Fuzzy Expert System for Type 2 Diabetes Mellitus (T2DM) Management Using Dual Inference Mechanism

Nonso Nnamoko, MSc; Farath Arshad, PhD; David England, PhD; Prof. Jiten Vora
School of Computing and Mathematical Science, Liverpool John Moores University, United Kingdom.
N.A.Nnamoko@2011.ljmu.ac.uk

Abstract
Fuzzy logic is an important technique for modeling uncertainty in expert systems (i.e., in cases where inferencing of conclusion from given evidence is difficult to ascertain). This paper proposes a fuzzy expert system framework that combines case-based and rule-based reasoning effectively to produce a usable tool for Type 2 Diabetes Mellitus (T2DM) management. The major targets are on combined therapies (i.e., lifestyle and pharmacologic), and the recognition of management data dynamics (trends) during reasoning. The Knowledge base (KB) is constructed using fuzzified input values which are subsequently defuzzified after reasoning, to produce crisp outputs to patients in the form of low-risk advice. The extended framework features a combined reasoning approach for simplified output in the form of decision support for clinicians. With seven operational input variables and two additional pre-set variables for testing, the results of the proposed work will be compared with other methods using similarity to expert’s decision as metrics.

Introduction
Diabetes Mellitus (DM) is a chronic condition marked by elevated levels of blood glucose. It is estimated to affect over 4.5% of the UK population and; current reports show this is likely to increase with the ageing population and a rise in obesity (Diabetes UK 2012). DM occurs when the level of blood glucose is raised because the body cannot use it properly. DM usually cannot be cured but can be managed by controlling blood glucose. Poorly managed, it can lead to serious long-term complications, and increases the risk of cardiovascular disease. Generally high quality DM support and management is inherently a costly, complex, labor-intensive and time consuming task; involving the analysis of an array of ambiguous datasets collected through support from health professionals alongside informal carers and patients efforts. With this in mind, healthcare service projections for the 21st century have taken a radical new dimension with more emphasis on Out of Hospital Care, and a strong participatory component from patients; especially in long-term and lifestyle related conditions such as DM. Since the focus is now on the provision of services closer to patients’ home, (Arshad and Dabhi 2009) people living with diabetes are faced daily with numerous challenges in managing their condition. Also the onus is now on healthcare providers to deliver services effectively. As a result, healthcare providers have increasingly sought to utilize the advantages that may be possible through information and communications technologies to meet the complexity of needs surrounding this multifaceted condition.

Like other lifelong conditions, treatment for T2DM management involves not only medications but also growing evidence, which has identified lifestyle adjustments as the key factor to delay progression to, and/or prevent other long-term complications (Gillies et al. 2007)(Herman et al. 2009)(The Diabetes Prevention Program Research Group 2012)(Diabetes Prevention Program Outcomes Study Research Group 2011). However, due to the controversial nature of lifestyle measures, its integration with pharmacologic therapy into intelligent management systems has received little attention in this domain. In the context of T2DM management, age, gender, body mass index (BMI), blood glucose (BG) levels, blood pressure (BP) levels, caloric diet and intensity of physical activity are the main risk factors to consider. The outcome of each of these factors directly or indirectly depends on one or more of the other(s) and, the overall reaction determine management outcomes. These factors are dynamic and T2DM management guidelines are general in nature, requiring personalisation to achieve better outcomes. Such an uncertainty is a strong challenge to approaches which use expert systems, particularly at the stage of inferencing/reasoning. Numerous research efforts have
tried to capture this variability using various concepts (mostly machine-learning (ML) classification algorithms), each with their limitations but fuzzy logic provides a much easier solution to dealing with uncertainties.

This paper aims to model an intelligent system capable of providing low-risk advice to patients in real time as well as support for therapeutic adjustments to medical practitioners, using the above mentioned risk factors as markers/determinants. Motivated by concepts from earlier researches, the proposed framework draws and translates knowledge from a diverse array of domains, (including artificial intelligence (AI), biomedical engineering and medicine) into a fuzzy inference mechanism using MATLAB. The fuzzy logic approach is intended to reduce the classification complexities of similar patterns which may exist between individuals requiring different healthcare paths.

**Background Research**

In the context of intelligent tool developments, AI researchers have prototyped a number of proactive tools (Montani et al. 2003)(Duke et al. 2008) for T2DM management. However, it is fair to say that such tools are very few in number. The majority of these tools focus on support for clinicians and only a few have been commercialised. One example of such tools is the DiaTrends, developed by Overlook software to help clinicians make informed therapeutic decisions in patient management (demo system available online at http://overlooksoftware.com/). Further research conducted with regards to the methodology of designs show that most developments have adopted case-based reasoning (CBR) only for the knowledge base system (KBS) development (Montani et al. 2003)(Duke et al. 2008). This is mainly due to their focus on decision support for clinicians who are faced daily with data overload; and is in part due to its success in managing other chronic illnesses (Bichindaritz and Marling 2006)(Bichindaritz 2008). From this viewpoint, CBR has proved successful in the subject domain in recent years by simply structuring real cases into problems, solutions and outcomes based on an expert’s problem detection strategies. However, issues still remain on how to utilize available data to produce direct support to patients.

Research into direct intelligent support for patients has received very little attention so far, because DM management guidelines are general in nature, require personalisation and involves various complementary management algorithms. Development of a single management algorithm, which combines essential elements of these individual algorithms effectively, is a great challenge for AI researchers. Also, the classification complexity of similar patterns which may exist between individuals requiring different care pathways becomes an even greater challenge. Examination of the literature related to modeling and classification applications in this domain revealed very little results. Among these, (Marling et al. 2008) Marling et al. applied rule-based routines to a case base to provide decision support, but this was only aimed at clinicians. No usable tool was found that has the ability to combine all lifestyle measures (diet and exercise) with other glycemic control determinants (blood pressure (BP), age and gender) to provide real-time support for patients. In addition, there is no definitive metric for generalized classification of these determinants within the AI community as yet. While the Glycemic Index Web Simulator (GIGISim) (Bulka et al. 2000)(Koleszynska 2007) and AIDA v4 (Lehmann and Deutsch 1992) holds huge promises, their capabilities excludes some vital markers such as exercise and BP measures.

**Proposed System**

This section describes the proposed framework and outlines research progress so far. Information regarding datasets and the selection criteria are highlighted. Figure 1 shows a high level contextual diagram of the proposed model. Our major contribution will focus on phase 1, particularly the “Assessment module” with highlights to possible methodology to achieve functionality in other modules.

![Figure 1: High level contextual diagram of proposed framework](image)

**Dataset**

Ideally, the database should contain over 40 essential parameters and attributes for DM management but...
publications concerning expert system development within this domain mostly utilise a subset of just 9 variables, namely; age, sex, BMI – weight & height, BG, BP (systolic), caloric diet, A1c, medical complications and medication. The framework presented in this paper will be based on these parameters.

Method
Given the dynamic nature of the parameters and the possibility of incomplete information, it is unlikely that inferencing of conclusions from available evidence will be exact. However, our approach using fuzzy logic holds a great deal of promises. Fuzzy logic has been successfully applied in other domains to solve uncertainty in expert systems (Altrock 1996), so effort in our research will utilise the advantages that may be possible through this technique. In addition, research shows that fuzzy logic techniques perform better than ML in classifying uncertain cases (Cintra et al. 2005). Our approach looks to improve classification results obtained through ML methods.

First we determine the input and output parameters. For this system, 9 input variables have been selected for inclusion in the reasoning to produce outputs in the form of recommendations. Then, the fuzzification of input values for inferencing. This involves classification – In the form of membership functions (MF), of each variable to provide meaningful criteria for the rule development (Siler and Buckley 2005). In determining MFs, information samples were first collected through research and consultation with a group of experts. These were further analysed by exploring 3 selection techniques (exemplification, direct rating and polling) (Bilgic and Turksen 1999), to obtain the best values. Further classification results have been obtained through clustering and we intend to optimise the ranges by applying fuzzy logic to determine the degree of membership of points in the search space of each cluster. In this paper, two functions (triangular & trapezoidal) were adopted for membership in the fuzzy values as shown in (1) & (2) respectively.

\[
\mu(x) = \begin{cases} 
0, & x \leq a \\
\frac{x-a}{b-a}, & a \leq x \leq b \\
\frac{c-x}{c-b}, & b \leq x \leq c \\
0, & c \leq x
\end{cases} \quad \ldots \ldots (1)
\]

\[
\mu(x) = \begin{cases} 
0, & x \leq a \\
\frac{x-a}{b-a}, & a \leq x \leq b \\
1, & b \leq x \leq c \\
\frac{d-x}{d-c}, & c \leq x \leq d \\
0, & d \leq x
\end{cases} \quad \ldots \ldots (2)
\]

Below is an example of deduced classification and MFs for BP (systolic):

**Systolic Blood Pressure**

Naturally, this parameter exhibits dynamic behavior, and even instantaneous values are inherently imprecise, so we divided this variable into 4 fuzzy sets: “Low”, “Medium”, “High” and “Very-high”. The MFs of “Low” and “Very-high” sets are trapezoidal while that of “Medium” and “High” sets are triangular. Table 1 and Figure 2 below depict the fuzzy set classifications and graphical representation of the MFs respectively. The fuzzy membership expressions are shown in (3).

<table>
<thead>
<tr>
<th>Input variable</th>
<th>Range</th>
<th>Fuzzy Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systolic Blood Pressure</td>
<td>127 – 153</td>
<td>Medium</td>
</tr>
<tr>
<td></td>
<td>142 – 172</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>154 &gt;</td>
<td>Very-high</td>
</tr>
</tbody>
</table>

**Table 1: Classification of systolic blood pressure**

![Figure 2: Membership functions of Systolic Blood Pressure](image)

\[
\mu_{Low}(x) = \begin{cases} 
1, & x \leq 111 \\
\frac{134 - x}{23}, & 111 \leq x \leq 134
\end{cases}
\]

\[
\mu_{med}(x) = \begin{cases} 
1, & x = 139 \\
\frac{153 - x}{14}, & 139 \leq x \leq 153 \\
\frac{142 - x}{15}, & 142 \leq x \leq 157 \\
1, & x = 157 \\
\frac{172 - x}{15}, & 157 \leq x \leq 172 \\
\frac{17 - x}{17}, & 174 \leq x \leq 171 \\
1, & 171 \leq x
\end{cases}
\]

The same principle applies to each of the selected input variables mentioned earlier. Efforts are in progress to develop an integrated management algorithm using elements of the various DM management algorithms with close links to the selected variables. This involves the building of a rule base (Assessment module) that links the selected variables in accordance with guidelines from the
various DM management algorithms. This provides low-risk advice to patients. An extended feature of the framework (phase 2) will be automated problem detection, similar to Marling’s contribution to 4DSS (Marling et al. 2008), to provide therapeutic adjustment recommendations for clinicians. The case base holds BG control problems structured according to expert’s (clinician) problem-detection strategies, while the segmented database provides a central data repository for the Assessment module. Further work will be carried out on the generation of usable metric for the integrated management algorithm.

**Results & Conclusion**

Identified input variables and their Membership functions have been defined and tested for guidelines compliance. Results will lead to further testing against classification ranges obtained through clustering as well as real expert’s (clinician) recommendations. Laboratory experiments so far reveal relationships between essential elements of the various DM management algorithms is achievable and efforts are in progress to define usable metrics for classifying the parameters highlighted earlier in this paper. The potentials of fuzzy logic for dealing with uncertainty looks sufficiently promising to reduce the classification complexities of similar patterns, which may exist between individuals requiring different healthcare pathways. Thus, the need for personalisation could be reduced through this concept. Also, the combined reasoning approach will help filter results for presentation to clinicians who are faced daily with enormous amount of patient management data. Bridging the gap between lifestyle and pharmacologic therapy through intelligent systems holds huge promise in DM management towards better outcomes.

**Acknowledgement**

We would like to thank the Royal Liverpool & Broadgreen University NHS Hospitals Trust (RLBUHT) and the Faculty of Technology & Environment at Liverpool John Moores University for providing full funding for this PhD research. Professor Jiten Vora, consultant in Diabetes and Endocrinology at RLBUHT provides clinical supervision for this work.

**References**

