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Smart Prediction Model For Unplanned Icu Transfer Based On Deep Learning Optimization : An Article Review

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ABSTRACT

Problem on units ICU already is problem which critical and already happened since long ago, for the ICU is one of the highest costs unit in hospitals, which made a system to predict activity on ICU is very demanding. COVID-19 shows the need for excellent time management in dealing with the abnormal flow of patients. Prediction of ICU transfer can be useful for patients and medical personnel to reduce medical cost and giving the time required by the nurses to prepare themselves for a huge patients flow. Reviews of related articles are carried out through the Google Scholar database. Screening then conducted based on identified article based on criteria eligibility. There are 7 final articles that assessed on a large scale data samples, method algorithm, and performance from the model which used on the article. Results obtained from this study which follow PRISM flow show a number of variable indicators that are commonly applied, namely: age, gender, liver function, blood pressure, pulse rate, temperature, respiratory rate, kgd and ECG data features. The best test results was achieved by research by Jonathan Rubin, et al due to the large number of varied data sets used, much more than other studies. This research also used adaptive boosting and gradient tree boosting approaches and evaluated with 4 main parameter that is accuracy, sensitivity, specificity, and AUC ROC. This study succeed in reaching performance evaluation model of 72.8% sensitivity, 76.3% specificity, 76.2% accuracy and 79.9% AUC ROC.

1. Introduction

The application of technology on health related fields is already become more diverse, one of it is the usage of Artificial Intelligence (AI) to increase the efficiency and performance of the medical staff in hospitals (Olive & Owens, 2018). AI plays a role in predicting, determining and recognizing various significant condition which could help ensuring the life of a patient, including emergency patients(Raita et al., 2019). Emergency patients require appropriate treatment faster and more responsive from medical personnel(Rojas et al., 2018). This is because the patient's condition is tend to be in critical states when arriving at the hospital and require immediate intensive help (Tonekaboni et al., 2022), (Goto et al., 2019).

The identification process also carried out as an initial step in knowing patients' symptomps, medical records, previous patient medical history and initial diagnosis taken into consideration for AI-based systems in predicting the necessity for the patient to be treated in emergency or ICU (Tyler J. Loftus et al., 2020). A number of fundamental consideration is also done when the patient is about to transfer the patient to the ICU unplannedly, because there is additional inpatient time, additional medical cost, restrictions visit and patients life and death condition (Ibrahim et al., 2021; Shickel et al., 2021; Tyler J. Loftus et al., 2020). Electronics Medical Records /EMR and deep learning processing used by the doctor as reference for making decisions to transfer patient to the room ICU at the moment (Ibrahim et al., 2021), (Romero-brufau et al., 2021), (Chen et al., n.d.).

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Lin and team (Lin et al., 2019) studying to predict the probability for adult patient to get comprehensive treatment based on the deep learning processed EMR so that medical staff could use that to give optimal treatment for the patient. Similar things also conveyed by Kennedy on his research in 2021 (Kennedy et al., 2021), that the result of good and accurate prediction could have a positive impact in ensuring the patients life. This study reached 80% accuracy and considered to be close to a doctor diagnoses.

Based on the studies mentioned, deep learning algorithm proved to be applicable to predict an accurate decision making, however to expand this study, the writer proposing to make a smart prediction model based on deep learning to predict unplanned possibilities of transfering patients to ICU, and so the topic for this study is “Smart Prediction Model for Unplanned ICU Transfer Based on Deep Learning Optimization”.

2. Research Methods

The methods used in this study are as follows (Tamara & Tahapary, 2020):

2.1 Eligibility Criteria

Articles in the inclusion is an article with the main topic or subject about ICU transfer prediction. Exclusion article is an article that does not have the theme of ICU transfer prediction as study subject, article without the subject of deep learning.

2.2 Search Strategy

Article searching was done manually via Google Scholar’s Database provided that the search for scientific articles at least in the last 3 years and uses the determined keyword. Article selection conducted by making limitations that only article written in English and Indonesia is allowed.

2.3 Collecting Data

The dataset in this study is in the form of articles/journals totaling 27 articles taken from Google Scholar under the category of ICU Transfer Based on Deep Learning Optimization.

2.4 Evaluation to Model Performance

Performance model prediction rated with comparison to standard score rule of obtained prediction performance (Accuracy, Sensitivity, Specificity, AUC- ROC, etc.). The level of accuracy on general cannot be rated alone because dta habit and data balance is still a factor to consider. If there is a dominant predictor data, high accuracy can be acquired by model prediction with only predict one possibility variation (eg: if dominant predictor data is 0 high accuracy will be achieved with model prediction will only produce output 0). The amount and source of data will also compared, so that this variable prediction article review could also be used as base theory reference for the upcoming study.

3. Result and Discussion

In this study, results are obtained by carrying out several processes starting from data preparation, filtering data on titles and abstracts to determine appropriateness, deleting duplicate, and reviewing the journal.

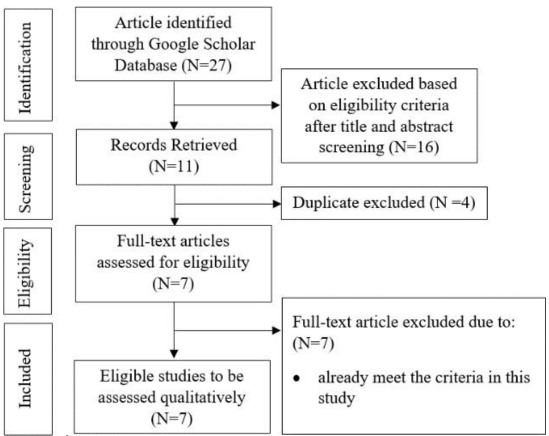

Fig 1. Data Processing

Table 1
Dataset

No.	Authors	Date (DD/MM/YYYY)	Data Type	Location
1	Jonathan Rubin, et al.	02/01/2018	EHR of 2 Medical Center	USA
…	…	…	…	…
27	Marcello Covino, et al.	26/08/2020	COVID-19 Require Intensive	Italy

Table 2
Data Table After Data Filtration

No.	Authors	Date (DD/MM/YYYY)	Data Type	Location
1	Jonathan Rubin, et al.	02/01/2018	EHR of 2 Medical Center	USA
…	…	…	…	…
11	Julien Grand-Clement, et al.	21/01/2021	Prediction of Mortality and ICU Transfer	Columbia

Researcher having a summary to whole journal contents based on parameters and variable indicator that needed for the reviews. Research on sudden ICU transfer of patients taken from the range time the last 5 year namely 2017-2022. Ben Wellner, et al. conducted a study in 2017 to predict the unplanned ICU transfer of patients using machine learning algorithms, namely logistic regression and neural networks with data training which obtained from patient's medical record ranged from January 1st until 31th December, 2013. To evaluate the performance of the method used a test with parameters ROC, specificity, sensitivity and PPV (combination value of sensitivity, specificity, and prevalence) has to be done. The best results obtained from the model used achieves a sensitivity of 80%, specificity 80.5%, and PPV 5.2%.

In the year 2018, Jonathan rubin, et al doing another research in predicting a patient transfers to emergency units through an ensemble model. The method used is based on adaptive boosting and gradient tree boosting . Data samples were taken from electronic medical records over the time range 5.5 year with indicator variable such as age, gender, heart function, blood pressure, pulse, temperature, respiratory rate, and heart rate. As for performance results which obtained with parameter test is accuracy (0.77 vs. 0.69), sensitivity (0.80 vs. 0.68), specificity (0.74vs. 0.70) and AUROC (0.85 vs. 0.73).

Table 4
Table After Duplicate Removal

No	Authors	Date (DD/MM/YYYY)	Data Type	Location
1	Jonathan Rubin,et al.	02/01/2018	EHR of 2 MedicalCenter	USA
2	Benjamin Shickles, et al.	22/02/2021	Cohort Study of ICUAdmission	USA
3	Yves Allenbach,et al.	19/10/2020	Cohort Study of COVID-19 AdultsPatients	Paris
4	Chun-An Chou,et al.	02/08/2019	ED Admission Data	Taiwan
5	Mickael Gette,et al.	18/05/2021	COVID-19 Patients'Admission	France
6	Ben weller, etal.	22/11/2017	EHR Data of 3Hospital	USA
7	Fu-Yuan Cheng,et al.	01/06/2020	COVID-19 patients' Admission	USA

With different indicator variable but kept referring on patients condition who are likely to be transferred suddenly to the emergency department (ICU), Chun-An Chou, et al. in 2019 studied 1049 patients

(736 medical controls and 313 unplanned ICU transfers) to create a recognition model decisions regarding sudden patient transfer. The model is based on mixed-integer optimization with accuracy >70% as the result

Similar subject was also re-examined in two different studies in 2020, the first study by Fu-Yuan Cheng, et al. is applying the machine learning method to predict the likelihood of covid-19 patients being transferred to ICU. There are no clear quantity regarding used datasets in this study,only the available time span was stated clear. Dataset in this study was taken from Mount Sinai Health Center ranged from February 26th until April 18th 2020. The indicator variables used to identify the patient's condition include: blood pressure, blood test results, electrocardiogram test results, etc. This research was successful in achieving a model performance evaluation of 72.8% sensitivity, 76.3% specificity, 76.2% accuracy and 79.9% AUC ROC. While in the research conducted by Yves Allenbach, et al. in the same year used data test with 175 patient sent to the General Service Unit, 49 patients were sent directly to the ICU unit, 68 patient which previously sent to the general service then moved to ICU, and 87 people grouped into general patients, 10 peoples as ICU patients and 43 normal patient which moved to units ICU as data validation. The model used in this study was measured by the specificity parameter with a performance score of 95%. Based on the research in recent years, Benjamin Shickel, et al and Mickael gette, et al. have done a research about the possibility of transferring patient to ICU. In Benjamin Shickles, et al, study, test data used consist on 32.184 permanent patients and 45,147 transfer patients who were subsequently tested with AUROC parameters and achieved accuracy of 95%. Whereas Mickael getters, et al in his research reached the accuracy of 83% in identifying patients who had the potential for sudden transfer to the ICU:

4. Conclusion

Smart optimization model proposed with deep learning approach for predicting unplanned transfer of patients to the ICU has been developed in a number of study in the last 5 year. Indicating variable which generally established in all studies to predict the probability of patients experiencing transfers include age, gender, liver function, blood pressure, pulse, temperature, respiratory rate, heart rate, blood sugar level, and electrocardiogram record. Articles with the best testing results achieved by study conducted by Jonathan rubin, et al because the amount of dataset used was far more variative compared to other study. This study also used the adaptive boost and gradient tree boost as an approach and evaluated with 4 main parameters namely accuracy, sensitivity, specificity, and AUC ROC. This study succeeded in achieving a model performance evaluation of 72.8% sensitivity, 76.3% specificity, 76.2% accuracy and 79.9% AUC ROC.

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