Novel logistic regression models to aid the diagnosis of dementia

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1. Introduction

Diagnoses of the common dementias of old age are operationally defined on the basis of different symptoms and neuropsychological profiles; in this process, clinicians use various sources of evidence in the reasoning process, which include evidence-based clinical guidelines, often supplemented by individual consultations (Scottish Intercollegiate Guidelines Network, 2006).

General practitioners play a pivotal role in establishing diagnosis of dementia and in providing ongoing support and intervention. Nonetheless, substantial literature (Cahill et al., 2008; Turner et al., 2004) shows their difficulties in fulfilling this role, especially for early detection of dementia. Since one of the reasons for this is the lack of readily available diagnostic instruments (Hansen, Hughes, Routley, & Robinson, 2008), efforts have been made to explore different screening measurements and methods: in recent years, clinical decision support systems have emerged which are growing rapidly and their trustworthiness is improving (Garg et al., 2005).

Different models have been proposed to provide decision support for the diagnosis of dementia. An application of Support Vector Machines (SVMs) has been studied by Klöppel et al. (2008): the study compared a fully automated computer-based diagnosis system for dementia pathologies using neuroimages with the diagnostic classification made by six radiologists with different levels of experience. Three different datasets were considered for comparative analysis between SVMs and radiologists; in the first two sets, the task was to detect sporadic Alzheimer’s disease: SVMs correctly classified 95% of the cases versus the 65–95% of radiologists in the first set while in the second set SVMs showed an accuracy of 93% compared to the 80–90% scored by radiologists. Finally, the SVM was asked to separate patients with sporadic Alzheimer’s disease from those with fronto-temporal lobar degeneration: SVMs scored an accuracy of 89% versus the 63–83% of radiologists. These results are not directly comparable with the model object of the present study (whose aim is the diagnosis of generic dementia), but they do demonstrate the potential of machine learning techniques applied to this medical domain (often outperforming specialists’ predictions), showing also that no prior knowledge is required to be included in the model in order to construct a good prediction tool.

Another study (Prince et al., 2008) built a computer-based model which could provide a dementia diagnosis according to DSM-IV criteria (American Psychiatric Association, 1994) and to the 10/66 dementia survey (Prince et al., 2007) in order to make a comparison between them. While the DSM-IV criteria are regarded as a gold-standard and used as a benchmark, the 10/66 dementia diagnostic algorithm takes into account a structured clinical mental state interview, a cognitive test battery, different informant interviews,
a neurological assessment and a questionnaire to detect behav-
ioral and psychological symptoms: the results from this screening
tests are then used to make a prediction on dementia diagnosis by
means of a logistic regression equation previously developed in a
pilot study. The tool has shown a sensitivity of 57.8% and a specific-
ity of 98.3% using the implementation of the DSM-IV criteria; a sen-
sitivity of 93.2% and a specificity of 96.8% was recorded using the
10/66 criteria. Although the very different number and type of col-
clected variables prevent us from a comparison with the results of
the present study (where a limited number of variables is col-
lected), however, this application shows that a model based on lo-
gistic regression (and so without a prior built-in knowledge) could
outperform the gold-standard guidelines.

A novel application (called DemNet) of Bayesian belief networks
(BBN) to provide medical decision support for the diagnosis of
dementia in primary care practice has been recently proposed by
Oteniya, Coles, and Cowie (2005); this was built as a “hand-crafted”
model, since it relies on domain experts’ knowledge. A BBN is a rep-
resentation of complex domains that are characterised by uncertainty
which enables inference of future uncertain events based on prior
related known events. More formally (Jensen, 2001) a BBN includes a set of nodes (or vertices) that represent the domain
variables, a set of directed edges which represent dependency rela-
tionships between the variables and a set of local probability tables,
one table per variable, which quantitatively encodes the strength of
each dependency relation. Standard benchmarks have shown that
good results are achieved in the diagnosis of dementia using BBN.
The developed model was implemented in a software system de-
digned to be used by clinical practice nurses involved in the primary
level assessment of patients suspected of having dementia; in an at-
tempt to optimise user friendliness and utility in a busy primary
care setting, the model sought to use numerically few parameters
which are consistent with a reasonably high diagnostic accuracy
(Cowie, Oteniya, & Coles, 2006).

The setting of this last application is quite agile (given the small
amount of information required to make a prediction) when com-
pared with the previously cited studies. However, they required
both technical expertise and domain experts’ knowledge for build-
ing the more sophisticated and complex Bayesian belief network
model. The present study builds on this previous research and the
aim of this study is to investigate whether a novel model can be
constructed that can outperform the considered benchmark
hand-crafted model. Consequently, a performance improvement
is expected using the same dataset and a common set of perfor-
ance metrics. A general framework for testing and possibly
improving such models is also implicitly presented.

The remainder of this paper is organized as follows: research
methods are described in Section 2, results are presented in Section
3, discussion and conclusions follow in Section 4 and 5 respectively.

2. Methods

2.1. Study sample

The collection of data has been carried out as part of previous
research (Oteniya, 2008): 164 patient records from clinical practice
were obtained from the Community Mental Health Team Elderly
(CMHTE), Kildean Hospital, Stirling. A clinical protocol detailing
the data requirements was developed and the necessary gover-
nance process was followed. Local Ethical Research Council ap-
proval was granted. Community Psychiatric Nurses (CPNs) from
CMHTE agreed to collect the data, as it aligned with the diagnostic
variables that they recorded during initial assessment of patients
where dementia was suspected. Each completed record consisted
of the CPNs initial assessment, as well as the actual diagnosis pro-
vided by a CMHTE diagnosing physician. It is worth noting that the
data regarding 50 out of 164 patients were not fully provided: at
least one value from collected variables was missing; when techni-
cally possible, records with missing data will be used in this study.

2.2. Collected variables

A set of 14 parameters has been evaluated within the consid-
ered sample of patients: specifically, 3 variables from standard
tests (Mini-Mental State Examination, Hachinski Ischemic Score
and Clock Drawing Test), 8 qualitative variables (investigating
the ability to carry out personal and domestic activities of daily liv-
ing, the current and subtle functioning, the global severity and the
possible presence of psychosis, memory impairment or tremors) and
3 variables about patients’ clinical condition and history (age
of each patient, duration of symptoms and whether they experi-
ced a clear progression in symptoms) were collected.

Collected variables from standard test are:

- Cognitive impairment (CI), which represents the result of the
  Mini-Mental State Examination (MMSE), used for detection of
  dementia in individuals with suspected cognitive impairment
  (Petersen et al., 2001), measured as the ratio between the score
  of the test and the maximum attainable score.
- Clock drawing test (CDT), which is used combined with the
  result of MMSE in screening for mild dementia (Brodaty &
  Moore, 1997); the result of the test is mapped as a dummy var-
  iable which states if the patient could successfully complete the
  test or not.
- Hachinski Ischemic Score (HI), which is generally used to dis-
  criminate Alzheimer’s disease from vascular dementia (Mor-
  ney et al., 1997); the result of the test has been normalized
  between 0 and 1.

Qualitative variables which have been collected are:

- Domestic activities of daily living (DADL), which reflects the
  individual’s ability to carry out activities such as shopping,
  housekeeping, finance management, food preparation and
  transportation.
- Personal activities of daily living (PADL), which reflects the in-
  dividual’s ability to carry out activities such as dressing, eating,
  ambulating and hygiene.
- Current functioning (CF), which reflects the individual’s ability
to function in daily life aggregating PADL and DADL.
- Subtle functioning (SF), which captures evidence of subtle
  changes in cognition such as progressive difficulty in balancing
  a cheque book.
- Global severity (GS), which represents the global severity of
  impairment; aggregates CF, CI and SF.

Each of these five variables has been mapped with two dummy
variables, the first one showing if at least a mild impairment was
present (adding the suffix “m” to the variable name) and the sec-
ond one stating if a severe impairment was present (adding the
suffix “s”). The other recorded qualitative variables are:

- Psychosis (PS), which captures non-cognitive symptoms associ-
  ated with dementia such as impaired connection to reality,
  auditory or visual hallucinations and delusions; the variable is
  mapped with two dummy variables: the first one showing if
  symptoms are at least equivocal (PSe) and the second one stat-
  ing if they are definitely present (PsP).
- Memory impairment (MI), which records the possible presence
  of memory impairment (dummy variable).
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