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# MEDICAL DECISION SUPPORT SYSTEM WITH INTEGRATED MACHINE LEARNING FOR CLINICAL PREDICTION

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## ABSTRACT
Healthcare clinical decision-making is already impacted by forecasts or suggestions given by data-driven technologies. Numerous machine learning applications, particularly for outcome prediction models, have been reported in the most recent clinical literature. These outcomes range from death and cardiac arrest to acute renal damage and arrhythmia. In this article, we provide a framework that makes it possible to make medical decisions in the face of incomplete information. Ontology-based automated reasoning serves as its fundamental building block, and machine learning techniques are combined to improve the current working models of patient datasets in order to deal with the issue of missing data. In this review article, we summarize the state-of-the-art in related works covering data processing, inference, and model evaluation, in thecontext of outcome prediction models developed using data extracted from electronic health records. In short, we demonstrate the potential for machine learning to support a task where there is a critical need from medical professionals by coping with missing or noisy patient data and enabling the use of multiple medical datasets.
KEYWORDS: Machine Learning in medicine, Feature extraction and classification, Knowledge representation and reasoning.

## INTRODUCTION
Recent advances in artificial intelligence (AI) aim to have a positive influence on clinical practice and medicine [1]. With several successful applications in automated speech recognition, computer vision applications, and natural language processing, machine learning (ML), an application of AI, finds patterns in vast amounts of medical data to generate predictions about the future [2]. Applications of machine learning (ML) have found success in a number of medical fields, including disease prediction [3] using a variety of data modalities, such as speech signals and medical imaging [4], [5], and clinical outcome prediction to detect deterioration, such as cardiac arrest, mortality, or intensive care unit (ICU) admission [6]. This article's goal is to give a technological assessment of current studies on clinical outcome prediction models that highlight the many domains in which they have been used. Medical decision support systems (MDSS) map patient information to promising diagnostic and treatment paths. The value of such systems has been shown in various healthcare settings [7]. The properties of data, including representation,heterogeneity, availability andinteroperability play a critical role in ensuring the success of MDSS. A decision making process should use all relevant data from many distributed systems (instead of a single data source) to maximize its effectiveness, but real-world medical decisions are often based on incomplete information due to the challenges that appear when engaging in data synthesis if we seek to enforce these properties. Patient monitoring tools, such as early warning systems [8], are widespread across different hospital wards to continuously assess for patient deterioration. The definition of what exactly

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constitutesclinical deterioration has evolved over time based on the data collection and processing techniques. Early attempts to define clinical deterioration focused on medical neglect and its end result of clinical complications. Subsequent studies focused on more discrete clinical events, such as severe sepsis, unexpected cardiac arrest, ICU admission or mortality [9], and tend to select one or more end-point measures of clinical deterioration. Such events incur high costs of prolonged hospital stays, litigation, staff time, impact on patients and staff, and broader economic consequences [10].Our system leverages the benefits of machine learning, structured knowledge representation, and logic-based inference in a novel fashion. We demonstrate on real world data that it is capable of providingrobust, intelligent decision support, despite the complexity of medical relationships and the inter dependencies inherent in medical decisions.

## LITERATURE SURVEY

The framework of outcome prediction models also varies across the literature. Some studies predict the risk of an outcome only once using the patient"s first N hoursof data after admission, such as 24 or 48 hours. Others choose to predict the risk of an outcome, such as ICU readmission, usingthe patient"s last N hours of data prior to discharge. Another common methodology isto develop a real-time alerting score, which computes the risk of deterioration every timea set of clinical observations is collected [11], as in clinical early warning systems[12].

In order to validate our proposed framework, we created a proof of concept implementation focused around the knowledge management component and the query execution component from an existing ontological decision support system design [13]. We chose insomnia treatment as our line of inquiry, and used the following real-world datasets:

Patient records drawn from the Center for Disease Control (CDC) Behavioral Risk Factor Surveillance System (BRFSS) telephone survey. The BRFSS dataset contains a wide array of respondentinformation including age, race, sex, and geographic location, along with information about a wide range of common medical conditions like cancer, asthma, mental illness, and diabetes. Many behavioral risk factors including alcohol consumption, drug use, and sleep deprivation are also tracked. The dataset contains information on 450,000 individuals defining over 450 attributes for each individual. All of the data isnumerically coded and stored in a structured format similar to a relational database.

A prescription protocol drawn from the Mayo Clinic for use as expert decision making rules describing when to prescribe various sleep aids.

A drug interaction registry to identify drug-to-drug interactions.

Various types of data can be used to develop outcome prediction models, such as imaging, speech, or claims data [14]. Here, we focus on data extracted from electronic health records (EHR), which are beingincreasingly deployed in hospitals worldwide. EHRs are used in hospitals to store longitudinal information of patients collected in a care delivery setting. First, EHRs are complex as they may include structured and unstructured data; an exampleof the latter is textual information which could require natural language processing techniques to process [15]. Additionally, categorical data, such as diagnostic coding, may adopt different coding systems across different institutions.

## MACHINE LEARNING BASED ELECTRONIC HEALTH RECORDS

Knowledge management component: To instantiate the knowledge managementcomponent of the system design, we createda simplified ontology to define the relevant key concepts and their various relationships, shown in Figure 1. We created inference rules in accordance with the Behavioral Risk Factor Surveillance system (BRFSS) codebook which defined the semantics ofdifferent values for the data attributes,to

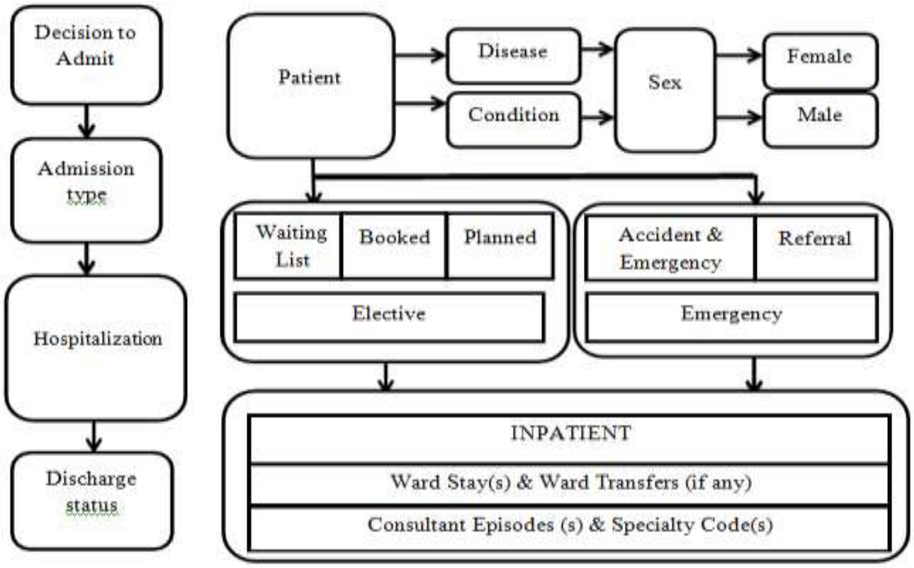


Fig.1 CHART FLOW FOR REPRESENTING THE ELECTRONIC RECORDS OF PATIENTSADMITTED IN HOSPITAL

transform the numerically coded BRFSS data records into corresponding instances of the „Patient" concept. These rules were then applied to all records to create a semantic knowledge-store of the BRFSS dataset.

Another important dimension is data completeness, which may be defined as "the proportion of observations that are actually recorded in the system". Incompleteness of EHRs can be a result of health service fragmentation due to inefficientcommunication following patient transfer among institutions; the recording of data taking place only during healthcare episodesthat correspond to illness, or the increased personalization of attributes per patient. Completeness may also vary acrossinstitutions based on adopted protocols.

Hand-crafted Features: Domain expertise is commonly used to provide guidance on the design of the data pre-processing pipeline. This involves

(i) Preliminary feature selection from the input space,

(ii) Designing hand-crafted features and

(iii) Incorporating prior knowledge of the structure of the data in the model design.

Data Standardization: ML algorithms require further data preparation steps to ensure stability of learning. Here, related works reduce the noise, scarcity and irregularity of the clinical data, as well as align the scales of the various predictor variables.

Time-Series Modeling: Time-seriesmodeling is widely used in studies pertaining to early warning models. It is often used either (i) to infer a pattern of the physiological trajectory or (ii) as an interpolation technique to overcome thesparsity and irregularity of physiological data.

Query Execution Component:Toinstantiate our query execution component, we combined a semantic reasoner called„Euler Proof Mechanism: EulerSharp with the WEKA machine learning toolkit. The semantic reasoner provided the main mechanism for logic-based decision making in the system, while WEKA acted in a supporting role to impute missing data.

Learning-based system: In order to assess the usefulness of our hybrid system over a purely learning-based system, we Those statistical methods mainly assess the performance of the model in terms ofaccuracy metrics.

Performance Metrics:Model discrimination refers to the model"s ability in separatingclasses of interest. In the context of outcomeprediction models, we will here refer to patients who experience an adverse outcomeas the positive class, and those who do not as the negative class. Many ML models are trained to compute the probability of the positive class, which is then converted to a binary value by fixing a decision threshold. The predictions are then compared to thetrue labels and can classify into one of four categories:

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**(1)** True Positives (TP):This modelcorrectly predicts the positive class.

**(2)** True Negatives (TN):Thismodelcorrectly predicts the negative class.

**(3)** False Positives (FP):Thismodelincorrectly predicts the positive class and

**(4)** False Negatives (FN):This model incorrectly predicts the negative class. Accuracy, which summarizes the proportion of correctly classified samples across all samples, is highly biased when using highlyimbalanced datasets. Therefore, other metrics are usually considered. Sensitivity, or the True Positive Rate (TPR), assesses the model‟s ability to correctly predict the positive class.

$$TPR = \frac{TP}{TP+FN} \qquad (1)$$

Began by evaluating the performance of four different machine learning algorithms

(decision stump, C4.5-R8, Bagging and AdaBoost) using the BRFSS dataset as follows. We generated 50 different

$$TNR = \frac{TN}{TN+FP} \qquad (2)$$

Specificity, also known as the True Negative Rate (TNR), assesses the model‟s ability to correctly predict the negative class. 2,500 exemplars and 5,000 exemplars, and used an information gain-based feature selection algorithm to reduce each set to its 30 most informative attributes.

RESULTS

The performance of supervised outcome prediction models on the testing set is evaluated using various statistical methods.The receiving operator characteristic (ROC) curve plots the TPR on the vertical axis and (1-TNR), also known as the False Positive Rate (FPR), on the horizontal axis. The integral under the curve is the Area underthe Receiving Operator Characteristic Curve (AUROC). The AUROC assesses the model‟s overall diagnostic ability as the decision threshold is varied. Precision, also known as the Positive Predictive Value (PPV), assesses the proportion of correctly predicted positive class across all of the true positive class. analysis. The progress of the field relies on increased multidisciplinary collaborationsbetween ML research scientists and clinicians.

While it will take time for both parties to speak the same language, we hopethat this review would demystify the overall The Precision-Recall curve, where recall is essentially sensitivity, plots the TPR on the horizontal axis and the Precision on the vertical axis and integrates the area under the curve. The integral under the curve is theArea under Precision-Recall Curve(AUPRC).

The following graph represents the accuracyand F1 score of the proposed machine learning based EHR system was developed which gives efficient and accurate resultswhen compared with other methods. The efficiency of the proposed method is represented with the help of followingdiagram which is shown in Fig.2 below

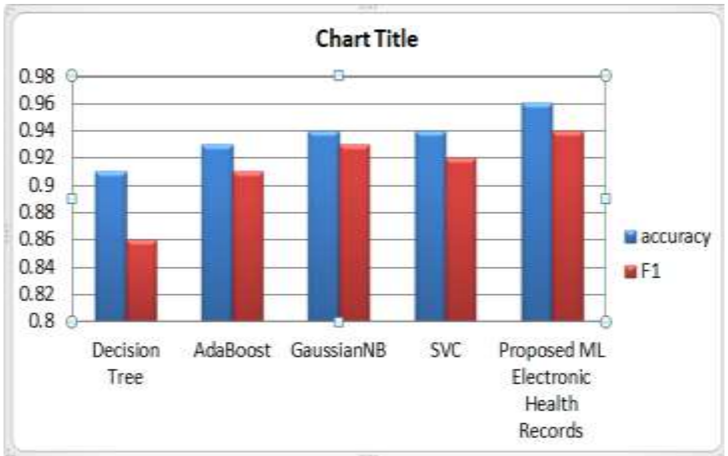


Fig.2: COMPARISON GRAPH ON PROPOSEDML BASED EHR SYSTEM FOR STORING MEDICAL DATA

**CONCLUSION**

The prediction of clinical outcomes is essential to detect deterioration in a timely manner and to reduce the burden of clinical staff. The development of the ML pipelines and their subsequent performance can alsobe improved by accounting for a few considerations.While recently developed ML models perform well within retrospective studies, validating their success in practice requires prospective ML pipeline and summarize the assumptionsand techniques of the state-of-the-art.

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