Supporting Patient Nutrition in Critical Care Units

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Abstract.
Critical Care Unit (CCU) patients often benefit from being referred to dietitians for various reasons. This can help improve recovery time, resulting in more effective utilisation of valuable resources within the NHS (National Health Service) in the United Kingdom. However, said resources are often in high demand with scarce availability. Therefore, in this paper we propose an AI-based dashboard that can help clinicians automatically identify such patients, thereby reducing workload as well as cognitive load on clinical staff. We have trained various machine learning classifiers using various physiological measures of CCU patients and have identified a Support Vector Machine (SVC) classifier as the best performing model (AUC: 0.78). Our investigation shows promise results that significantly improve quality of patient care within the NHS. In future we intend to undertake more extensive evaluation of the dashboard developed as well as extend this work to paediatric patients.

Keywords: Critical Care Units, Patient Referrals, Clinical Decision Support, Supervised Classification, KNN.

1 Introduction

Critical Care Units (CCUs) are the sections of hospitals where severely ill patients are treated. Their importance has been widely appreciated during the current Covid-19 pandemic where millions of ill people were treated in such units across the globe [1]. The condition of each patient at admission to the unit and their potential recovery route will dictate requirements for appropriate nutrition. This will require relevant assessment by a qualified dietitian. An early referral to such a healthcare professional can have a positive impact on the patient's outlook, rate and quality of recovery [2].

There are differences in the dietary / nutritional requirements of patients depending on their health condition at admission to the unit. There are also considerable differences between the nutritional needs of adult and children patients. Critical Care Units employ smart beds that collect a lot of data about a patient. The significance of a lot of these data is lost either due to the way it recorded and stored, or due to the inability of being able to interrelate it with other data relating to a patient's health and using it to support effective decision making.

This work attempts to improve the situation by employing machine learning in analysing patient data and enhancing the speed and accuracy of prioritization of referring patients to dietitians in a Critical Care Unit, focusing on adult patients only. The authors present an early attempt in automating the referral process alleviating the burden on nursing staff who could be overwhelmed by the demand in patient care.

A number of supervised classification models were chosen for processing the patient data that was collected from different databases within the hospital and the NHS records systems and a comparative evaluation was performed. The challenge in collecting, collating and filtering the data is a major problem in the case of NHS (National Health System) in the United Kingdom as different hospitals may use different systems and the formatting of data storage is not always compatible across these [3]. Thus a lot of preparation work is required and this may raise challenges to the use of data supporting automated decision support for staff at the CCUs.

At the time of writing the Dashboard application presented here is being upgraded with further evaluation pending. The work is ongoing and further results are expected to be available over the next few months.

2 Problem Definition

Dietitians, as well as many other healthcare professionals, are in high demand among various other organizations and publicly funded hospitals often struggle to find such resources to staff their critical care units. At the same time they are important resources and their effective utilisation can support not just the quality of care of patients at hand, but the effective management of CCU beds which are at a premium [4].

With the advent of smart beds, a large number of physiological measurements are automatically collected for all patients under critical care in the CCU. This data is currently available to CCU staff, but due to cognitive overload, they often miss patients that require attention and there are no automated mechanisms in place to help them identify such patients.

Many patients are also sedated and need regular monitoring and external feeding. Furthermore, the data collected from patients is stored in many different places in the information system, and is often distributed across various information systems. An automated system that can automatically monitor and analyse patient data and flag patients that need referral and immediate attention by a dietitian, can significantly improve quality of patient care. Proper use of the data that is collected but not utilized to its full potential could prove a real catalyst in changing the quality of care that patients receive. Determining how routine clinical data collected in critical care units can be used to optimise patient outcomes, can lead to augmenting clinician decision-making and altering clinician behaviour to optimise patient clinical outcomes. Developing a system that can automatically screen CCU patients and prioritize the need to referral to a dietitian. Having alleviated the pressure of routine work on clinicians and dietitians could allow for further analysis of the collected data. With the aid of Machine Learning develop further interrelationships between health conditions, nutrition and its impact on health care and recovery.

3 Related Work

Critical Care Units (CCUs) are specific hospital wards where the sickest patients are admitted and where large amounts of detailed clinical data are collected (usually every hour) for the duration of the patient's stay. Many CCUs have moved from paper to clinical information systems to capture all this data from the patients' monitor, ventilator and other equipment such as drug infusions into a very extensive database. The data is captured using the facilities of smart beds that are utilized in CCUs gathering up to 200 different patient measurements. Gholami et al [5] though, have established that CCUs are not using such systems and this data to their advantage, with much of the data being captured not being analysed or used for maximal benefit. In an era of limited NHS resources, these digital resources have the potential to both optimise patient outcomes and make systems more efficient and effective.

Data analysis and machine learning have been explored on several research cases and have been utilised widely in health care and Critical Care Units. They are usually used to automate processes where problems are well known and fully defined and there the deliverables to efficiency and accuracy achieved are well within the expected levels [6, 7].

The goal for CCUs is to optimise the patients' survival, clinical outcomes and to reduce harm caused by therapies (iatrogenic harm). All critical care units have a number of recognised targets to improve outcomes such as maintaining an optimal level of sedation (not too high or low), maintain lung volumes delivered by the ventilator within a specific range to minimise lung injury and trying to deliver a minimum amount of nutrition to patients whilst they are critically ill. Yet these seemingly simple targets, are often not achieved. Nutritional practices have been long proven to have a direct relationship to clinical outcomes in patients in CCUs and particularly so in patients in the paediatric sections of CCUs [8].

Accessing data in effective and efficient way can contribute towards better utilization and leading to reaping the benefits of exploring it with machine learning algorithms. Although this has been identified as a priority and the United Kingdom has over the past few years made considerable plans and advances towards such a target, the status of patient and hospital records is such that still pauses a challenge for intelligent solutions [9].

4 An automation prototype

A prototype data dashboard was developed to demonstrate how an automated system could assist staff in screening patients, shown in Figure 1. The dashboard provides a quick overview to clinical staff about all patients in the CCU and at any time highlights those who need to see a dietitian. The dashboard shows the patient ID, and any relevant treatments that each patient is receiving, along with specialist feeding guidelines. Dietitian users of the system can filter patients accordingly, to prioritise seeing only those that are recommended for referral.

Patient prioritisation is based on an automated rule of thumb algorithm that staff nurses will have to apply manually and slowly over a range of data that could be confusing or could be interpreted inconsistently with fatigue building in during long shifts at intense working conditions. The data on the dashboard can be refreshed frequently during the day as new data can be captured from smart beds.

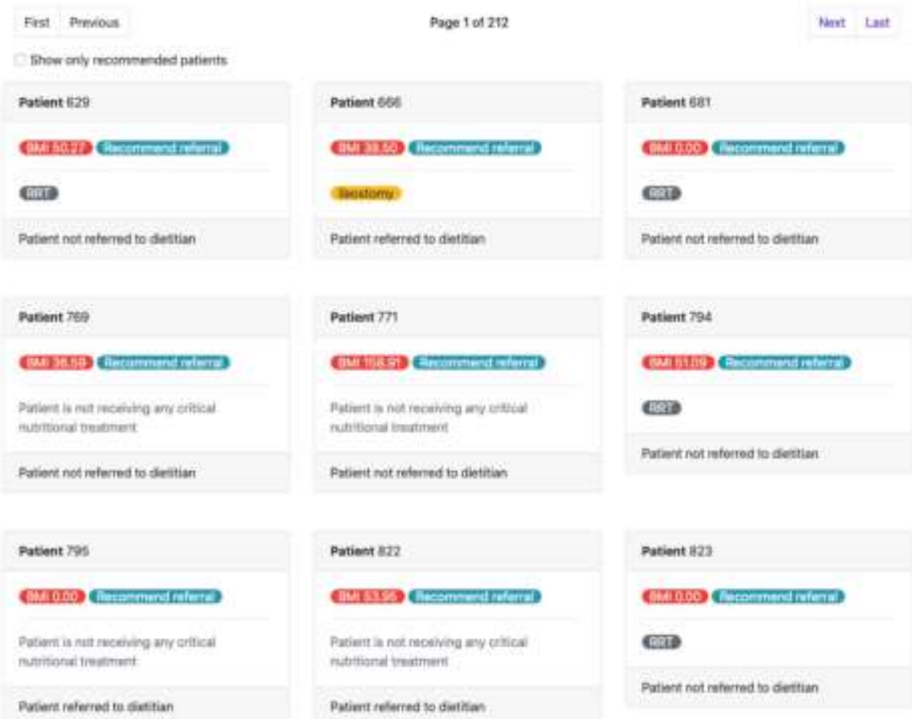


Fig. 1. Automated patient screening dashboard.

5 Applying Machine Learning

For Machine Learning purposes, the target variable was defined as a categorical variable indicating whether a patient should or should not be referred to a dietitian, thus formulating this as a classification problem.

5.1 Feature Extraction

The data in the hospital database is stored in a meta-model that is described elsewhere [2]. Treatments that patients receive as well as any interventions by clinical staff are recorded as *interventions*. Interventions in turn have *attributes*.

For example, when a patient receives parenteral feeding, a new intervention is created with attributes such as the volume of the feed, mix of solution being fed, time of feed etc. Interventions are linked to instances of patients being treated in the CCU by an *encounterID*. Every time a patient is admitted in the CCU, a new *encounterID* is assigned to the visit, which is linked to a unique *patientID*. Furthermore, each *encounterID* has an assessment form associated with it that contains free text data about the patient recorded by clinical staff. These forms include patient medical history at the time of admission. The first step in the ML process involved extracting features from this meta-model for further processing. To this end the data was first anonymised by removing the unique patient ID and replacing it with a pseudonymous number. The timestamps for the various interventions were also replaced by pseudo-dates to further anonymise the data. Relevant attributes for various interventions were extracted as separate features. For example, for parenteral feeding, the feed volume was extracted as a feature. All features were averaged by day. Table 1 shows all the features extracted.

Table 1. Features extracted from the hospital database.

Feature	Description
end tidal co2	CO_2 emitted at the end of an exhalation
feed vol	Volume of solution administered
feed vol adm	Volume of feed administered
fio2	The fraction of oxygen administered to patients on ventilators
fio2_ratio	PaO_2/FiO_2
Insp_time	The time taken to inhale air into the lungs
Oxygen_flow_rate	The rate at which oxygen is administered
Peep	Pressure in the lungs above atmospheric Pressure
Pip	Peak Inspiratory Pressure
resp rate	Spontaneous respiratory rate
Sip	Set Inspiratory Pressure
tidal vol Tidal Volume	Tidal Volume
tidal vol actual Actual Tidal Volume	Actual Tidal Volume
tidal vol kg Tidal Volume/KG	Tidal Volume/KG
tidal vol spon	Spontaneous Tidal Volume
Bmi	Body-Mass Index

5.2 Feature Engineering

The BMI of the patients was calculated from their height and weight and outliers as well as missing values were filtered as part of the cleaning process. Furthermore, if a patient's record contained a note from a dietitian, indicating that the patient had been referred to a dietitian, the corresponding target variable was set to 1, otherwise it was set to 0. This allowed the problem to be formulated as supervised classification problem. Missing values for included features were replaced with 0.

5.3 Model Training

Various supervised classification models were chosen for this step. Since the target classes were unbalanced in this case (80% non-referrals vs 20% referrals), the AUC rather than the overall accuracy was chosen as the performance metric. Based on hyperparameter tuning coupled with 10-fold cross validation, the best performing models for each algorithm were compared using the AUC. Training vs test sets were also compared (70/30 split) in order to check whether overfitting had occurred.

5.4 Evaluation

The models were evaluated using the Area Under the Curve (AUC). The performance of the models was evaluated using the test dataset and validated against the training dataset. Furthermore, sensitivity analysis was performed by imputing the missing values using a KNN Imputer and the results compared against the non-imputed datasets.

5.5 Results

Figure 2 shows the feature importance as determined by a Random Forest Classifier. Based on these results, four features were shortlisted; feed_vol, oxygen_flow_rate, resp_rate and bmi. Figure 3 shows the AUCs of the models when applied to the four short listed features, while Figure 4 shows the AUCs of the models when validated against the training data. The best performing model is a Random Forest Classifier with an AUC of 0.83. However, the results of the validation data show that it is likely overfit (AUC 0.87). Therefore, for practical purposes we consider the SVC to be the best performing model (AUCs 0.78).

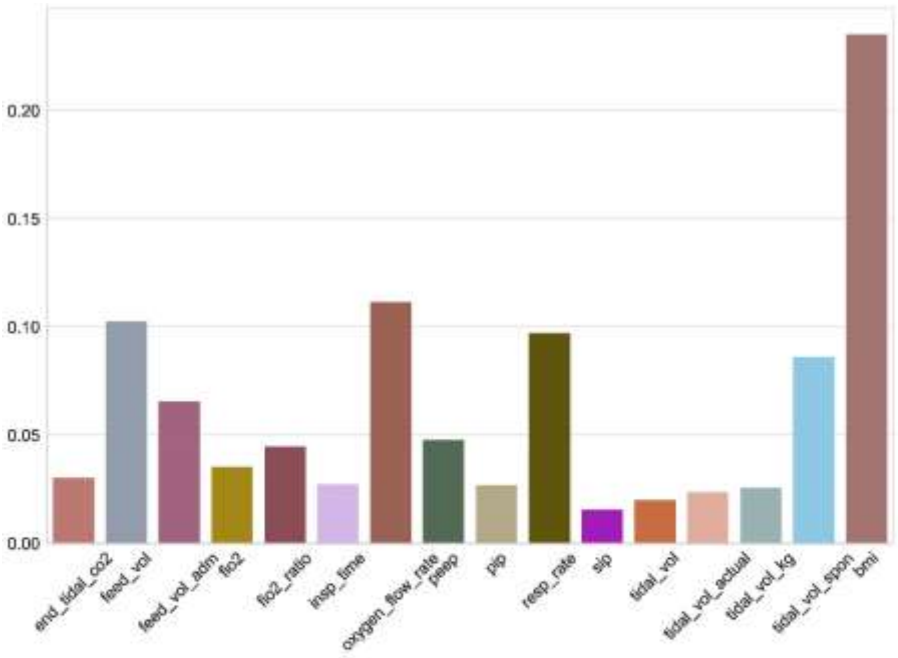
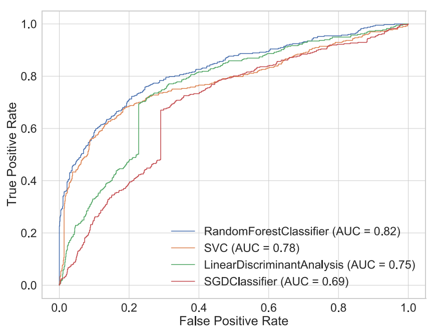


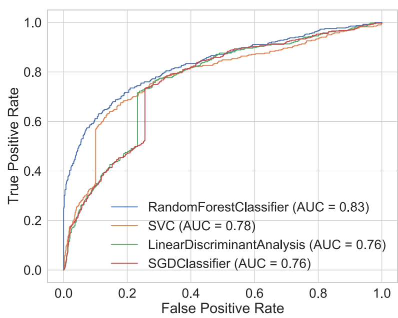
Fig. 2. Feature importance as returned by a Random Forest Classifier.

6 Sensitivity Analysis

A sensitivity analysis was also performed by filling in the missing values using a K-Nearest Neighbor algorithm to impute the missing values. The results of the training and validation sets are shown in Figures 3 and 4. The results clearly demonstrate the missing values do not demonstrably affect the resultant models, indicating that our models are robust. Table 2 shows the hyperparameters for the best performing classifiers.

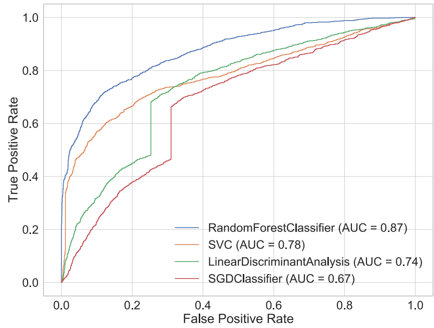


Against test dataset

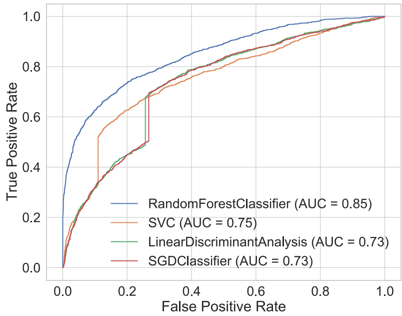


Against imputed test set

Fig. 3 AUCs of the various models at training



Against the training dataset.



Against the imputed training set

Fig. 4. AUCs of the various models at validation

Table 2. Parameters giving the best results for the various models.

Classifier	**Best parameters**
random forest	max depth: 7
svc	kernel: rbf
linear discriminant	solver: svd
sgd	alpha: 0.01, loss: modified_huber, penalty: l2

7 Discussion and Conclusions

Often patients admitted in CCUs would benefit from being attended by a dietitian. This can help improve recovery time as well as patient outcomes, resulting in more effective management of CCU beds which are often at a premium. Smart beds that monitor various patient physiological measurements allow automatic monitoring of patients, thus introducing the possibility of using AI-based solutions to automatically identify patients that would benefit from being referred to dietitians. This would also help reduce cognitive load on clinical staff as the various patient physiological measurements are often quite numerous and scattered across different elements of the system, making it difficult for the clinical staff to manually monitor the measurements.

To this end, we have developed a dashboard that allows clinicians to identify at a glance what patients should be referred to a dietitian. The dashboard uses an AI-based approach to identify the patients. We formulate the problem of referring patients to dietitians as a classification problem with the various patient physiological measurements as inputs to the classifiers. Our investigation shows that four measurements in particular; feed_vol, oxygen_flow_rate, resp_rate and bmi; are high predictors of the target variable. This finding is at odds with the established clinical guidelines issued by the NHS Trust and constitutes new information for clinicians. We also found that after experimenting with various classification algorithms, an SVC classifier performs the best (AUC: 0.78).

Future directions include transferring the learning from this project to paediatric patients as well as enhancing the dashboard and undertaking further evaluation of the models developed during this project.

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