An Annotation Driven Rule-based Algorithm for Suggesting Multiple 12-lead ECG Interpretations

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Abstract

The 12-lead Electrocardiogram (ECG) is ubiquitously used as a diagnostic support tool to detect cardiovascular disease. However, it is difficult to read and is often incorrectly interpreted. This study aims to further previous research, which used of a set of interactive questions and prompts to guide an interpreter through the ECG reporting process. The model was named 'Interactive Progressive based ECG Interpretation' (IPI). In this study, the IPI model has been augmented with an automatic diagnoses suggestion tool following annotated analysis of an ECG. To accomplish this, a rule-based algorithm has been created to assess the interpreters' ECG annotations to each of the interactive questions in the IPI model. This Differential Diagnoses Algorithm (DDA) was implemented using web technologies such as JavaScript and uses a modern device agnostic and language independent storage format (JSON) for defining the rules. Hence, by augmenting the IPI model with the DDA we hypothesize that this will further lower the number of interpretation errors and increase diagnostic accuracy in ECG interpretation.

1. Introduction

Cardiovascular Disease (CVD) is regarded as a substantial economic and medical burden around the world [1], [2]. To help combat this, diagnostic tools such as the Electrocardiogram (ECG) have been implemented to help a clinician detect cardiac abnormalities. As cardiac abnormalities are often manifested in the ECG, it is an important tool for non-invasive assessment of patients' cardiac health. Due to the prevalence and severity of CVD it is vital to enhance the ECG in the upcoming digitisation process [3], thus enabling accurate and efficient treatment.

Although the ECG is at the forefront of detecting cardiac abnormalities, it is frequently incorrectly interpreted with up to 33% of ECG interpretations containing errors of significant importance [4]. Expert clinicians are also known to act impulsively and offer ECG diagnoses originating from first impressions or intuition

[5], [6][7]. Typically an ECG is printed on graph paper and presented to an interpreter in a 3x4 grid format with each cell representing one of the 12 ECG leads [8]. This can also be accompanied by an extension of Lead II to help assess cardiac rhythm (3x4 + 1R). This presentation of ECG signals can deliver significant cognitive load [9], thereby contributing to the depletion of an interpreters' cognitive thinking ability. Therefore, to help alleviate this cognitive workload and to decrease diagnostic time, this format of ECG presentation is often supplemented by computer analysis, often presenting the interpreter with an automatically generated ECG interpretation and diagnosis.

Routinely, computerised ECG diagnostics is composed of four main steps; 1) Signal pre-processing, 2) QRS detection, 3) feature extraction and 4) signal classification [10]. Computerised analysis of severe cardiac conditions such as Acute Myocardial Infarction (40.7% error rate) and upper degree AV blocks (75% error rate) are often inaccurate [11]. Many previous investigations into computerised ECG diagnostics corroborate and indicate the unreliability of computerised diagnoses, which can lead to both improper use of medical resources and adverse patient treatment planning [12]–[15]. Therefore, computerised ECG interpretation should always be overread by a clinician, especially in non-sinus rhythms [16].

Furthermore, since current computerised ECG interpretation often only provides a single diagnosis, it can contribute to a number of cognitive biases, (1) anchoring bias (fixation on a premature suggestion/answer/diagnosis/interpretation), (2) confirmation bias (seeking features/annotations to confirm rather than falsify a diagnosis) or (3) premature closure (acceptance of a diagnosis before verification) [17], [18].

To combat these concerns and to provide a de-biasing strategy [19]–[21], a decision support algorithm has been developed to provide multiple potential ECG diagnoses. Presenting multiple possible interpretations, is likely to encourage a differential diagnosis. Moreover, since the algorithm is semi-automatic and is based on features (annotations) inputted by the human interpreter, we hypothesis that the algorithm may have greater accuracy when compared to conventional computer ECG diagnostics. This is due to conventional algorithms

focusing on automatically extracted features from signals that are often noisy and difficult to process [16].

2. Model design

The IPI model has been described in the authors' previous paper [22]. The model de-contructs 12-lead ECG interpretation into five sub-components each consisting of structured questions presented over five sequential web-based user-interfaces. The model's segments are as follows; Segment 1: Interpretation of the rhythm strip, Segment 2: Interpretation of the P-wave morphology, Segment 3: Interpretation of the limb leads, Segment 4: Interpretation of the QRS morphology, Segment 5: Review the full 12-lead ECG to assess R wave progression and lead misplacement.

Following assessment of all ECG reporting components for all five segments, Segment 5 was augmented with the Differential Diagnoses Algorithm (DDA), wherein a set of potential ECG diagnoses is presented to an interpreter based on their own annotations having analysed the ECG. To encourage a differential diagnosis, the list of potential ECG diagnoses is accompanied with diagnostic criteria. After considering these diagnoses, this segment requires a conclusive interpretation to be provided by the interpreter.

3. Model implementation

The DDA was developed using emerging web technologies to allow the best possible user experiences and to facilitate use ubiquitously across devices and platforms. Hypertext Mark-up Language version 5 (HTML5) was implemented to present and structure webpages across various web browsers, while Cascading Style Sheets (CSS3) was used to create an engaging user The programming language of the web, JavaScript, along with the subsidiary JQuery library, was used to allow interactive participation from interpreters. This was implemented via reactive animations when collecting or presenting data, or interpreter annotations. All data and interpreter annotations are collected via toggling buttons or sliding range inputs. All data is saved to a MySQL database through the implementation of Asynchronous JavaScript and XML (AJAX) and the Hypertext Pre-processing language (PHP).

JavaScript Object Notation (JSON) was chosen to store ECG Rule criteria for the DDA. JSON was selected as the preferred storage format due to it being a lightweight data-interchange format. Although it uses the JavaScript syntax it is also a language independent data structure, and therefore could be integrated directly in both the server-side and client-side elements of a system [23]. If semantically annotated, structured JSON data is also a self-describing human-readable data format. i.e. both human and machine interpreters can read/interpret a dataset and

identify that the document contains information referring to an ECG [24]. JavaScript was used to implement the rule-based algorithm, which collects interpreter annotations and uses the JSON criteria to match these annotations against a possible diagnosis. The algorithm searches, filters and returns potential ECG diagnoses from the ECG criteria JSON data object. These results are then rendered onto segment 5 of the IPI system through adding HTML5 elements using the jQuery 'append()' method in real-time.

4. Methodology



Figure 1. Example presentation of potential ECG diagnoses before an interpreter is expected to provide a final diagnosis for each ECG in the study. This figure also illustrates how an interpreter can present the suggestions based on most criteria matches, prevalence in society or severity of diagnosis

A rule-based algorithm is continuously executed upon each response to a question to produce automatic diagnostic suggestions. The algorithm first performs annotation validation and formatting. Subsequently, the algorithm conducts searches on a JSON data object file for ECG diagnostic criteria in order to presented any matches to an interpreter's current set of annotations. It then returns a list of ECG names arranged by the frequency of matches between interpreter annotations and recognised ECG criterion.

Upon toggling a button or sliding a range input, the algorithm is invoked and the following series of events

occur; 1) a variable is created and assigned the annotation value from the button press or range input 2) an array is created for each variable which is populated later in the process 3) once these declarations have been made, a request to load data from a JSON file stored on a webserver is made 3a) The request searches the data file for ECG diagnostic criteria matching the assigned variables at each given stage of interpretation, 3b) once matching criteria has been identified the name of the ECG with matching criterion is deposited in the relevant variable arrays which were previously declared, 4) each array is then deposited inside a master array. 5) To enable a presentation of ECG names based on frequency of matching criterion unique ECG names were indexed and counted. This arrangement was stored in a key-value paired JavaScript object with the ECG name as the key and a count of the frequency of criterion matches as the value. 6) The JavaScript object is then sorted based on the frequency value and deposited into an ordered array. 7) Each value in this array is then outputted into an HTML list item and rendered onto Segment 5 of the IPI sequence in the interpreter's browser. Pseudo-code can be seen for this process in Algorithm 1.

Differential diagnosis

If an interpreter requires more information about a suggested diagnosis, provisions have been enabled. When an interpreter selects a diagnosis from the list of suggested diagnoses, a list of diagnostic criteria is displayed for that item. To achieve this a number of steps took place; 1) A check is performed to determine if the criteria is currently displayed or hidden. 2a) If the criteria are currently hidden;

- A request to load data from the same JSON data file is made. This algorithm searches the data file for an ECG name which corresponds to the selected suggested diagnosis.
- ii) If a match is discovered, each criterion from the selected ECG is returned
- iii) The criteria are then displayed in an unordered HTML list below the selected suggested diagnosis, on the interpreter's browser.

2b) If the criteria are currently displayed;

- i) The criteria are hidden
- ii) The criteria are then removed from the webpage

We believe this DDA algorithm provides a supplement of multiple potential diagnoses and could reduce cognitive biases during diagnosis. The list of suggested diagnoses with relative criteria, facilitates differential diagnosis by an interpreter based on the interpreter's ECG annotations. Thus, this is an optimal man-machine model for ECG interpretation since the human is better at recognising patterns and shapes in noisy signals whereas the machine is better at reasoning based on a large set of rules.

The suggestion algorithm also provides the opportunity for

self-validation and can in addition act as a safety mechanism to help catch missed co-abnormalities.

Algorithm 1. Pseudo-code illustrating the algorithm used to generate and present multiple potential ECG diagnoses based on an interpreter's annotations.

JSON structure

The JSON data file was created in a format to allow a semantically structured information hierarchy. Other eXtensible Markup Language (XML) data structures have been created in this way to store ECG datasets (ecgML[25], ecgRuleML[26] and XML-BSPM [27]). Each dataset contains an ID, ECG diagnosis name, ECG diagnosis grouping, a list of diagnostic criteria and references.

5. Conclusion

We believe that there is potential to reduce inaccuracies, and the oversight of co-abnormalities during ECG interpretation by using the IPI model in combination with the DDA algorithm, which provides a set of potential diagnoses for an interpreter to consider. We hypothesize that this model will lower the number of interpretation errors and increase diagnostic accuracy in ECG interpretation.

6. Further research

An enhancement to the proposed algorithm could be achieved through an interactive presentation of the final suggested which have been ordered by specific ECG criteria weighting. This could allow presentation based on each of the matched criterion's degree of importance in each specific ECG diagnosis.

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