אוניברסיטת אריאל

הפקולטה למדעי הטבע

מחלקת מדעי המחשב ומתמטיקה

במסלול מדעי הנתונים ובינה מלאכותית

סקירת ספרות בנושא

Enteral feeding intolerance

מוגש על ידי שקד גופין

מנחה: דר' אורית רפאלי

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עבודה זו מוגשת כחלק מהדרישות להשלמת התואר

"BSc Computer Science & Mathematics "

תקציר

Feeding intolerance (FI) is a general term that indicates an intolerance of enteral nutrition (EN) feeding for any clinical reason, including vomiting, high gastric residual, diarrhea, gastrointestinal bleeding, and the presence of entero-cutaneous fistulas. resulting in poor outcomes and nutrition.

Enteral feeding intolerance (EFI) is a common feature in critically ill patients worldwide, and often results in not achieving nutritional targets.

It may also be associated with significant morbidity, leading to increased mortality and ICU length of stay.

However, there is no clear, widely agreed-upon definition available, with various studies rarely using the same definition.

A systematic review of 72 studies estimated prevalence of EFI of 38% (95% CI 31–46) but demonstrated large variability in defining EFI. Upper gastrointestinal tract intolerance reflected by large GRVs (with or without other gastrointestinal symptoms) was used in 63/72 studies, with a median volume defining a “large” GRV of 250 mL (range 75–500 mL).

By using Machine Learning researchers are hoping to find more insights on how to measure EFI more accurately.

תוכן העניינים

Chapter 1: Non-

Enteral tolerance in critically ill patients

Chapter 2:

**Identifying Distinct Subgroups of Intensive Care Unit Patients: A Machine Learning Approach**

Identifying subgroups of intensive care unit (ICU) patients with similar clinical needs and trajectories may provide a framework for more efficient ICU care through the design of care platforms tailored around patients’ shared needs.

However, objective methods for identifying these ICU patient subgroups are lacking. In this article they used a machine learning approach to empirically identify ICU patient subgroups through clustering analysis and evaluate whether these groups might represent appropriate targets for care redesign efforts.

They performed clustering analysis using data from patients’ hospital stays to retrospectively identify patient subgroups from a large, heterogeneous ICU population.

The data came from Kaiser Permanente Northern California (KPNC), a healthcare delivery system serving 3.9 million members.

And consisting of ICU patients aged ≥ 18 years with an ICU admission between January 1, 2012, and December 31, 2012 at one of 21 KPNC hospitals.

Measurements and Main Results

They used clustering analysis to identify putative clusters among 5,000 patients randomly selected from 24,884 ICU patients. To assess cluster validity, They evaluated the distribution and frequency of patient characteristics, and the need for invasive therapies. They then applied a classifier built from the sample cohort to the remaining 19,884 patients to compare the derivation and validation clusters. Clustering analysis successfully identified six clinically-recognizable subgroups that differed significantly in all baseline characteristics and clinical trajectories, despite sharing common diagnoses. In the validation cohort, the proportion of patients assigned to each cluster was similar and demonstrated significant differences across clusters for all variables.

Method used:

In their clustering analysis they algorithmically placed similar patients into distinct subgroups so as to minimize within-cluster heterogeneity and maximize between-cluster separation.

They selected a random sample of 5,000 (20.1% of total)

And chose Sixteen of the 23 clinical features to use in the clustering analyses.

The clustering analysis was implemented on the sample over a pre-specified number of clusters, from 2 through 9. Based on the consensus clustering results, they chose to assess their surrogate validation measures on the putative cluster memberships with k=6 clusters.

The six identified clusters differed significantly in all patient and hospitalization characteristics, and exhibited highly distinct features that were clinically recognizable subgroups of ICU patients.

Enabling them to use machine learning methods to yield new insight into optimizing the delivery of safe and efficient care

Specifically, that sepsis was the most common admitting diagnosis across multiple clusters, yet their model subgroups displayed very different clinical needs and trajectories.

רשימת מקורות