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Medical Workflow Design and Planning Using Node-RED Data Fusion

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Abstract

The space of clinical planning requires a complex arrangement of information, often not capable of being captured in a singular dataset. As a result, data fusion techniques can be used to combine multiple data sources as a method of enriching data to mimic and compliment the nature of clinical planning. These techniques are capable of aiding healthcare providers to produce higher quality clinical plans and better progression monitoring techniques. Clinical planning and monitoring are important facets of healthcare which are essential to improving the prognosis and quality of life of patients with chronic and debilitating conditions such as COPD. To exemplify this concept, we utilize a Node-Red-based clinical planning and monitoring tool that combines data fusion techniques using the JDL Model for data fusion and a domain specific language which features a self-organizing abstract syntax tree.

Keywords:

Medical Informatics, Biomedical Technology, Information Technology.

Introduction

All physicians and healthcare providers are required to participate in clinical planning either collaboratively or on their own. Clinical planning involves using diagnostic and other medically relevant information about a patient to discern a set of tests or medications to order, or instructions the patient must follow to aid in a diagnosis or improve their overall health. As a result, the process of clinical planning is a very mentally strenuous task that involves a large number of decisions to be made based on the information at hand. In addition to the mere step of planning a course of action for a patient, there are many administrative and procedural tasks to enact this plan required by a hospital or clinic to ensure the safety of patients and physicians in this process. These extra steps can add more strain on the healthcare provider, which can eventually result in poorer decision making as a result of physician burnout [1]. While many technological systems have attempted to counteract this, most have greatly contributed to this phenomenon of physician burnout [1]. While research has been done to try to explain why these systems are ill-fitted for clinical planning is the section where the authors introduce their work.

It is important to discuss that a contributing factor of frustration surrounding existing healthcare software often comes from a discrepancy between how physicians process information and perform their clinical workflows, and how the software systems function. Data fusion, a series of techniques utilised to combine a multitude of datasets for processing, however, more closely mimics how human's make decision due to the integration of multiple sources of information [13]. As a result, data fusion techniques has the capacity to provide a more well-rounded set of data which, in combination with the appropriate infrastructure, has the potential to address the existing software frustrations in healthcare.

Methods

Introduction

To provide an effective data fusion-based medical planning platform, it is important to incorporate a few enabling techniques to allow the platform to provide clinical inferences including prognosis. We are proposing a new methodology that captures the semantic context of clinical cases through the use of a domain specific language (DSL) that describes these cases and is used to guide, monitor, and infer the progression of the clinical cases through the linkage to dynamically evolving patient data that are updated from different sources including repositories over the cloud or sensors that are hooked to the patient(s). Additionally, our method, and later, the platform, need to be designed to be useful and meaningful to physicians and clinicians following the progress of these clinical cases. To show the effectiveness of our methodology, we decided to focus on Chronic Obstructive Pulmonary Disease (COPD) as it is a progressive type of chronic disease which can get worse over time. However, COPD is treatable with proper management and planning, as most patients with COPD can achieve good symptom control and quality of life, as well as reduced risk of other associated conditions (e.g. heart disease, lung cancer).

A Survey of Data Fusion Methodologies

To develop our methodology, we surveyed data fusion models, as well as other methodologies related to data fusion and DSLs. Firstly, we needed to select an appropriate data fusion model with which to base our methodology. The main data fusion models we can utilize to create our methodology are the Dasarathy Classification, the Waterfall Model, the Omnibus Model, the Boyd Control Loop, and the JDL Model. To describe each model in short, the Waterfall Model [9], the Boyd Control Loop [6], and the Omnibus Model [5] are each concerned with the flow of data during the data fusion process. The Waterfall Model follows data in a linear fashion through 3 levels, starting with raw data, moving through to feature extraction and feature fusion, and finishing with incorporating the data with human interaction to produce possible results. The Boyd Control Loop processes the data more circularly through four separate phases that may start again based on the outcome of the fourth phase. A derivation of the Boyd Control Loop, the Omnibus Model, works similarly but involves some modifications to each of the processes followed by the four stages.

In contrast to these three models, the Dasarathy Classification [8] and the JDL Model [7] work by performing refinement and fusion tasks based on different levels of data. An important aspect of the JDL Model is that each stage has the ability to refer back to previous stages for further refinement before producing output, something not present in the other fusion models. This is significant due to the nature of healthcare and clinical planning, where data is often dynamic and new data may affect the interpretation of previous data, resulting in a need for each stage of refinement and fusion capable of being interrupted or revisited at any time.

When discussing existing methodologies, we can refer to Yu Zheng's review methodology of cross-domain data fusion which discusses the different types of data fusion, as well as their strengths and weaknesses. Zheng discusses stage-based data fusion, which involves the loose coupling of datasets, feature-level-based data fusion, which involves the concatenation of each dataset, and semantic meaning-based data fusion, which involves focusing on the meaning of each feature while relating each dataset to each other [2]. The general conclusion that Zheng makes among the discussion of these types of data fusion is that semantic meaning-based data fusion often provides the most powerful form of data fusion, it often suffers from performance issues or discrepancies among dynamic and static datasets. As a result, despite the semantic meaning-based data fusion providing the most powerful relationships between datasets, we will use feature-level-based data fusion to avoid the negative aspects of semantic meaning-based data fusion.

The next resource utilized in the foundation of our methodology is Sarvesh Rawat and Surabhi Rawat's hybrid methodology for multi-sensor data fusion. It is described in this methodology that rough sets act to discover ambiguity and remove redundancy from datasets while performing data fusion [3]. These rough sets act as feature reduction and a pre-processing layer which allows for higher accuracy when used in conjunction with backpropagation neural networks. As a result of these findings, it is clear that a pre-processing layer acts to strengthen the data fusion process, and provide better results. In place of rough sets, however, we opted to utilize a DSL.

Due to the dynamic nature of the JDL model, our DSL must also be dynamic and capable of providing updates to the end user as their workflows progress. In order to provide a DSL capable of performing these tasks, we are using a self-organizing abstract syntax tree [4]. By utilizing a self-organizing abstract syntax tree we are able to best optimize the data fusion workflows and interactions with the users via the DSL.

Lastly, to be able to adequately support a methodology that impacts workflow-based procedures and tasks, the implementation of the methodology is reliant on a workflow-based platform. Examples of these types of platforms include n8n.io, Verj.io, TACTIC, and Node-Red. While all of these platforms feature flow-based programming, which is essential for a workflow-based software, Node-Red provides the most robust integrations with other platforms, such as MySQL, AWS, and Google. Node-Red can also make use of JavaScript and Python, which is not nearly as seamlessly integrated among other flow-based programming platforms.

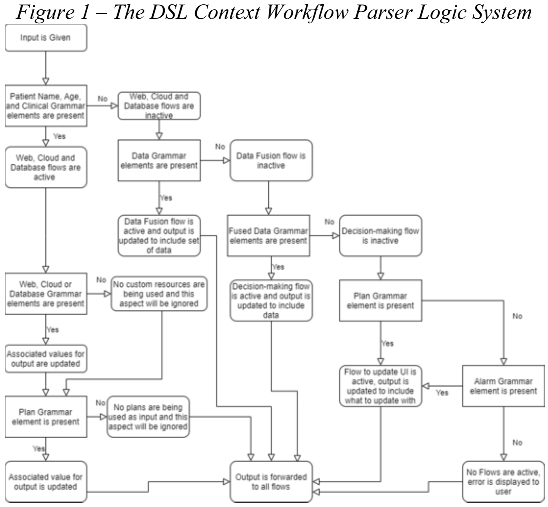
The DSL Implementation

It has been discussed that a pre-processing step is necessary for improving the outcomes of data fusion techniques. Our pre-processing step, the DSL, incorporates syntax that allows users to identify important patient information directly (such as symptoms described by the patient during an appointment or intake in an emergency room), incorporate data sources such as integration with lab reports or their EMR that may be located in a database, the cloud, or on a website, as well configure as custom alerts based on a patient's status for monitoring. Most notably, users are able to define a set of rules to guide any data fusion tasks by using a series of observations and results. Observations act as potential data points that may be observed before undergoing fusion, such as tachycardia. Healthcare providers may define a list of observations that must be present in order for that rule to be triggered. Results are the following actions that are noted in the clinical plan, such as ordering a medication or a lab test. Similar to observations, any number of results may be defined for each rule.

The DSL makes use of two systems: the DSL Context Workflow Parser, exemplified in Figure 1, and the Data Fusion Interpreter shown in Figure 2. The first system, the DSL Context Workflow Parser, ensures that the appropriate actions are being undertaken based on the syntax that is present and the current moment. For example, if a dataset, or multiple datasets are received, the system is able to proceed with data fusion tasks, however, if these elements are not present, data fusion will not occur.

The second of these systems, the Data Fusion Interpreter, ensures that the different tasks and procedures performed by the system are capable of being enacted or revisited based on different system inputs, whether that be input directly from the user or coming from within the system itself. This is a direct implementation of the interaction data processing and fusion tasks are required to undergo while utilizing the JDL model.

Figure 1 – The DSL Context Workflow Parser Logic System



The Data Fusion Implementation

The most important aspect of this tool, data fusion, is what allows the tool to provide feedback and clinical plans to the users. The data fusion process makes use of all provided sources of data, as well as the user-defined DSL rules to be able to create the resulting clinical plan.

Due to the fact that we are using feature-level-based data fusion, we are taking each dataset and concatenating them into one cohesive dataset. Despite having one singular dataset at this stage, we still must utilize our DSL rules to properly refine the data. This is done by creating a NxM binary one-hot encoded matrix where N is the number of rules, and M is the number of results given by the DSL. For each rule, if all the necessary observations are present in the dataset obtained by concatenation, then the associated results are represented by a

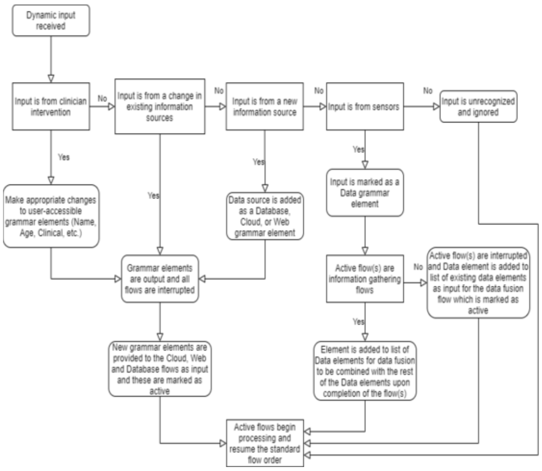


Figure 2 – The Data Fusion Interpreter Logic System

1 in the appropriate row and column. For example, if a rule requires the observation of low blood oxygenation, and the result is an order of pure oxygen, the column representative of pure oxygen will have a row for that rule. This will proceed for each rule. This process is shown in Figure 3.

Data = [Hypoxiema, Anemia, Oxygen]

Relationship = [Hypoxemia, Oxygen]

Binary One-hot Encoded Matrix:

$$\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

Figure 3 – Result Definition via DSL Rules

There is also the presence of negative results that have the ability to negate a relationship between a given rule and its results. An example of such a negative relationship exists between a penicillin allergy and an order for Amoxicillin. This rule would include the negative result for Amoxicillin, and when encountered in the processing stage, any instance of a 1 under the amoxicillin column will become a 0. After all rules have been appropriately applied to the data, the remaining results will be displayed to the user as the clinical plan.

Results

To demonstrate the efficacy of the proposed data fusion-based clinical planning and monitoring tool, we have implemented three care pathways as DSL rules to provide examples of different use-cases. As we have focused our domain on COPD, the first implementation followed the Alberta Health Services COPD Pathway [10]. The pathway is described using the DSL syntax in Figure 4. In this scenario we are describing a patient who is presenting with tachycardia, hypertension, anemia, fluid in the lungs, increased coughing, and sputum. As a result of these symptoms gathered via a variety of data sources, the following recommended clinical plan output by the system can be seen in Figure 5.

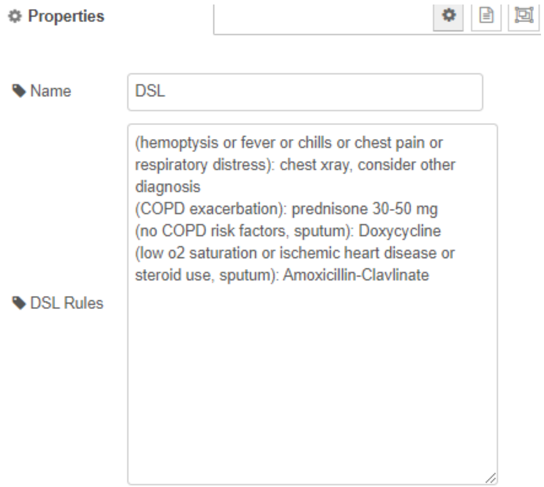


Figure 4 – The COPD Pathway Rule Syntax

Similarly, we have utilized the Lung Health Foundation's Adult Emergency Department Asthma Care Pathway [11], due to the fact that COPD and Asthma are often interrelated illnesses. A representation of this pathway utilizing the system's DSL syntax can be found in Figure 6. The resulting clinical plan of a patient who presents with moderate asthma, low blood oxygenation, and tachycardia is shown in Figure 7.

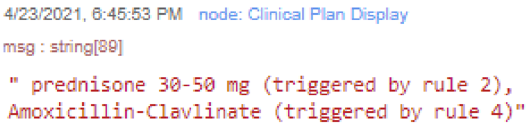


Figure 5 – The COPD Patient's Clinical Plan

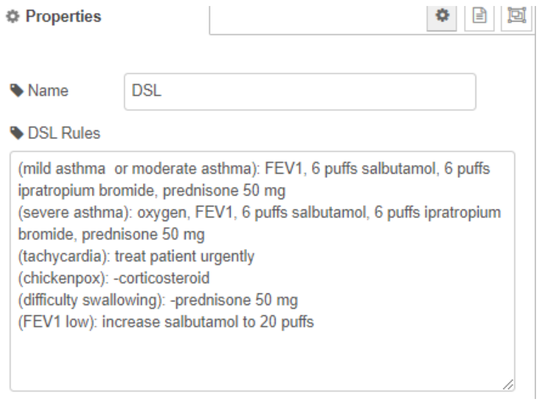


Figure 6 – The Asthma Pathway Rule Syntax

The last example we will discuss is the Connecticut Children's Community Acquired Pneumonia pathway [12] seen in Figure

8. Figure 9 displays the clinical plan for a patient's initial admission workup who is presenting with empyema and penicillin allergy.

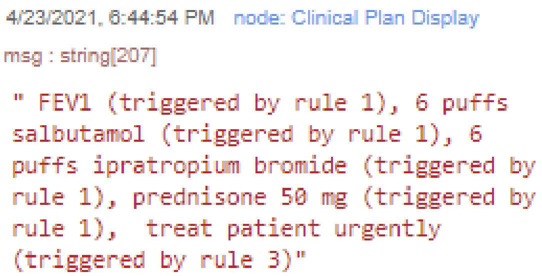


Figure 7 – The Asthma patient's Clinical Plan

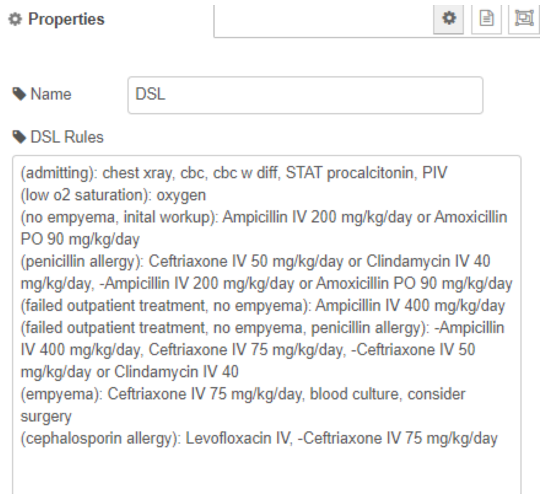


Figure 8 – The Pneumonia Pathway Rule Syntax

Discussion

While the discussed tool is primarily being applied to the care of patients diagnosed with COPD, it is possible to expand this methodology to adequately provide clinical planning capabilities for other diagnoses. This can be done by extrapolating related care pathways available for these diagnoses, or consulting with multiple physicians and hospital administrators capable of the important rules the DSL will enact within the tool.

It is also important to acknowledge future work that will be required to support the integration of hospital or clinic-based data sources to be utilized as part of the fusion process. Interoperability between sensors, EMR/EHR records, lab reports, and other important data sources is a challenging task that has not been discussed as part of this methodology, however, is essential to the process of development of the tool for use among healthcare providers.

We also acknowledge that, while feature-level-based fusion provides an adequate method of fusion for the presented purposes, there is the potential for exploration into other fusion types. Most notably, there may be important discussion into the effects semantic meaning-based fusion may have on this methodology, and what improvements may be made by doing so.

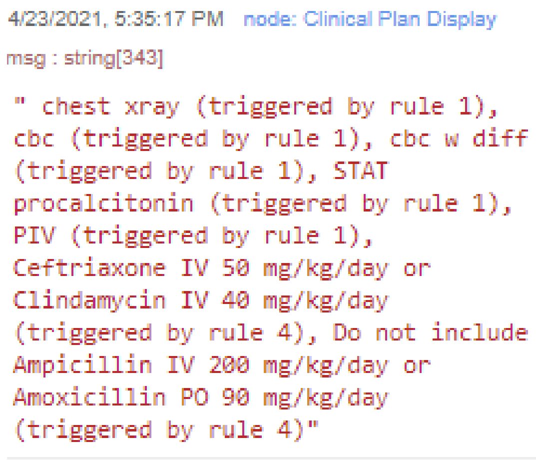


Figure 9 – The Pneumonia Patient's Clinical Plan

Conclusions

During the clinical planning and monitoring processes, healthcare providers are required to make use of a variety of vital information sources to adequately make informed decisions about their patients. A failure to have access to all of these sources in a reasonable manner, either directly as the healthcare provider or via software, can result in poorer clinical plans. To overcome these difficulties, we have proposed a data fusion-based tool that has the capacity to incorporate all relevant data sources in order to allow for fully-informed decisions to be made in the process of providing a clinical plan or monitoring a patient. This proposed tool makes use of feature-level-based data fusion and a DSL with an self-organizing abstract syntax tree for preprocessing.

Implemented in Node-Red with a combination of Python and Javascript prgramming, the data fusion tool has the capacity to combine a variety of data sources that are essential to clinical planning and monitoring (patient vital sensors, EMR/EHR, lab reports, etc.). These data sources are pre-processed by the user-defined DSL rules, and, based on these rules, have the ability to provide a suggested clinical plan based on all of the provided information. The effectiveness of this tool is demonstrated by implementing COPD, Asthma, and Pneumonia care pathways as DSL rules which are adequately able to provide clinical plans as a result of the data fusion process.

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