systems and Signal Processing, 102*, 312-328.

DeVita, M. A., Smith, G. B., Adam, S. K., Adams-Pizarro, I., Buist, M., Bellomo, R., et al. (2010). "Identifying the hospitalised patient in crisis"—a consensus conference on the afferent limb of rapid response systems. *Resuscitation, 81*(4), 375-382.

Dey, R., and Salemt, F. M. (2017). 'Gate-variants of gated recurrent unit (GRU) neural networks'. *The 2017 IEEE 60th international midwest symposium on circuits and systems (MWSCAS)*, 1597-1600.

Dhande, G., and Shaikh, Z. (2019). 'Analysis of Epochs in Environment based Neural Networks Speech Recognition System'. *The 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, 605-608.

Dictionary, C. (2008). 'Cambridge advanced learner's dictionary'. *PONS-Worterbucher, Klett Ernst Verlag GmbH*.

Dictionary, M.-W. (2016). Thesaurus (2014). *Retrieved from www. merriam-webster. com*.

Ding, Y., and Fu, X. (2016). 'Kernel-based fuzzy c-means clustering algorithm based on genetic algorithm'. *Neurocomputing, 188*, 233-238.

Ding, Y., Li, X., and Wang, Y. (2016). 'Mortality prediction for ICU patients using just-in-time learning and extreme learning machine'. *The 2016 12th World Congress on Intelligent Control and Automation (WCICA)*, 939-944.

Donald, R., Howells, T., Piper, I., Chambers, I., Citerio, G., Enblad, P., et al. (2012). 'Early warning of EUSIG-defined hypotensive events using a Bayesian Artificial Neural Network'. In *Intracranial Pressure and Brain Monitoring XIV* (pp. 39-44): Springer.

Dong, C., Loy, C. C., He, K., and Tang, X. (2015). 'Image super-resolution using deep convolutional networks'. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 38*(2), 295-307.

Dong, Y., and Peng, C.-Y. J. (2013). 'Principled missing data methods for researchers'. *SpringerPlus, 2*(1), 222.

Douglis, F., Shur, D. H., Sommer, J. M., and Van der Merwe, J. E. (2018). 'Unified web hosting and content distribution': *Google Patents*.

Douw, G., Schoonhoven, L., Holwerda, T., van Zanten, A. R., van Achterberg, T., and van der Hoeven, J. G. (2015). 'Nurses' worry or concern and early recognition of deteriorating patients on general wards in acute care hospitals: a systematic review'. *Critical Care, 19*(1), 230.

Dovydaitis, L., and Rudžionis, V. (2017). 'Identifying Lithuanian native speakers using voice recognition'. *The International Conference on Business Information Systems*, 79-84.

Duckitt, R., Buxton-Thomas, R., Walker, J., Cheek, E., Bewick, V., Venn, R., et al. (2007). 'Worthing physiological scoring system: derivation and validation of a physiological early-warning system for medical admissions. An observational, population-based single-centre study'. *British Journal of Anaesthesia, 98*(6), 769-774.

Dunlay, S. M., Weston, S. A., Jacobsen, S. J., and Roger, V. L. (2009). 'Risk factors for heart failure: a population-based case-control study'. *The American Journal of Medicine, 122*(11), 1023-1028.

Ebner, D. M., and McKenzie, J. E. (2006). 'Method for continuous monitoring of patients to detect the potential onset of sepsis': *Google Patents*.

Edelson, D., Carey, K., Winslow, C., and Churpek, M. (2018). 'Less is more: detecting clinical deterioration in the hospital with machine learning using only age, heart rate and respiratory rate'. In *C15. Critical Care: Big Data and Artificial Intelligence in Critical Illness* (pp. A4444-A4444): American Thoracic Society.

El Naqa, I., and Murphy, M. J. (2015). 'What is machine learning?' In *Machine Learning in Radiation Oncology* (pp. 3-11): Springer.

Elfwing, S., Uchibe, E., and Doya, K. (2013). 'Scaled free-energy based reinforcement learning for robust and efficient learning in high-dimensional state spaces'. *Frontiers in Neurorobotics, 7*, 3.

Elman, J. L. (1990). 'Finding structure in time'. *Cognitive Science, 14*(2), 179-211.

Eren, S. E., Karakukcu, C., Ciraci, M. Z., Ustundag, Y., and Karakukcu, M. (2018). 'Activated partial thromboplastin time derivative curves: helpful diagnostic tool in mixing test interpretation'. *Blood Coagulation & Fibrinolysis, 29*(4), 410-414.

Esteban, C., Staeck, O., Baier, S., Yang, Y., and Tresp, V. (2016). 'Predicting clinical events by combining static and dynamic information using recurrent neural networks'. *The 2016 IEEE International Conference on Healthcare Informatics (ICHI)*, 93-101.

Evans, N., and Dhatariya, K. (2012). 'Assessing the relationship between admission glucose levels, subsequent length of hospital stay, readmission and mortality'. *Clinical Medicine, 12*(2), 137.

Everitt, B., and Skrondal, A. (2002). 'The Cambridge dictionary of statistics' *(Vol. 44): Cambridge University Press Cambridge.*

Faghihi, V., Reinschmidt, K. F., and Kang, J. H. (2014). 'Construction scheduling using genetic algorithm based on building information model'. *Expert Systems with Applications, 41*(16), 7565-7578.

Feller-Kopman, D. J., and Schwartzstein, R. M. (2018). 'Mechanisms, causes, and effect s of hypercapnia'. *Up To Date. Waltham, MA: Up To Date Inc*.

Feng, C., Elazab, A., Yang, P., Wang, T., Zhou, F., Hu, H., et al. (2019). 'Deep learning framework for Alzheimer’s disease diagnosis via 3D-CNN and FSBi-LSTM'. *IEEE Access, 7*, 63605-63618.

Feng, M., McSparron, J. I., Kien, D. T., Stone, D. J., Roberts, D. H., Schwartzstein, R. M., et al. (2018). 'Transthoracic echocardiography and mortality in sepsis: analysis of the MIMIC-III database'. *Intensive Care Medicine, 44*(6), 884-892.

Ferdman, M., Adileh, A., Kocberber, O., Volos, S., Alisafaee, M., Jevdjic, D., et al. (2012). 'Clearing the clouds: a study of emerging scale-out workloads on modern hardware'. *ACM Sigplan Notices, 47*(4), 37-48.

Fernández-Delgado, M., Cernadas, E., Barro, S., and Amorim, D. (2014). 'Do we need hundreds of classifiers to solve real world classification problems?' *The Journal of Machine Learning Research, 15*(1), 3133-3181.

Fieselmann, J. F., Hendryx, M. S., Helms, C. M., and Wakefield, D. S. (1993). 'Respiratory rate predicts cardiopulmonary arrest for internal medicine inpatients'. *Journal of General Internal Medicine, 8*(7), 354-360.

Findlay, G. (2012). 'Time to intervene?: a review of patients who underwent cardiopulmonary resuscitation as a result of an in-hospital cardiopulmonary arrest': *National Confidential Enquiry into Perioperative Deaths (NCEPOD)*.

Finlay, G. D., Rothman, M. J., and Smith, R. A. (2014). 'Measuring the modified early warning score and the Rothman index: advantages of utilizing the electronic medical record in an early warning system'. *Journal of Hospital Medicine, 9*(2), 116-119.

Finn, C., Goodfellow, I., and Levine, S. (2016). 'Unsupervised learning for physical interaction through video prediction'. *The Advances in neural information processing systems*, 64-72.

Fischer, T., and Krauss, C. (2018). 'Deep learning with long short-term memory networks for financial market predictions'. *European Journal of Operational Research, 270*(2), 654-669.

Flenady, T., Dwyer, T., and Applegarth, J. (2017). 'Accurate respiratory rates count: So should you!' *Australasian Emergency Nursing Journal, 20*(1), 45-47.

Fletcher, S., and Cuthbertson, B. (2010). 'Outreach, epistemology and the evolution of critical care'. *Anaesthesia, 65*(2), 115-118.

Forgey, M. (2017). 'Wilderness medicine'*: Beyond First Aid*: Rowman & Littlefield.

Forkan, A. R. M., Branch, P., Jayaraman, P. P., and Ferretto, A. (2019). 'An Internet-of-Things Solution to Assist Independent Living and Social Connectedness in Elderly.' *ACM Transactions on Social Computing, 2*(4), 1-24.

Forkan, A. R. M., and Khalil, I. (2016). 'A probabilistic model for early prediction of abnormal clinical events using vital sign correlations in home-based monitoring'. *The 2016 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 1-9.

Forkan, A. R. M., Khalil, I., and Atiquzzaman, M. (2017). 'ViSiBiD: A learning model for early discovery and real-time prediction of severe clinical events using vital signs as big data'. *Computer Networks, 113*, 244-257.

Forman, D. E., and Alexander, K. P. (2016). 'Frailty: a vital sign for older adults with cardiovascular disease'. *Canadian Journal of Cardiology, 32*(9), 1082-1087.

Frenzel, J. F. (1993). 'Genetic algorithms'. *IEEE potentials, 12*(3), 21-24.

Futoma, J. (2018). 'Gaussian process-based models for clinical time series in healthcare'. *Duke University*.

Gal, Y., and Ghahramani, Z. (2016). 'A theoretically grounded application of dropout in recurrent neural networks'. *The Advances in neural information processing systems*, 1019-1027.

Gancarz, M., Wawrzyniak, J., Gawrysiak-Witulska, M., Wiącek, D., Nawrocka, A., and Rusinek, R. (2017). 'Electronic nose with polymer-composite sensors for monitoring fungal deterioration of stored rapeseed'. *International Agrophysics, 31*(3), 317.

Gao, F., Cai, M.-X., Lin, M.-T., Xie, W., Zhang, L.-Z., Ruan, Q.-Z., et al. (2019). 'Prognostic value of international normalized ratio to albumin ratio among critically ill patients with cirrhosis'. *European Journal of Gastroenterology & Hepatology, 31*(7), 824-831.

Gao, X., Zhou, Y., Amir, M. I. H., Rosyidah, F. A., and Lee, G. M. (2017). 'A hybrid genetic algorithm for multi-emergency medical service center location-allocation problem in disaster response'. *International Journal of Industrial Engineering, 24*(6).

Gardiner, E. J., Willett, P., and Artymiuk, P. J. (2001). 'Protein docking using a genetic algorithm'. *Proteins: Structure, Function, and Bioinformatics, 44*(1), 44-56.

Gareth, J., Daniela, W., Trevor, H., and Robert, T. (2013). 'An introduction to statistical learning: with applications in R': *Spinger.*

Garla, V. N., and Brandt, C. (2012). 'Ontology-guided feature engineering for clinical text classification'. *Journal of Biomedical Informatics, 45*(5), 992-998.

Ge, W., Huh, J.-W., Park, Y. R., Lee, J.-H., Kim, Y.-H., and Turchin, A. (2018). 'An Interpretable ICU Mortality Prediction Model Based on Logistic Regression and Recurrent Neural Networks with LSTM units'. *The AMIA Annual Symposium Proceedings*, 460.

Gelman, A., Hill, J., Su, Y.-S., Yajima, M., Pittau, M., Goodrich, B., et al. (2013). 'MI: Missing data imputation and model checking'. *R Package Version 0.9-93*.

Gerry, S., Birks, J., Bonnici, T., Watkinson, P. J., Kirtley, S., and Collins, G. S. (2017). 'Early warning scores for detecting deterioration in adult hospital patients: a systematic review protocol'. *BMJ Open, 7*(12), e019268.

Gers, F. A., and Schmidhuber, J. (2000). 'Recurrent nets that time and count'. *The Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks. IJCNN 2000. Neural Computing: New Challenges and Perspectives for the New Millennium*, 189-194.

Gers, F. A., Schmidhuber, J., and Cummins, F. (1999). 'Learning to forget: Continual prediction with LSTM'.

Ghahramani, Z. (2003). 'Unsupervised learning'. *The Summer School on Machine Learning*, 72-112.

Ghassemi, M., Naumann, T., Doshi-Velez, F., Brimmer, N., Joshi, R., Rumshisky, A., et al. (2014). 'Unfolding physiological state: Mortality modelling in intensive care units'. *The Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 75-84.

Ghassemi, M., Pimentel, M. A., Naumann, T., Brennan, T., Clifton, D. A., Szolovits, P., et al. (2015). 'A multivariate timeseries modeling approach to severity of illness assessment and forecasting in ICU with sparse, heterogeneous clinical data'. *The Twenty-Ninth AAAI Conference* on *Artificial Intelligence*.

Ghosh, S., Chakraborty, P., Cohn, E., Brownstein, J. S., and Ramakrishnan, N. (2016). 'Characterizing diseases from unstructured text: A vocabulary driven word2vec approach'. *The Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*, 1129-1138.

Ghosh, S., Li, J., Cao, L., and Ramamohanarao, K. (2017). 'Septic shock prediction for ICU patients via coupled HMM walking on sequential contrast patterns'. *Journal of Biomedical Informatics, 66*, 19-31.

Glick, B., and Mache, J. (2018). 'Using jupyter notebooks to learn high-performance computing'. *Journal of Computing Sciences in Colleges, 34*(1), 180-188.

Goldberg, D. E. (1989). 'Genetic algorithms in search'. *Optimization, and MachineLearning*.

Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., et al. (2000). 'PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals'. *Circulation, 101*(23), e215-e220.

Goldhill, D. R., and Sumner, A. (1998). 'Outcome of intensive care patients in a group of British intensive care units'. *Critical Care Medicine, 26*(8), 1337-1345.

Goldstein, B. A., Navar, A. M., and Carter, R. E. (2017a). 'Moving beyond regression techniques in cardiovascular risk prediction: applying machine learning to address analytic challenges'. *European Heart Journal, 38*(23), 1805-1814.

Goldstein, B. A., Navar, A. M., Pencina, M. J., and Ioannidis, J. (2017b). 'Opportunities and challenges in developing risk prediction models with electronic health records data: a systematic review'. *Journal of the American Medical Informatics Association, 24*(1), 198-208.

Gomez, A. (2016). 'Backpropogating an LSTM: a numerical example'. *Aidan Gomez blog at Medium*.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning*: MIT press.

Gottesman, O., Johansson, F., Komorowski, M., Faisal, A., Sontag, D., Doshi-Velez, F., et al. (2019). 'Guidelines for reinforcement learning in healthcare'. *Nature Medicine, 25*(1), 16-18.

Granholm, A., Pedersen, N., Lippert, A., Petersen, L., and Rasmussen, L. S. (2016). 'Respiratory rates measured by a standardised clinical approach, ward staff, and a wireless device'. *Acta Anaesthesiologica Scandinavica, 60*(10), 1444-1452.

Graves, A. others. 2012. 'Supervised sequence labelling with recurrent neural networks'. Vol. 385: *Springer*.

Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., et al. (2018). 'Recent advances in convolutional neural networks'. *Pattern Recognition, 77*, 354-377.

Guimarães, P. O., Lopes, R. D., Alexander, J. H., Thomas, L., Hellkamp, A. S., Hijazi, Z., et al. (2019). 'International normalized ratio control and subsequent clinical outcomes in patients with atrial fibrillation using warfarin'. *Journal of Thrombosis and Thrombolysis, 48*(1), 27-34.

Gulli, B., Ciatolla, J. A., and Barnes, L. (2011). 'Emergency care and transportation of the sick and injured': *Jones & Bartlett Learning*.

Gupta, P., Malhotra, P., Narwariya, J., Vig, L., and Shroff, G. (2019). 'Transfer Learning for Clinical Time Series Analysis using Deep Neural Networks': *Springer*.

Hall, W. B., Willis, L. E., Medvedev, S., and Carson, S. S. (2012). 'The implications of long-term acute care hospital transfer practices for measures of in-hospital mortality and length of stay'. *American Journal of Respiratory and Critical Care Medicine, 185*(1), 53-57.

Harthun, N. L., Kongable, G. L., Baglioni Jr, A., Meakem, T. D., and Kron, I. L. (2005). 'Examination of sex as an independent risk factor for adverse events after carotid endarterectomy'. *Journal of Vascular Surgery, 41*(2), 223-230.

Harutyunyan, H., Khachatrian, H., Kale, D. C., Steeg, G. V., and Galstyan, A. (2017). 'Multitask learning and benchmarking with clinical time series data'. *arXiv preprint arXiv:1703.07771*.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). 'The elements of statistical learning: data mining, inference, and prediction': *Springer Science & Business Media*.

Hawkes, C., Booth, S., Ji, C., Brace-McDonnell, S. J., Whittington, A., Mapstone, J., et al. (2017). 'Epidemiology and outcomes from out-of-hospital cardiac arrests in England'. *Resuscitation, 110*, 133-140.

Haykin, S. (2007). 'Neural networks: a comprehensive foundation': *Prentice-Hall, Inc.*

Henning, A., and Krawiec, C. (2020). 'Sinus tachycardia'. *StatPearls [Internet]*.

Henriksen, D. P., Brabrand, M., and Lassen, A. T. (2014). 'Prognosis and risk factors for deterioration in patients admitted to a medical emergency department'. *PloS One, 9*(4), e94649.
Henriksson, A., Conway, M., Duneld, M., and Chapman, W. W. (2013). 'Identifying synonymy between SNOMED clinical terms of varying length using distributional analysis of electronic health records'. *The AMIA Annual Symposium Proceedings*, 600.
Hickey, B., and Heneghan, C. (2002). 'Screening for paroxysmal atrial fibrillation using atrial premature contractions and spectral measures'. *The Computers in Cardiology*, 217-220.
Hinton, G. E., Srivastava, N., Krizhevsky, A., Sutskever, I., and Salakhutdinov, R. R. (2012). 'Improving neural networks by preventing co-adaptation of feature detectors'. *arXiv preprint arXiv:1207.0580*.
Hochreiter, S., and Schmidhuber, J. (1997). 'Long short-term memory'. *Neural Computation, 9*(8), 1735-1780.
Hodgson, L. E., Dimitrov, B. D., Congleton, J., Venn, R., Forni, L. G., and Roderick, P. J. (2017). 'A validation of the National Early Warning Score to predict outcome in patients with COPD exacerbation'. *Thorax, 72*(1), 23-30.
Holcomb, G. W., Murphy, J. P., and Ostlie, D. J. (2014). *Ashcraft's Pediatric Surgery E-Book: Expert Consult-Online+ Print*: Elsevier Health Sciences.
Holland, J. H. (1992). 'Genetic algorithms'. *Scientific American, 267*(1), 66-73.
Holt, B. (2011). 'Writing and Querying MapReduce Views in CouchDB: Tools for Data Analysts': " *O'Reilly Media, Inc.*".
Honkoop, P. J., Simpson, A., Bonini, M., Snoeck-Stroband, J. B., Meah, S., Chung, K. F., et al. (2017). 'MyAirCoach: the use of home-monitoring and mHealth systems to predict deterioration in asthma control and the occurrence of asthma exacerbations; study protocol of an observational study'. *BMJ Open, 7*(1), e013935.
Hoogendoorn, M., El Hassouni, A., Mok, K., Ghassemi, M., and Szolovits, P. (2016). OPrediction using patient comparison vs. modeling: a case study for mortality predictionO. *The 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2464-2467.
Hou, L., Zhu, J., Kwok, J., Gao, F., Qin, T., and Liu, T.-y. (2019). ONormalization helps training of quantized LSTMO. *The Advances in Neural Information Processing Systems*, 7346-7356.
Houston, M. C. (2011). 'The importance of potassium in managing hypertension'. *Current Hypertension Reports, 13*(4), 309-317.
Hu, S. B., Wong, D. J., Correa, A., Li, N., and Deng, J. C. (2016a). 'Prediction of clinical deterioration in hospitalized adult patients with hematologic malignancies using a neural network model'. *PloS One, 11*(8).
Hu, S. B., Wong, D. J., Correa, A., Li, N., and Deng, J. C. (2016b). 'Prediction of clinical deterioration in hospitalized adult patients with hematologic malignancies using a neural network model'. *PloS One, 11*(8), e0161401.
HUA, B. K. (2017). 'An optimization method based on genetic algorithm for heart rate variability analysis in the prediction of the onset of cardiac arrhythmia'.
Huang, C.-L., and Wang, C.-J. (2006). 'A GA-based feature selection and parameters optimizationfor support vector machines'. *Expert Systems with Applications, 31*(2), 231-240.
Hug, C. W., and Szolovits, P. (2009). 'ICU acuity: real-time models versus daily models'. *The AMIA annual symposium proceedings,* 260.

Hughes, L. S., Phillips, R. L., DeVoe, J. E., and Bazemore, A. W. (2016). 'Community vital signs: taking the pulse of the community while caring for patients'. *J Am Board Fam Med, 29*(3), 419-422.

Ilyas, I. F., and Chu, X. (2019). *Data cleaning*: Morgan & Claypool.

Inglese, M., Madelin, G., Oesingmann, N., Babb, J., Wu, W., Stoeckel, B., et al. (2010). 'Brain tissue sodium concentration in multiple sclerosis: a sodium imaging study at 3 tesla'. *Brain, 133*(3), 847-857.

Ioffe, S., and Szegedy, C. (2015). 'Batch normalization: Accelerating deep network training by reducing internal covariate shift'. *arXiv preprint arXiv:1502.03167*.

Jaques, N., Taylor, S., Sano, A., and Picard, R. (2017). 'Multimodal autoencoder: A deep learning approach to filling in missing sensor data and enabling better mood prediction'. *The 2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*, 202-208.

Jiang, D., Peng, C., Chen, Y., Fan, Z., and Garg, A. (2017). 'Probability distribution pattern analysis and its application in the Acute Hypotensive Episodes prediction'. *Measurement, 104*, 180-191.

Jiaxiang, R. X. Z. B. Z. (2001). 'Simulation of temperature field in the furnace body of large bof by finite element analysis [j']. *Shanghai Metals, 5*.

Jo, S., Lee, J. B., Jin, Y. H., Jeong, T. O., Yoon, J. C., Jun, Y. K., et al. (2013). 'Modified early warning score with rapid lactate level in critically ill medical patients: the ViEWS-L score'. *Emergency Medicine Journal, 30*(2), 123-129.

Jo, Y., Lee, L., and Palaskar, S. (2017). 'Combining LSTM and latent topic modeling for mortality prediction'. *arXiv preprint arXiv:1709.02842*.

Joel, G. E. (1995). Desarrollo Web con PHP, PostgrSQL y MySQL. *2da. Edición*.

Johnson, A. E., Aboab, J., Raffa, J. D., Pollard, T. J., Deliberato, R. O., Celi, L. A., et al. (2018). 'A comparative analysis of sepsis identification methods in an electronic database'. *Critical Care Medicine, 46*(4), 494.

Johnson, A. E., Dunkley, N., Mayaud, L., Tsanas, A., Kramer, A. A., and Clifford, G. D. (2012). 'Patient specific predictions in the intensive care unit using a Bayesian ensemble'. *The 2012 Computing in Cardiology*, 249-252.

Johnson, A. E., Kramer, A. A., and Clifford, G. D. (2013). 'A new severity of illness scale using a subset of acute physiology and chronic health evaluation data elements shows comparable predictive accuracy'. *Critical Care Medicine, 41*(7), 1711-1718.

Johnson, A. E., Kramer, A. A., and Clifford, G. D. (2014). 'Data preprocessing and mortality prediction: The Physionet/CinC 2012 challenge revisited'. *The Computing in Cardiology 2014*, 157-160.

Johnson, A. E., Pollard, T. J., and Mark, R. G. (2017a). 'Reproducibility in critical care: a mortality prediction case study'. *The Machine Learning for Healthcare Conference*, 361-376.

Johnson, A. E., Pollard, T. J., Shen, L., Li-wei, H. L., Feng, M., Ghassemi, M., et al. (2016). 'MIMIC-III, a freely accessible critical care database'. *Scientific Data, 3*, 160035.

Johnson, A. E., Stone, D. J., Celi, L. A., and Pollard, T. J. (2017b). 'The MIMIC Code Repository: enabling reproducibility in critical care research'. *Journal of the American Medical Informatics Association, 25*(1), 32-39.

Johnson Jr, J. E., Blanes, R., Sheng, D., and Narayanan, A. (2019). 'Face Recognition for Fast Information Retrieval and Record Lookup'.

Jones, D., Mitchell, I., Hillman, K., and Story, D. (2013). 'Defining clinical deterioration'. *Resuscitation, 84*(8), 1029-1034.

Joshi, M., Ashrafian, H., Aufegger, L., Khan, S., Arora, S., Cooke, G., et al. (2019). 'Wearable sensors to improve detection of patient deterioration'. *Expert Review of Medical Devices, 16*(2), 145-154.

Joshi, R., and Szolovits, P. (2012). 'Prognostic physiology: modeling patient severity in intensive care units using radial domain folding'. *The AMIA Annual Symposium Proceedings*, 1276.

Joshi, S., Gunasekar, S., Sontag, D., and Ghosh, J. (2016). 'Identifiable phenotyping using constrained non-negative matrix factorization'. *arXiv preprint arXiv:1608.00704*.

Junwei, K., Yang, H., Junjiang, L., and Zhijun, Y. (2019). 'Dynamic prediction of cardiovascular disease using improved LSTM'. *International Journal of Crowd Science*.

Kamio, T., Van, T., and Masamune, K. (2017). 'Use of machine-learning approaches to predict clinical deterioration in critically ill patients: a systematic review'. *International Journal of Medical Research & Health Sciences, 6*(6), 1-7.

Kandel, E. R., Schwartz, J. H., Jessell, T. M., Biochemistry, D. o., Jessell, M. B. T., Siegelbaum, S., et al. (2000). 'Principles of neural science' (Vol. 4): *McGraw-hill New York.*

Karelova, R. (2020). 'Possibilities of an artificial neural network use to control oxygen consumption in a converter shop'. *The IOP Conference Series: Materials Science and Engineering*, 012129.

Karsoliya, S. (2012). 'Approximating number of hidden layer neurons in multiple hidden layer BPNN architecture'. *International Journal of Engineering Trends and Technology, 3*(6), 714-717.

Kate, R. J., Perez, R. M., Mazumdar, D., Pasupathy, K. S., and Nilakantan, V. (2016). 'Prediction and detection models for acute kidney injury in hospitalized older adults'. *BMC Medical Informatics and Decision Making, 16*(1), 39.

Kelly, C. (2018). 'Respiratory rate 1: why measurement and recording are crucial'. *Nursing Times, 114*(4), 23-24.

Kendale, S., Kulkarni, P., Rosenberg, A. D., and Wang, J. (2018). 'Supervised machine-learning predictive analytics for prediction of postinduction hypotension'. *Anesthesiology: The Journal of the American Society of Anesthesiologists, 129*(4), 675-688.

Khan, Y., Ostfeld, A. E., Lochner, C. M., Pierre, A., and Arias, A. C. (2016). 'Monitoring of vital signs with flexible and wearable medical devices'. *Advanced Materials, 28*(22), 4373-4395.

Kingma, D. P., and Ba, J. (2014). 'Adam: A method for stochastic optimization'. *arXiv preprint arXiv:1412.6980*.

Kivipuro, M., Tirkkonen, J., Kontula, T., Solin, J., Kalliomäki, J., Pauniaho, S.-L., et al. (2018). 'National early warning score (NEWS) in a Finnish multidisciplinary emergency department and direct vs. late admission to intensive care'. *Resuscitation, 128*, 164-169.

Knaus, W. A., Wagner, D. P., Draper, E. A., Zimmerman, J. E., Bergner, M., Bastos, P. G., et al. (1991). 'The APACHE III prognostic system: risk prediction of hospital mortality for critically III hospitalized adults'. *Chest, 100*(6), 1619-1636.

Knaus, W. A., Zimmerman, J. E., Wagner, D. P., Draper, E. A., and Lawrence, D. E. (1981). 'APACHE-acute physiology and chronic health evaluation: a physiologically based classification system'. *Critical Care Medicine, 9*(8), 591-597.

Kolbæk, M., Yu, D., Tan, Z.-H., and Jensen, J. (2017). 'Multitalker speech separation with utterance-level permutation invariant training of deep recurrent neural networks'. *IEEE/ACM Transactions on Audio, Speech, and Language Processing, 25*(10), 1901-1913.

Kolte, D., Khera, S., Aronow, W. S., Palaniswamy, C., Mujib, M., Ahn, C., et al. (2015). 'Regional variation in the incidence and outcomes of in-hospital cardiac arrest in the United States'. *Circulation, 131*(16), 1415-1425.

Konak, A., Coit, D. W., and Smith, A. E. (2006). 'Multi-objective optimization using genetic algorithms: A tutorial'. *Reliability Engineering & System Safety, 91*(9), 992-1007.

Korach, Z. T., Yang, J., Rossetti, S. C., Cato, K. D., Kang, M.-J., Knaplund, C., et al. (2020). 'Mining clinical phrases from nursing notes to discover risk factors of patient deterioration'. *International Journal of Medical Informatics, 135*, 104053.

Kossaifi, J., Panagakis, Y., Anandkumar, A., and Pantic, M. (2019). 'Tensorly: Tensor learning in python'. *The Journal of Machine Learning Research, 20*(1), 925-930.

Kotecha, D., Flather, M. D., Altman, D. G., Holmes, J., Rosano, G., Wikstrand, J., et al. (2017). 'Heart rate and rhythm and the benefit of beta-blockers in patients with heart failure'. *Journal of the American College of Cardiology, 69*(24), 2885-2896.

Kovatchev, B. P., Otto, E., Cox, D., Gonder-Frederick, L., and Clarke, W. (2006). 'Evaluation of a new measure of blood glucose variability in diabetes'. *Diabetes Care, 29*(11), 2433-2438.

Kret, M. E., and Sjak-Shie, E. E. (2019). 'Preprocessing pupil size data: Guidelines and code'. *Behavior Research Methods, 51*(3), 1336-1342.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). 'Imagenet classification with deep convolutional neural network's. *The Advances in neural information processing systems*, 1097-1105.

Kuki, Á., Nagy, L., Zsuga, M., and Kéki, S. (2011). 'Fast identification of phthalic acid esters in poly (vinyl chloride) samples by direct analysis in real time (DART) tandem mass spectrometry'. *International Journal of Mass Spectrometry, 303*(2-3), 225-228.

Kumar Manaswi, N. (2018).' Deep learning with applications using python: chatbots and face, object, and speech recognition with tensorflow and keras': *Apress*.

Kumar, N., Lolla, V. N., Keogh, E., Lonardi, S., Ratanamahatana, C. A., and Wei, L. (2005). 'Time-series bitmaps: a practical visualization tool for working with large time series databases'. *The Proceedings of the 2005 SIAM international conference on data mining*, 531-535.

Kumar, R., and Kumar, R. (2019). 'Optimizing requirement analysis by the use of meta-heuristic in Search Based Software Engineering'. *International Journal of Electrical & Computer Engineering (2088-8708), 9*.

Kumar, S. V. K. R. (2014). 'Analysis of feature selection algorithms on classification: a survey'.

Kury, F. S., Huser, V., and Cimino, J. J. (2015). 'Reproducing a prospective clinical study as a computational retrospective study in MIMIC-I'I. *The AMIA Annual Symposium Proceedings*, 804.

Kyurkchiev, V., and Kyurkchiev, N. (2017). 'A family of recurrence generated functions based on the” half-hyperbolic tangent activation function”'. *Biomedical Statistics and Informatics, 2*(3), 87-94.

Labach, A., Salehinejad, H., and Valaee, S. (2019). 'Survey of dropout methods for deep neural networks'. *arXiv preprint arXiv:1904.13310*.

Lai, H.-J., Tan, T.-H., Lin, C.-S., Chen, Y.-F., and Lin, H.-H. (2020). 'Designing a clinical decision support system to predict readmissions for patients admitted with all-cause conditions'. *Journal of Ambient Intelligence and Humanized Computing*, 1-10.

Längkvist, M., Karlsson, L., and Loutfi, A. (2014). 'A review of unsupervised feature learning and deep learning for time-series modeling'. *Pattern Recognition Letters, 42*, 11-24.

Larsen, J., and Goutte, C. (1999). 'On optimal data split for generalization estimation and model selection'. *The Neural Networks for Signal Processing IX: Proceedings of the 1999 IEEE Signal Processing Society Workshop (Cat. No. 98TH8468)*, 225-234.

Larsen, J., Nonboe, L., Hintz-Madsen, M., and Hansen, L. K. (1998). 'Design of robust neural network classifiers'. *The Proceedings of the 1998 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP'98 (Cat. No. 98CH36181)*, 1205-1208.

Larsen, J., Svarer, C., Andersen, L. N., and Hansen, L. K. (2012). 'Adaptive regularization in neural network modeling'. In *Neural Networks: Tricks of the Trade* (pp. 111-130): Springer.

Le Gall, J.-R., Lemeshow, S., and Saulnier, F. (1993). 'A new simplified acute physiology score (SAPS II) based on a European/North American multicenter study'. *JAMA, 270*(24), 2957-2963.

Le Lagadec, M. D., and Dwyer, T. (2017). 'Scoping review: the use of early warning systems for the identification of in-hospital patients at risk of deterioration'. *Australian Critical Care, 30*(4), 211-218.

Lee, H., Shin, S.-Y., Seo, M., Nam, G.-B., and Joo, S. (2016). 'Prediction of ventricular tachycardia one hour before occurrence using artificial neural networks'. *Scientific Reports, 6*, 32390.

Lee, J. (2017). 'Patient-specific predictive modeling using random forests: an observational study for the critically ill'. *JMIR Medical Informatics, 5*(1), e3.

Lee, J., and Mark, R. G. (2010a). 'A hypotensive episode predictor for intensive care based on heart rate and blood pressure time series'. *The 2010 Computing in Cardiology*, 81-84.

Lee, J., and Mark, R. G. (2010b). 'An investigation of patterns in hemodynamic data indicative of impending hypotension in intensive care'. *Biomedical Engineering Online, 9*(1), 62.

Lee, J., and Maslove, D. M. (2017). 'Customization of a severity of illness score using local electronic medical record data'. *Journal of Intensive Care Medicine, 32*(1), 38-47.

Lee, J., Maslove, D. M., and Dubin, J. A. (2015). 'Personalized mortality prediction driven by electronic medical data and a patient similarity metric'. *PloS One, 10*(5).

Lee, Y. S., Choi, J. W., Park, Y. H., Chung, C., Park, D. I., Lee, J. E., et al. (2018). 'Evaluation of the efficacy of the National Early Warning Score in predicting in-hospital mortality via the risk stratification'. *Journal of Critical Care, 47*, 222-226.

Lehman, L.-w., Saeed, M., Long, W., Lee, J., and Mark, R. (2012). 'Risk stratification of ICU patients using topic models inferred from unstructured progress notes'. *The AMIA annual symposium proceedings*, 505.

Levinson, D. R., and General, I. (2010). 'Adverse events in hospitals: national incidence among Medicare beneficiaries'. *Department of Health and Human Services Office of the Inspector General*.
Li, L., Zhao, Y., Jiang, D., Zhang, Y., Wang, F., Gonzalez, I., et al. (2013). 'Hybrid Deep Neural Network--Hidden Markov Model (DNN-HMM) Based Speech Emotion Recognition'. *The 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 312-317.
Li, Q., and Clifford, G. D. (2012). 'Signal quality and data fusion for false alarm reduction in the intensive care unit'. *Journal of Electrocardiology, 45*(6), 596-603.
Li, Y., Wu, F.-X., and Ngom, A. (2018). 'A review on machine learning principles for multi-view biological data integration'. *Briefings in Bioinformatics, 19*(2), 325-340.
Lieblich, J., and Utiger, R. D. (1972). 'Triiodothyronine radioimmunoassay'. *The Journal of Clinical Investigation, 51*(1), 157-166.
Lin, C. (2018). The Many Faces of Septic Shock: 'A General Framework for Disease Prediction using Generated Visualizations'.
Lin, C., Zhang, Y., Ivy, J., Capan, M., Arnold, R., Huddleston, J. M., et al. (2018a). 'Early diagnosis and prediction of sepsis shock by combining static and dynamic information using convolutional-LSTM'. *The 2018 IEEE International Conference on Healthcare Informatics (ICHI)*, 219-228.
Lin, C., Zhangy, Y., Ivy, J., Capan, M., Arnold, R., Huddleston, J. M., et al. (2018b). 'Early diagnosis and prediction of sepsis shock by combining static and dynamic information using convolutional-LSTM'. *The 2018 IEEE International Conference on Healthcare Informatics (ICHI)*, 219-228.
Lin, Y.-W., Zhou, Y., Faghri, F., Shaw, M. J., and Campbell, R. H. (2019). 'Analysis and prediction of unplanned intensive care unit readmission using recurrent neural networks with long short-term memory'. *PloS One, 14*(7).
Lipton, Z. C., Kale, D. C., Elkan, C., and Wetzel, R. (2015). 'Learning to diagnose with LSTM recurrent neural networks'. *arXiv preprint arXiv:1511.03677*.
Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., et al. (2017). 'A survey on deep learning in medical image analysis'. *Medical Image Analysis, 42*, 60-88.
Liu, V., Kipnis, P., Rizk, N. W., and Escobar, G. J. (2012). 'Adverse outcomes associated with delayed intensive care unit transfers in an integrated healthcare system'. *Journal of Hospital Medicine, 7*(3), 224-230.
Lokhandwala, S., McCague, N., Chahin, A., Escobar, B., Feng, M., Ghassemi, M. M., et al. (2018). 'One-year mortality after recovery from critical illness: A retrospective cohort study'. *PloS One, 13*(5).
Lukoseviciute, K., and Ragulskis, M. (2010). 'Evolutionary algorithms for the selection of time lags for time series forecasting by fuzzy inference systems'. *Neurocomputing, 73*(10-12), 2077-2088.
Lundberg, J. S., Perl, T. M., Wiblin, T., Costigan, M. D., Dawson, J., Nettleman, M. D., et al. (1998). 'Septic shock: an analysis of outcomes for patients with onset on hospital wards versus intensive care units'. *Critical Care Medicine, 26*(6), 1020-1024.
Luo, Y., Xin, Y., Joshi, R., Celi, L., and Szolovits, P. (2016). 'Predicting ICU mortality risk by grouping temporal trends from a multivariate panel of physiologic measurements'. *The Thirtieth AAAI Conference on Artificial Intelligence*.

Machado, M. V., and Cortez-Pinto, H. (2013). 'Non-invasive diagnosis of non-alcoholic fatty liver disease. A critical appraisal'. *Journal of Hepatology, 58*(5), 1007-1019.

Madelin, G., Lee, J.-S., Regatte, R. R., and Jerschow, A. (2014). 'Sodium MRI: methods and applications'. *Progress in Nuclear Magnetic Resonance Spectroscopy, 79*, 14-47.

Madelin, G., and Regatte, R. R. (2013). 'Biomedical applications of sodium MRI in vivo'. *Journal of Magnetic Resonance Imaging, 38*(3), 511-529.

Madsen, L. B. (2014). 'Data-Driven healthcare: how analytics and BI are transforming the industry': *John Wiley & Sons*.

Majeed, P. G., and Kumar, S. (2014). 'Genetic algorithms in intrusion detection systems: A survey'. *International Journal of Innovation and Applied Studies, 5*(3), 233.

Malka, R., Nathan, D. M., and Higgins, J. M. (2016). 'Mechanistic modeling of hemoglobin glycation and red blood cell kinetics enables personalized diabetes monitoring'. *Science Translational Medicine, 8*(359), 359ra130-359ra130.

Mangrum, J. M., and DiMarco, J. P. (2000). 'The evaluation and management of bradycardia'. *New England Journal of Medicine, 342*(10), 703-709.

Mao, Y., Chen, W., Chen, Y., Lu, C., Kollef, M., and Bailey, T. (2012). 'An integrated data mining approach to real-time clinical monitoring and deterioration warning'. *The Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1140-1148.

Mardini, L., Lipes, J., and Jayaraman, D. (2012). 'Adverse outcomes associated with delayed intensive care consultation in medical and surgical inpatients'. *Journal of Critical Care, 27*(6), 688-693.

Martindale, J., Roberts, A., and Are, S. (2020). 'Decision Support Tool For Determining Patient Length Of Stay Within An Emergency Department': *Google Patents*.

Masud, M. M., and Al Harahsheh, A. R. (2016). 'Mortality prediction of ICU patients using lab test data by feature vector compaction & classification'. *The 2016 IEEE International Conference on Big Data (Big Data)*, 3404-3411.

Mathukia, C., Fan, W., Vadyak, K., Biege, C., and Krishnamurthy, M. (2015). 'Modified Early Warning System improves patient safety and clinical outcomes in an academic community hospital'. *Journal of Community Hospital Internal Medicine Perspectives, 5*(2), 26716.

McDowell, T. Y., Lawrence, J., Florian, J., Southworth, M. R., Grant, S., and Stockbridge, N. (2018). 'Relationship between International normalized ratio and outcomes in modern trials with warfarin controls'. *Pharmacotherapy: The Journal of Human Pharmacology and Drug Therapy, 38*(9), 899-906.

McEvoy, F. J., and Amigo, J. M. (2013). 'Using machine learning to classify image features from canine pelvic radiographs: evaluation of partial least squares discriminant analysis and artificial neural network models'. *Veterinary Radiology & Ultrasound, 54*(2), 122-126.

McGaughey, J., Alderdice, F., Fowler, R., Kapila, A., Mayhew, A., and Moutray, M. (2007). 'Outreach and Early Warning Systems (EWS) for the prevention of intensive care admission and death of critically ill adult patients on general hospital wards'. *Cochrane Database of Systematic Reviews*(3).

McPhee, S. J., Papadakis, M. A., and Rabow, M. W. (2010). 'Current medical diagnosis & treatment 2010': *McGraw-Hill Medical New York*:.

Mehta, R., and Chinthapalli, K. (2019). 'Glasgow coma scale explained'. *BMJ, 365*.

Merity, S., Keskar, N. S., and Socher, R. (2017). 'Regularizing and optimizing LSTM language models'. *arXiv preprint arXiv:1708.02182*.

Miao, H., Li, B., Sun, C., and Liu, J. (2019). 'Joint learning of degradation assessment and RUL prediction for aeroengines via dual-task deep LSTM networks'. *IEEE Transactions on Industrial Informatics, 15*(9), 5023-5032.

Min, S., Lee, B., and Yoon, S. (2017). 'Deep learning in bioinformatics'. *Briefings in Bioinformatics, 18*(5), 851-869.

Mindikoglu, A. L., Dowling, T. C., Weir, M. R., Seliger, S. L., Christenson, R. H., and Magder, L. S. (2014). 'Performance of chronic kidney disease epidemiology collaboration creatinine-cystatin C equation for estimating kidney function in cirrhosis'. *Hepatology, 59*(4), 1532-1542.

Mochizuki, K., Shintani, R., Mori, K., Sato, T., Sakaguchi, O., Takeshige, K., et al. (2017). 'Importance of respiratory rate for the prediction of clinical deterioration after emergency department discharge: a single-center, case–control study'. *Acute Medicine & Surgery, 4*(2), 172-178.

Mohan, N. (2018). 'Predicting Post-Procedural Complications Using Neural Networks on MIMIC-III Data'.

Mokart, D., Lambert, J., Schnell, D., Fouché, L., Rabbat, A., Kouatchet, A., et al. (2013). 'Delayed intensive care unit admission is associated with increased mortality in patients with cancer with acute respiratory failure'. *Leukemia & lymphoma, 54*(8), 1724-1729.

Moody, G. B., and Lehman, L.-w. H. (2009). 'Predicting acute hypotensive episodes: The 10th annual physionet/computers in cardiology challenge'. *The 2009 36th Annual Computers in Cardiology Conference (CinC)*, 541-544.

Moridani, M. K., Setarehdan, S. K., Nasrabadi, A. M., and Hajinasrollah, E. (2018). 'A novel approach to mortality prediction of ICU cardiovascular patient based on fuzzy logic method'. *Biomedical Signal Processing and Control, 45*, 160-173.

Mulligan, A. (2010). 'Validation of a physiological track and trigger score to identify developing critical illness in haematology patients'. *Intensive and Critical Care Nursing, 26*(4), 196-206.

Naik, G. S., Waikar, S. S., Johnson, A. E., Buchbinder, E. I., Haq, R., Hodi, F. S., et al. (2019). 'Complex inter-relationship of body mass index, gender and serum creatinine on survival: exploring the obesity paradox in melanoma patients treated with checkpoint inhibition'. *Journal for Immunotherapy of Cancer, 7*(1), 89.

Nargesian, F., Samulowitz, H., Khurana, U., Khalil, E. B., and Turaga, D. S. (2017). 'Learning Feature Engineering for Classification'. *The IJCAI*, 2529-2535.

Nejedly, P., Plesinger, F., Viscor, I., Halamek, J., and Jurak, P. (2019). 'Prediction of Sepsis Using LSTM Neural Network With Hyperparameter Optimization With a Genetic Algorithm'. *The 2019 Computing in Cardiology (CinC)*, Page 1-Page 4.

Nepal, S., Ranjan, R., and Choo, K.-K. R. (2015). 'Trustworthy processing of healthcare big data in hybrid clouds'. *IEEE Cloud Computing, 2*(2), 78-84.

Neto, A. S., Deliberato, R. O., Johnson, A. E., Bos, L. D., Amorim, P., Pereira, S. M., et al. (2018). 'Mechanical power of ventilation is associated with mortality in critically ill patients: an analysis of patients in two observational cohorts'. *Intensive Care Medicine, 44*(11), 1914-1922.

Neubauer, A., Nies, C., Schepkin, V. D., Hu, R., Malzacher, M., Chacón-Caldera, J., et al. (2017). 'Tracking protein function with sodium multi quantum spectroscopy in a 3D-tissue culture based on microcavity arrays'. *Scientific Reports, 7*(1), 1-9.

Newman, S. (2017). 'Do Not Disturb: Vital Sign Monitoring as a Predictor of Clinical Deterioration in Monitored Patients'. *Kentucky Nurse, 65*(2).

Ng, K., Steinhubl, S. R., deFilippi, C., Dey, S., and Stewart, W. F. (2016). 'Early detection of heart failure using electronic health records: practical implications for time before diagnosis, data diversity, data quantity, and data density'. *Circulation: Cardiovascular Quality and Outcomes, 9*(6), 649-658.

Ong, M. E. H., Ng, C. H. L., Goh, K., Liu, N., Koh, Z. X., Shahidah, N., et al. (2012). 'Prediction of cardiac arrest in critically ill patients presenting to the emergency department using a machine learning score incorporating heart rate variability compared with the modified early warning score'. *Critical Care, 16*(3), R108.

Ordoñez, P., Schwarz, N., Figueroa-Jiménez, A., Garcia-Lebron, L. A., and Roche-Lima, A. (2016). 'Learning stochastic finite-state transducer to predict individual patient outcomes'. *Health and Technology, 6*(3), 239-245.

Ouwerkerk, R. (2011). 'Sodium mri'. In *Magnetic Resonance Neuroimaging* (pp. 175-201): Springer.

Padilla, R. M., and Mayo, A. M. (2018). 'Clinical deterioration: A concept analysis'. *Journal of Clinical Nursing, 27*(7-8), 1360-1368.

Pan, Q., Wang, S., and Zhang, J. (2019). 'Prediction of Alzheimer's Disease Based on Bidirectional LSTM'. *The Journal of Physics: Conference Series*, 052030.

Pan, S. (2018). 'Indoor Human Information Acquisition from Physical Vibrations'. *Carnegie Mellon University*.

PANDA, B. S. 'Expert System Development for Retrieval of Missing Data through Soft Computing Techniques'.

Panday, R. N., Minderhoud, T. C., Alam, N., and Nanayakkara, P. W. (2017). 'Prognostic value of early warning scores in the emergency department (ED) and acute medical unit (AMU): A narrative review'. *European Journal of Internal Medicine, 45*, 20-31.

Peiffer, T., Ruyssinck, J., Decruyenaere, J., De Turck, F., Ongenae, F., and Dhaene, T. (2016). 'Early detection of positive blood cultures using recurrent neural networks on time series data'. *The 25th Belgian-Dutch conference on Machine Learning* (BeneLearn 2016).

Petit, C., Bezemer, R., and Atallah, L. (2018). 'A review of recent advances in data analytics for post-operative patient deterioration detection'. *Journal of Clinical Monitoring and Computing, 32*(3), 391-402.

Pham, T., Tran, T., Phung, D., and Venkatesh, S. (2016). 'Deepcare: A deep dynamic memory model for predictive medicine'. *The Pacific-Asia Conference on Knowledge Discovery and Data Mining*, 30-41.

Physicians, R. C. o., Nolan, J., Soar, J., Smith, G., Tuckey, M., Scott, J., et al. (2019). 'Autoantibodies to lipids in bronchoalveolar fluid of patients with acute respiratory distress syndrome'. *Journal of the Intensive Care Society, 20*(2_suppl), 1-253.

Pirracchio, R. (2016). 'Mortality prediction in the ICU based on mimic-ii results from the super icu learner algorithm (sicula) project'. In *Secondary Analysis of Electronic Health Records* (pp. 295-313): Springer.

Plate, J., Hietbrink, F., Leenen, L., Eijkemans, M., and Peelen, L. (2018a). 'Predicting clinical deterioration at the Intermediate Care Unit: comparing a joint modelling approach with a long short-term recurrent neural network'.

Optimizing Care for the Critically Ill Surgical Patient: the Role of the IMCU, 207.

Plate, J. D., Peelen, L. M., Leenen, L. P., and Hietbrink, F. (2018b). 'Validation of the VitalPAC early warning score at the intermediate care unit'. *World Journal of Critical Care Medicine, 7*(3), 39.

Pollard, T. J., Johnson, A. E., Raffa, J. D., Celi, L. A., Mark, R. G., and Badawi, O. (2018). 'The eICU Collaborative Research Database, a freely available multi-center database for critical care research'. *Scientific Data, 5*, 180178.

Porcu, V. (2018). 'SciPy and NumPy'. In *Python for Data Mining Quick Syntax Reference* (pp. 177-200): Springer.

Porth, C. (2011). 'Essentials of pathophysiology: concepts of altered health states': *Lippincott Williams & Wilkins*.

Potes, C., Conroy, B., Xu-Wilson, M., Newth, C., Inwald, D., and Frassica, J. (2017). 'A clinical prediction model to identify patients at high risk of hemodynamic instability in the pediatric intensive care uni't. *Critical Care, 21*(1), 282.

Powell, S. K., and Tahan, H. M. (2018). 'Case management: A practical guide for education and practice': *Lippincott Williams & Wilkins*.

Purushotham, S., Meng, C., Che, Z., and Liu, Y. (2017). 'Benchmark of deep learning models on large healthcare mimic datasets'. *arXiv preprint arXiv:1710.08531*.

Quinten, V. M., van Meurs, M., Olgers, T. J., Vonk, J. M., Ligtenberg, J. J., and ter Maaten, J. C. (2018). 'Repeated vital sign measurements in the emergency department predict patient deterioration within 72 hours: a prospective observational study'. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine, 26*(1), 57.

Rafiq, M., Keel, G., Mazzocato, P., Spaak, J., Savage, C., and Guttmann, C. (2018). 'Deep learning architectures for vector representations of patients and exploring predictors of 30-day hospital readmissions in patients with multiple chronic conditions'. *The International Workshop on Artificial Intelligence in Health*, 228-244.

Ramchoun, H., Idrissi, M. A. J., Ghanou, Y., and Ettaouil, M. (2016). 'Multilayer Perceptron: Architecture Optimization and Training'. *IJIMAI, 4*(1), 26-30.

Ramgopal, S., Elmer, J., Escajeda, J., and Martin-Gill, C. (2018). 'Differences in prehospital patient assessments for pediatric versus adult patients. *The Journal of pediatrics, 199*, 200-205. e206.

Rangarajan, P. (2014). 'Imperial babel: translation, Exoticism, and the Long Nineteenth Century': *Fordham Univ Press*.

Rashedi, E., Nezamabadi-Pour, H., and Saryazdi, S. (2013). 'A simultaneous feature adaptation and feature selection method for content-based image retrieval systems'. *Knowledge-Based Systems, 39*, 85-94.

Rasmussen, M., Espelund, U., Juul, N., Yoo, A., Sørensen, L., Sørensen, K., et al. (2018). 'The influence of blood pressure management on neurological outcome in endovascular therapy for acute ischaemic stroke'. *British Journal of Anaesthesia, 120*(6), 1287-1294.

Reddy, B. K., and Delen, D. (2018). 'Predicting hospital readmission for lupus patients: An RNN-LSTM-based deep-learning methodology'. *Computers in Biology and Medicine, 101*, 199-209.

Reed, M. J., McGrath, M., Black, P. L., Lewis, S., McCann, C., Whiting, S., et al. (2018). 'Detection of physiological deterioration by the SNAP40 wearable device compared to standard monitoring devices in the emergency department: the SNAP40-ED study'. *Diagnostic and Prognostic Research, 2*(1), 1-9.

Reith, F. C., Lingsma, H. F., Gabbe, B. J., Lecky, F. E., Roberts, I., and Maas, A. I. (2017). 'Differential effects of the Glasgow Coma Scale Score and its Components: An analysis of 54,069 patients with traumatic brain injury'. *Injury, 48*(9), 1932-1943.

Reyes-García, J., Galeana-Zapién, H., Galaviz-Mosqueda, A., and Torres-Huitzil, C. (2018). 'Evaluation of the impact of data uncertainty on the prediction of physiological patient deterioration'. *IEEE Access, 6*, 38595-38606.

Ripoll, V. J. R., Vellido, A., Romero, E., and Ruiz-Rodríguez, J. C. (2014). 'Sepsis mortality prediction with the Quotient Basis Kernel'. *Artificial Intelligence in Medicine, 61*(1), 45-52.

Robinson, A., and Fallside, F. (1987). 'The utility driven dynamic error propagation'.

Rodrigues, J., Gamboa, H., Kublanov, V., and Dolganov, A. (2019). 'Storage of Biomedical Signals: Comparative Review of Formats and Databases'. *The 2019 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON)*, 0652-0656.

Rodwell, V. W. (2003). 'Catabolism of proteins and of amino acids nitrogen'. *Harper's Illustrated Biochemistry, 26th edn, New York, McGraw-Hill Medical*, 242-248.

Roelofs, R., Shankar, V., Recht, B., Fridovich-Keil, S., Hardt, M., Miller, J., et al. (2019). 'A Meta-Analysis of Overfitting in Machine Learning'. *The Advances in Neural Information Processing Systems*, 9175-9185.

Rogoza, W. (2019). 'Method for the prediction of time series using small sets of experimental samples'. *Applied Mathematics and Computation, 355*, 108-122.

Rojas, J. C., Carey, K. A., Edelson, D. P., Venable, L. R., Howell, M. D., and Churpek, M. M. (2018). 'Predicting intensive care unit readmission with machine learning using electronic health record data'. *Annals of the American Thoracic Society, 15*(7), 846-853.

Romanelli, D., and Farrell, M. W. (2020). 'AVPU (Alert, Voice, Pain, Unresponsive)'. In *StatPearls [Internet]*: StatPearls Publishing.

Ross, M., Wei, W., and Ohno-Machado, L. (2014). "Big data" and the electronic health record. *Yearbook of Medical Informatics, 23*(01), 97-104.

Roy, S. K., Krishna, G., Dubey, S. R., and Chaudhuri, B. B. (2019). 'Hybridsn: Exploring 3-d-2-d cnn feature hierarchy for hyperspectral image classification'. *IEEE Geoscience and Remote Sensing Letters*.

Rozen, G., Kobo, R., Beinart, R., Feldman, S., Sapunar, M., Luria, D., et al. (2013). 'Multipole analysis of heart rate variability as a predictor of imminent ventricular arrhythmias in ICD patients.' *Pacing and Clinical Electrophysiology, 36*(11), 1342-1347.

Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1985). 'Learning internal representations by error propagation': California Univ San Diego La Jolla Inst for Cognitive Scienceo. Document Number)

Russell, S., and Norvig, P. (2002). 'Artificial intelligence: a modern approach'.

Rylander, S. G. B., and Gotshall, B. (2002). 'Optimal population size and the genetic algorithm'. *Population, 100*(400), 900.

Sachdeva, J., Kumar, V., Gupta, I., Khandelwal, N., and Ahuja, C. K. (2013). 'Segmentation, feature extraction, and multiclass brain tumor classification'. *Journal of Digital Imaging, 26*(6), 1141-1150.

Sadeghi, R., Banerjee, T., and Romine, W. (2018). 'Early hospital mortality prediction using vital signals'. *Smart Health, 9*, 265-274.

Sadler, J. M., Goodall, J. L., Behl, M., and Morsy, M. M. (2018). 'Leveraging Open Source Software and Parallel Computing for Model Predictive Control

Simulation of Urban Drainage Systems Using EPA-SWMM5 and Python'. *The International Conference on Urban Drainage Modelling*, 988-992.

Saeed, M., Villarroel, M., Reisner, A. T., Clifford, G., Lehman, L.-W., Moody, G., et al. (2011). 'Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II): a public-access intensive care unit database'. *Critical Care medicine, 39*(5), 952.

Safaei, S., Safaei, V., Safaei, S., Woods, Z., Arabnia, H. R., and Gutierrez, J. B. (2018). 'The SWAG Algorithm; a Mathematical Approach that Outperforms Traditional Deep Learning. Theory and Implementation'. *arXiv preprint arXiv:1811.11813*.

Salazar, J. H. (2014). 'Overview of urea and creatinine'. *Laboratory Medicine, 45*(1), e19-e20.

Santamaria Ariza, M., Zambon, I., S. Sousa, H., Campos e Matos, J. A., and Strauss, A. (2020). 'Comparison of forecasting models to predict concrete bridge decks performance. *Structural Concrete'.*

Savio, A., and GrañA, M. (2013). 'Deformation based feature selection for computer aided diagnosis of Alzheimer's disease.' *Expert Systems with Applications, 40*(5), 1619-1628.

Scalzo, F., Liebeskind, D., and Hu, X. (2012). 'Reducing false intracranial pressure alarms using morphological waveform features'. *IEEE Transactions on Biomedical Engineering, 60*(1), 235-239.

Schilling, R. J., and Harris, S. L. (2011). 'Fundamentals of digital signal processing using MATLAB': *Nelson Education*.

Schmid, F., Goepfert, M. S., and Reuter, D. A. (2013). 'Patient monitoring alarms in the ICU and in the operating room'. *Critical Care, 17*(2), 216.

Schmidt, R. L., LoPresti, J. S., McDermott, M. T., Zick, S. M., and Straseski, J. A. (2018). 'Does reverse triiodothyronine testing have clinical utility? An analysis of practice variation based on order data from a National Reference Laboratory'. *Thyroid, 28*(7), 842-848.

Schuster, M., and Paliwal, K. K. (1997). 'Bidirectional recurrent neural networks'. *IEEE Transactions on Signal Processing, 45*(11), 2673-2681.

Seide, F., Li, G., Chen, X., and Yu, D. (2011). 'Feature engineering in context-dependent deep neural networks for conversational speech transcription'. *The 2011 IEEE Workshop on Automatic Speech Recognition & Understanding*, 24-29.

Seymour, C., Liu, V., Wulf, D., and Angus, D. (2017). 'D15 critical care: do we have a crystal ball? predicting clinical deterioration and outcome in critically ill patients': Screening Criteria For Community Acquired Sepsis Prior To Evidence Of Clinical Suspicion Of Infection In The Electronic Health Record. *American Journal of Respiratory and Critical Care Medicine, 195*.

Shah, S., Ledbetter, D., Aczon, M., Flynn, A., and Rubin, S. (2016). 2: 'Early prediction of patient deterioration using machine learning techniques with time series data'. *Critical Care Medicine, 44*(12), 87.

Shen, D., Wu, G., and Suk, H.-I. (2017). 'Deep learning in medical image analysis'. *Annual Review of Biomedical Engineering, 19*, 221-248.

Sheng, K., Li, Z., and Zhou, D. (2017). 'A Storage Method for Large Scale Moving Objects Based on PostGI'S. In *Information Technology and Intelligent Transportation Systems* (pp. 623-632): Springer.

Shewalkar, A. N. (2018). 'Comparison of RNN, LSTM and GRU on Speech Recognition Data'.

Shi, Z., Lin, H., Liu, L., Liu, R., Hayakawa, S., Harada, S., et al. (2019). 'FurcaNet: An end-to-end deep gated convolutional, long short-term memory, deep neural networks for single channel speech separation'. *arXiv preprint arXiv:1902.00651*.

Shiach, C. R., Campbell, B., Poller, L., Keown, M., and Chauhan, N. (2002). 'Reliability of point-of-care prothrombin time testing in a community clinic: a randomized crossover comparison with hospital laboratory testing'. *British Journal of Haematology, 119*(2), 370-375.

Shotton, H., and Findlay, G. (2012). 'Time to intervene: patients who had an in-hospital cardiorespiratory arrest: MA Healthcare London'.

Shukla, R. K., and Bhatt, C. B. (2018). 'Review of Early Warning Scoring System as a Primary Diagnostic Tool in Critically ill Patient'. *International Journal of Applied Engineering Research, 13*(16), 12783-12787.

Sica, D. A., Struthers, A. D., Cushman, W. C., Wood, M., Banas Jr, J. S., and Epstein, M. (2002). 'Importance of potassium in cardiovascular disease'. *The Journal of Clinical Hypertension, 4*(3), 198-206.

Singer, M., Deutschman, C. S., Seymour, C. W., Shankar-Hari, M., Annane, D., Bauer, M., et al. (2016). 'The third international consensus definitions for sepsis and septic shock (Sepsis-3)'. *JAMA, 315*(8), 801-810.

Skocik, M., Collins, J., Callahan-Flintoft, C., Bowman, H., and Wyble, B. (2016). 'I tried a bunch of things: the dangers of unexpected overfitting in classification'. *BioRxiv*, 078816.

Smith, G. B., Prytherch, D. R., Meredith, P., Schmidt, P. E., and Featherstone, P. I. (2013). 'The ability of the National Early Warning Score (NEWS) to discriminate patients at risk of early cardiac arrest, unanticipated intensive care unit admission, and death'. *Resuscitation, 84*(4), 465-470.

Soar, J., Nolan, J. P., Böttiger, B. W., Perkins, G. D., Lott, C., Carli, P., et al. (2015). 'European resuscitation council guidelines for resuscitation 2015: section 3. Adult advanced life support'. *Resuscitation, 95*, 100-147.

Solms, A., Frede, M., Berkowitz, S. D., Hermanowski-Vosatka, A., Kubitza, D., Mueck, W., et al. (2019). 'Enhancing the Quality of Rivaroxaban Exposure Estimates Using Prothrombin Time in the Absence of Pharmacokinetic Sampling'. *CPT: Pharmacometrics & Systems Pharmacology, 8*(11), 805-814.

Sondhi, S., Sharma, R., Merwaha, R., Mahajan, K., Mehta, A., and Dev, M. (2018). 'Temporary Pacemaker Induced Ventricular Fibrillations in Cath Lab Due to R on T Phenomenon'.

Song, H., Dai, J., Luo, L., Sheng, G., and Jiang, X. (2018). 'Power transformer operating state prediction method based on an LSTM network'. *Energies, 11*(4), 914.

Spångfors, M., Arvidsson, L., Karlsson, V., and Samuelson, K. (2016). 'The national early warning score: translation, testing and prediction in a Swedish setting'. *Intensive and Critical Care Nursing, 37*, 62-67.

Springenberg, J. T., Dosovitskiy, A., Brox, T., and Riedmiller, M. (2014). 'Striving for simplicity: The all convolutional net'. *arXiv preprint arXiv:1412.6806*.

Staudemeyer, R. C., and Morris, E. R. (2019). 'Understanding LSTM--a tutorial into Long Short-Term Memory Recurrent Neural Networks'. *arXiv preprint arXiv:1909.09586*.

Stergiou, C., Psannis, K. E., Kim, B.-G., and Gupta, B. (2018). 'Secure integration of IoT and cloud computing'. *Future Generation Computer Systems, 78*, 964-975.

Stewart, S. N., Kelly K, Mason M. (2009). 'Adding insult to injury:a review of the care of patients who died in hospital with a primary diagnoses of acute kidney injury (acute renal failure)'. *A report by the National Confidential Enquiry into Patient Outcome and Deatho. Document Number)*

Stewart , S. N., Kelly K, Mason M (Ed.) (2011). National Confedintial Enquiry into Patient Outcome and Death (NCEPOD).

Strömsöe, A., Svensson, L., Axelsson, Å. B., Claesson, A., Göransson, K. E., Nordberg, P., et al. (2015). .Improved outcome in Sweden after out-of-hospital cardiac arrest and possible association with improvements in every link in the chain of survival.. *European Heart Journal, 36*(14), 863-871.

Subbe, C., Kruger, M., Rutherford, P., and Gemmel, L. (2001a). 'Validation of a modified Early Warning Score in medical admissions'. *QJM, 94*(10), 521-526.

Subbe, C. P., Kruger, M., Rutherford, P., and Gemmel, L. (2001b). 'Validation of a modified Early Warning Score in medical admissions'. *QJM, 94*(10), 521-526.

Sun, Z.-L., Huang, D.-S., Zheng, C.-H., and Shang, L. (2006). 'Optimal selection of time lags for TDSEP based on genetic algorithm'. *Neurocomputing, 69*(7-9), 884-887.

Suyundikov, A., Stevens, J. R., Corcoran, C., Herrick, J., Wolff, R. K., and Slattery, M. L. (2015). 'Accounting for dependence induced by weighted KNN imputation in paired samples, motivated by a colorectal cancer study'. *PloS One, 10*(4), e0119876.

Svyatkovskiy, A., Kates-Harbeck, J., and Tang, W. (2017). 'Training distributed deep recurrent neural networks with mixed precision on GPU clusters'. In *Proceedings of the Machine Learning on HPC Environments* (pp. 1-8).

Swigris, J., Zhou, X., Wamboldt, F., Du Bois, R., Keith, R., Fischer, A., et al. (2009). 'Exercise peripheral oxygen saturation (SpO2) accurately reflects arterial oxygen saturation (SaO2) and predicts mortality in systemic sclerosis'. *Thorax, 64*(7), 626-630.

Sztajzel, J. (2004). 'Heart rate variability: a noninvasive electrocardiographic method to measure the autonomic nervous system'. *Swiss Medical Weekly, 134*(35-36), 514-522.

Tan, C. L., Cooke, E. K., Leib, D. E., Lin, Y.-C., Daly, G. E., Zimmerman, C. A., et al. (2016). 'Warm-sensitive neurons that control body temperature'. *Cell, 167*(1), 47-59. e15.

Tan, M., Santos, C. d., Xiang, B., and Zhou, B. (2015). 'LSTM-based deep learning models for non-factoid answer selection'. *arXiv preprint arXiv:1511.04108*.

Tato, A., and Nkambou, R. (2018). 'Improving adam optimizer'.

Taylor, C. J. (2015). '2012 Benjamin Franklin Medal in Computer and Cognitive Science presented to Vladimir Vapnik'. *Journal of the Franklin Institute, 352*(7), 2579-2584.

Teasdale, G., Maas, A., Lecky, F., Manley, G., Stocchetti, N., and Murray, G. (2014). 'The Glasgow Coma Scale at 40 years: standing the test of time'. *The Lancet Neurology, 13*(8), 844-854.

Tennant, R., and Wiggers, C. J. (1935). 'The effect of coronary occlusion on myocardial contraction'. *American Journal of Physiology-Legacy Content, 112*(2), 351-361.

Thangaraj, R., Pant, M., Abraham, A., and Bouvry, P. (2011). 'Particle swarm optimization: hybridization perspectives and experimental illustrations'. *Applied Mathematics and Computation, 217*(12), 5208-5226.

Thienpont, B., Steinbacher, J., Zhao, H., D'Anna, F., Kuchnio, A., Ploumakis, A., et al. (2016). 'Tumour hypoxia causes DNA hypermethylation by reducing TET activity'. *Nature, 537*(7618), 63.

Thong, T., and Raitt, M. H. (2007). 'Predicting imminent episodes of ventricular tachyarrhythmia using heart rate'. *Pacing and Clinical Electrophysiology, 30*(7), 874-884.

Thrall, J. H., Li, X., Li, Q., Cruz, C., Do, S., Dreyer, K., et al. (2018). 'Artificial intelligence and machine learning in radiology: opportunities, challenges, pitfalls, and criteria for success'. *Journal of the American College of Radiology, 15*(3), 504-508.

Tilly, K. F., Belton, A. B., and McLachlan, J. F. (1995). 'Continuous monitoring of health status outcomes: experience with a diabetes education program'. *The Diabetes Educator, 21*(5), 413-419.

Tripodi, A., and Chantarangkul, V. (2017). 'Lupus Anticoagulant Testing: Activated Partial Thromboplastin Time (APTT) and Silica Clotting Time (SCT)'. In *Hemostasis and Thrombosis* (pp. 177-183): Springer.

Tsoukalas, A., Albertson, T., and Tagkopoulos, I. (2015). 'From data to optimal decision making: a data-driven, probabilistic machine learning approach to decision support for patients with sepsis'. *JMIR medical informatics, 3*(1), e11.

Ueda, P., Woodward, M., Lu, Y., Hajifathalian, K., Al-Wotayan, R., Aguilar-Salinas, C. A., et al. (2017). 'Laboratory-based and office-based risk scores and charts to predict 10-year risk of cardiovascular disease in 182 countries: a pooled analysis of prospective cohorts and health surveys'. *The lancet Diabetes & endocrinology, 5*(3), 196-213.

Vahid, A., Mückschel, M., Neuhaus, A., Stock, A.-K., and Beste, C. (2018). 'Machine learning provides novel neurophysiological features that predict performance to inhibit automated responses'. *Scientific Reports, 8*(1), 1-15.

van Galen, L. S., Struik, P. W., Driesen, B. E., Merten, H., Ludikhuize, J., van der Spoel, J. I., et al. (2016). 'Delayed recognition of deterioration of patients in general wards is mostly caused by human related monitoring failures: a root cause analysis of unplanned ICU admissions'. *PloS One, 11*(8), e0161393.

Vasilevskis, E. E., Kuzniewicz, M. W., Dean, M. L., Clay, T., Vittinghoff, E., Rennie, D. J., et al. (2009). 'Relationship between discharge practices and intensive care unit in-hospital mortality performance: evidence of a discharge bias'. *Medical Care*, 803-812.

Vincent, C., Neale, G., and Woloshynowych, M. (2001). 'Adverse events in British hospitals: preliminary retrospective record review'. *BMJ, 322*(7285), 517-519.

Vincent, J.-L., Moreno, R., Takala, J., Willatts, S., De Mendonça, A., Bruining, H., et al. (1996). 'The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure': *Springer-Verlag*.

Visa, S., Ramsay, B., Ralescu, A. L., and Van Der Knaap, E. (2011). 'Confusion Matrix-based Feature Selection'. *MAICS, 710*, 120-127.

Visintainer, P. (2020). 'When Sinus Tachycardia Becomes Too Much: Negative Effects of Excessive Upright Tachycardia on Cardiac Output in Vasovagal Syncope, Postural Tachycardia Syndrome, and Inappropriate Sinus Tachycardia'.

Voulodimos, A., Doulamis, N., Doulamis, A., and Protopapadakis, E. (2018). 'Deep learning for computer vision: A brief review'. *Computational Intelligence and Neuroscience, 2018*.

Vovk, V., Papadopoulos, H., and Gammerman, A. (2015). 'Measures of Complexity': *Springer*.
Walker, H. K., Hall, W. D., and Hurst, J. W. (1990). 'Peripheral Blood Smear--Clinical Methods: The History, Physical, and Laboratory Examinations': *Butterworths*.
Wang, X., and Miikkulainen, R. (2020). 'MDEA: Malware Detection with Evolutionary Adversarial Learning''. *arXiv preprint arXiv:2002.03331*.
Wang, X., Takaki, S., and Yamagishi, J. (2017). A simple RNN-plus-highway network for statistical parametric speech synthesis'. In *Technical Report, NII-2017-003E*: National Institute of Informatics.
Wang, Y., Kung, L., and Byrd, T. A. (2018).' Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations'. *Technological Forecasting and Social Change, 126*, 3-13.
Wang, Z., Sun, Y., Yang, X., and Li, S. (2019). 'Hybrid optimisation method of improved genetic algorithm and IFT for linear thinned array'. *The Journal of Engineering, 2019*(20), 6457-6460.
Ward, L., Agrawal, A., Choudhary, A., and Wolverton, C. (2016a). 'A general-purpose machine learning framework for predicting properties of inorganic materials'. *NPJ Computational Materials, 2*, 16028.
Ward, L., Agrawal, A., Choudhary, A., and Wolverton, C. (2016b). 'A general-purpose machine learning framework for predicting properties of inorganic materials'. *NPJ Computational Materials, 2*(1), 1-7.
Wassertheil-Smoller, S., McGinn, A., Haring, B., Kamensky, V., and Alderman, M. (2019). 'Diastolic Blood Pressure Levels and Mortality Among Older Women: Results From the Women's Health Initiative Long Life Study'. *Circulation, 140*(Suppl_1), A17173-A17173.
Wellner, B., Grand, J., Canzone, E., Coarr, M., Brady, P. W., Simmons, J., et al. (2017). 'Predicting unplanned transfers to the intensive care unit: a machine learning approach leveraging diverse clinical elements'. *JMIR Medical Informatics, 5*(4), e45.
Wickramasinghe, N. (2017). 'Deepr: a convolutional net for medical records'.
Williams, B., Alberti, G., Ball, C., Ball, D., Binks, R., and Durham, L. (2012). 'Royal College of Physicians, National Early Warning Score (NEWS), Standardising the assessment of acute-illness severity in the NHS, London'.
Williams, R. J., and Peng, J. (1990). 'An efficient gradient-based algorithm for on-line training of recurrent network trajectories'. *Neural Computation, 2*(4), 490-501.
Woodward, K., Trujillo, T., Schuch, R., and Anderson, E. C. (1956). 'Correlation of total body potassium with body-water'. *Nature, 178*(4524), 97-98.
Woollett, E. L. T. (2017). 'Maxima by Example: Ch. 14: Fitting a Model Function to Data'.
Wu, X., Wang, Y., Mao, J., Du, Z., and Li, C. (2014). 'Multi-step prediction of time series with random missing data'. *Applied Mathematical Modelling, 38*(14), 3512-3522.
Wunsch, H., Guerra, C., Barnato, A. E., Angus, D. C., Li, G., and Linde-Zwirble, W. T. (2010). 'Three-year outcomes for Medicare beneficiaries who survive intensive care'. *JAMA, 303*(9), 849-856.
Wuttke, M., Li, Y., Li, M., Sieber, K. B., Feitosa, M. F., Gorski, M., et al. (2019). 'A catalog of genetic loci associated with kidney function from analyses of a million individuals'. *Nature Genetics, 51*(6), 957.
Xiao, R., King, J., Villaroman, A., Do, D. H., Boyle, N. G., and Hu, X. (2018). 'Predict in-hospital code blue events using monitor alarms through deep learning

approach'. *The 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 3717-3720.

Xu, C., Yao, J., Lin, Z., Ou, W., Cao, Y., Wang, Z., et al. (2018). 'Alternating multi-bit quantization for recurrent neural networks'. *arXiv preprint arXiv:1802.00150*.

YADAV, S., and BIST, A. S. (2016). 'Genetic algorithm based feature selection for extreme learning machines'. *Asian Journal of Mathematics and Computer Research*, 34-39.

Yan, P., Guo, H., Wang, G., De Man, R., and Kalra, M. K. (2018). 'Hybrid deep neural networks for all-cause Mortality Prediction from LDCT Images'. *arXiv preprint arXiv:1810.08503*.

Yi, L., Dong, N., Yun, Y., Deng, B., Ren, D., Liu, S., et al. (2016). 'Chemometric methods in data processing of mass spectrometry-based metabolomics: A review'. *Analytica Chimica Acta, 914*, 17-34.

YİĞİT, A., and IŞIK, Z. (2020). 'Applying deep learning models to structural MRI for stage prediction of Alzheimer’s disease.' *Turkish Journal of Electrical Engineering & Computer Sciences, 28*, 196-210.

Yilmaz, K., Karaböcüoglu, M., Citak, A., and Uzel, N. (2002). 'Evaluation of laboratory tests in dehydrated children with acute gastroenteritis'. *Journal of Paediatrics and Child Health, 38*(3), 226-228.

Young, M. P., Gooder, V. J., Mc Bride, K., James, B., and Fisher, E. S. (2003). 'Inpatient transfers to the intensive care unit: delays are associated with increased mortality and morbidity'. *Journal of General Internal Medicine, 18*(2), 77-83.

Yu, C., Qi, X., Ma, H., He, X., Wang, C., and Zhao, Y. (2020a). 'LLR: Learning learning rates by LSTM for training neural network's. *Neurocomputing*.

Yu, K., Zhang, M., Cui, T., and Hauskrecht, M. (2020b). 'Monitoring ICU Mortality Risk with A Long Short-Term Memory Recurrent Neural Network'. *The Pac Symp Biocomput*.

Yuan, X., Huang, B., Wang, Y., Yang, C., and Gui, W. (2018). 'Deep learning-based feature representation and its application for soft sensor modeling with variable-wise weighted SAE'. *IEEE Transactions on Industrial Informatics, 14*(7), 3235-3243.

Zadravecz, F. J., Tien, L., Robertson-Dick, B. J., Yuen, T. C., Twu, N. M., Churpek, M. M., et al. (2015). 'Comparison of mental-status scales for predicting mortality on the general ward's. *Journal of Hospital Medicine, 10*(10), 658-663.

Zaremba, W., Sutskever, I., and Vinyals, O. (2014). 'Recurrent neural network regularization'. *arXiv preprint arXiv:1409.2329*.

Zhai, H., Brady, P., Li, Q., Lingren, T., Ni, Y., Wheeler, D. S., et al. (2014). 'Developing and evaluating a machine learning based algorithm to predict the need of pediatric intensive care unit transfer for newly hospitalized children'. *Resuscitation, 85*(8), 1065-1071.

Zhang, F., Cai, N., Wu, J., Cen, G., Wang, H., and Chen, X. (2018a). 'Image denoising method based on a deep convolution neural network'. *IET Image Processing, 12*(4), 485-493.

Zhang, J., and Centola, D. (2019). 'Social networks and health: new developments in diffusion, online and offline'. *Annual Review of Sociology, 45*, 91-109.

Zhang, K., Xu, G., Chen, L., Tian, P., Han, C., Zhang, S., et al. (2020). 'Instance transfer subject-dependent strategy for motor imagery signal classification using deep convolutional neural networks'. *Computational and Mathematical Methods in Medicine, 2020*.

Zhang, K., Zuo, W., Chen, Y., Meng, D., and Zhang, L. (2017a). 'Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising'. *IEEE Transactions on Image Processing, 26*(7), 3142-3155.

Zhang, X., Zou, Y., Li, S., and Xu, S. (2018b). 'Product yields forecasting for FCCU via deep bi-directional LSTM network'. *The 2018 37th Chinese Control Conference (CCC)*, 8013-8018.

Zhang, Y., Chen, G., Yu, D., Yaco, K., Khudanpur, S., and Glass, J. (2016). 'Highway long short-term memory rnns for distant speech recognition'. *The 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 5755-5759.

Zhang, Y., Lin, C., Chi, M., Ivy, J., Capan, M., and Huddleston, J. M. (2017b). 'LSTM for septic shock: Adding unreliable labels to reliable predictions'. *The 2017 IEEE International Conference on Big Data (Big Data)*, 1233-1242.

Zhang, Y., and Ling, C. (2018). 'A strategy to apply machine learning to small datasets in materials science'. *NPJ Computational Materials, 4*(1), 1-8.

Zhao, J., Mao, X., and Chen, L. (2019). 'Speech emotion recognition using deep 1D & 2D CNN LSTM networks'. *Biomedical Signal Processing and Control, 47*, 312-323.

ZHAO, P., LIU, Z.-q., and WANG, M.-j. (2006). 'Foundation of Black Body Furnace Temperature Time Series Prediction Model Based on BPNN [J]'. *Industrial Measurement, 1*.

Zhao, Y., Chen, D., Luo, Y., Li, H., Deng, B., Huang, S.-B., et al. (2013). 'A microfluidic system for cell type classification based on cellular size-independent electrical propertie's. *Lab on a Chip, 13*(12), 2272-2277.

Zheng, H., and Shi, D. (2018). 'Using a LSTM-RNN based deep learning framework for ICU mortality prediction'. *The International Conference on Web Information Systems and Applications*, 60-67.

Zimmerman, J. E., Kramer, A. A., McNair, D. S., and Malila, F. M. (2006). 'Acute Physiology and Chronic Health Evaluation (APACHE) IV: hospital mortality assessment for today's critically ill patients'. *Critical Care Medicine, 34*(5), 1297-1310.

LIST OF PUBLICATIONS

This list contains the papers that are generated based on this research.
They are:

1. Tariq Ibrahim Abdel Latif Al-Shawaheen, Mehrdad Moghbel, Yuan Wen Hau, Chia Yee Ooi, Use of learning approaches to predict clinical deterioration in patients based on various variables: a review of the literature, *Artificial Intelligence Review*, 13 March 2021 (Q1, IF = 5.747).
2. Tariq Ibrahim Abdel Latif Al-Shawaheen, Yuan Wen Hau, Nizar Ass'Ad, Mahmoud M. Abualsamen, A Novel and Reliable Framework of Patient Deterioration Prediction in Intensive Care Unit Based on Long Short-Term Memory-Recurrent Neural Network, *IEEE Access*, Vol. 9, pg. 3894-3918, 24 December 2020 (Q1, IF = 3.745).
3. Tariq Ibrahim Abdel Latif Al-Shawaheen and Yuan Wen Hau, A New Model for Tracking Deterioration of Vital Signs by Means of Artificial Neural Network, *Journal of Theoretical and Applied Information Technology (JATIT)*, Vol. 97, No. 14, pg. 3809-3818, 31 July 2019. (Q1, IF = 0.628)